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Dissertation

Testing Weak-Form Market Efficiency of Developing Markets: Evidence from the Baltic Stock Exchange

"This dissertation is submitted in part requirement for the Degree of MSc in Money, Banking and Finance at the University of St Andrews, Scotland. I declare that this Dissertation is 10,000 words in length. I have read and fully understand the University Code on Academic Misconduct. I hereby declare that the attached piece of work is my own. It is written in my own words and I have acknowledged all of the sources that I have drawn upon"

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Dissertation Summary

This dissertation tries to provide and extensive study of Baltic Stock Markets by using the Efficient Market Hypothesis approach. There are four most influential Baltic Stock Market indexes analyzed for evaluation of market efficiency in Estonia, Latvia and Lithuania. The study uses two research methods– statistical and technical. Statistical approach is used to search for predictability patterns in time series via different testing methodology applied on daily returns. The methods used in statistical approach are: unit root tests, variance ratio tests, Kolmogorov-Smirnov goodness of fit test, runs test, autocorrelations tests, and cointegration and Granger causality indicators. A further approach of technical analysis is used to check whether existing predictability, if found, could be profitably exploited within the simple trading rule approach. The double moving average trading strategy is employed in order to indicate if any additional information could be used to predict future asset prices. In such a way, both methods are testing whether random walk model is rejected for Baltic stock markets and what is the level of efficiency they are operating in. The period of analysis cover more than 12 years of daily data, which is divided into two periods of transitional and post-crisis period. Logical intuition suggests that markets are less efficient in transitional season, and rather more stable and better structured in the second term of their functioning. According to the past empirical research, Lithuanian, Latvian and Estonian markets are not entirely efficient in any period of time. However, the level of relative weak-form efficiency is found to be different across the markets. Prior to estimation of empirical results author predicted all equity markets being equally inefficient subject to information absorption, however, examination proved assumption to be incorrect. Fundamental analysis provided significant inference of random walk hypothesis validity in each stock index series, without significant contradictions between different testing procedures. Statistical approach contributed to return predictability disclosure and technical analysis provided capacity for this correlation to be exploited.

1 Introduction

Financial markets are greatly important in country's economy due to many reasons. They create liquidity, improve international trade, accumulate wealth of investors and help economic agents to make more accurate forecasts of future development in financial industry. (Blake, 2004) It is widely accepted that large and developed financial markets are more efficient by means of their thickness in trading, competent liquidity, low transaction costs, and quick absorption of new information. Conversely, emerging and less developed markets are assumed to be relatively thinner, less liquid and actually much less responsive in the context of informational change. When financial market is considered to be inefficient, there have to be some patterns in asset movements which might become foreseen.

In the time of stock markets analysis, researchers create theories and methods in order to prove or contradict returns predictability. Fama (1970) updated the theory of randomness in stock markets and decided to divide market efficiency into three forms: weak, semi-strong and strong. All three forms testify market being efficient but in different levels of information. Less developed and emerging markets are suitable only for weak-form market efficiency investigation because of the lack of sufficient information to assess semi-strong and strong form of efficiency.

Among the empirical evidences, studies are usually divided into two parts: fundamental research and technical analysis. Statistical approach uses a variety of parametric and non-parametric tests to capture serial correlations in return series. If there are significant autocorrelations in time series, present returns are likely to be dependent across their lagged values therefore leading to the rejection of random walk hypothesis. Whenever statistical dependence of returns is found, technical analyses are employed to see if returns' predictability can be exploited as a profit making strategy. Non-parametric tests and trading rules have been employed into studies from early 20th century when Roberts (1959), Cowles (1960) and Alexander (1961) analyzed sequences and possible trends within returns. Fama (1965) concluded in his first analysis that no indication of dependence between price changes was found from runs tests. Further research by Sweeney (1986), Fama and Blume (1966), Hudson (1995), Brock (1992) revealed that trading rules might be informative and useful for profiteering only with respect to some limitations, such as transaction and operational costs.

This paper is split into 7 parts. Chapter 2 provides a brief history of developing Baltic Stock Markets and the empirical evidences that have already been performed on these countries in the former decade. Considering the literature of academic papers and books there is a little research done on these financial markets in contrast of other Eastern and Western European countries. This might be explained by a rather short history of financial markets in this region, as countries are still recovering after the Soviet occupation. Despite the short history of Baltic Exchange, last decade exhibits convincing improvements and noticeable innovations in the environment and structure of financial markets. Chapter 2 also presents theoretical background of Random Walk Hypothesis (RWH) and Efficient Market Hypothesis (EMH), and how these theories are related.

Chapter 3 gives comprehensive literature review and emphasizes relevant ideas for this dissertation – an essential part for the comparison of empirical work with other studies in this research fields. Chapter 4 introduces reader to financial data and clarifies its reliability. There are particular specifications on data cutting into two sub-sample periods, which should provide significant insights on changing stock index performance in each country. Descriptive analysis of dataset is also provided at this stage.

Chapter 5 introduces the empirical framework which will be used for quantitative research and hypothesis will be proposed. Fundamental analysis part is considerably larger and mostly important, thus it will be divided into three unnamed parts. Initially it will be started with non-parametric section where two tests of Runs and Kolmogorov-Smirnov will be performed and interpreted. The following section will contain Univariate analysis of time series of stock indexes, including tests of autocorrelations, unit root and variance ratio. The most significant patterns of return similarities were found for Estonian and Lithuanian equity markets during the full sample, apart from Latvian market, which rejected RWH in the transition period but appeared to be martingale in the second sub-period. Further, several multivariate analyses will be performed in order to see how statistical variables are interrelated together and Granger caused by one another.

Chapter 6 analyses technical analysis of pat papers and empirical evidences on validity of trading rules. Demonstration of double moving average trading rule will be performed and interpreted for four Baltic Stock market indexes. The implications on significance of trading rule will be provided in methodology and estimations' sub-sections.

Finally, chapter 7 gives the overall study conclusion with the discussion on how the methodology of the study might be improved by using different data or analytical approach.

2 Historical and Theoretical Background

2.1 Baltic Market Environment

Estonia, Latvia and Lithuania stock markets have fairly brief history compared to developed equity markets in Europe. The initial establishment of Tallinn Stock Exchange in Estonia, Riga Stock Exchange in Latvia and Vilnius Stock Exchange in Lithuania eventuated in 1920, 1926 and 1937 respectively. Shortly these exchanges were closed at the beginning of the Second World War and only in the late 1990s - after collapse of the Soviet Union - Baltic Stock Exchange resumed its operations. The first to open was Vilnius Stock exchange in 1993, followed by Latvian and Estonian stock markets in 1995. Once markets opened they were thin, poorly structured and rather inefficient. During the period 2002-2004 the Baltic stock markets emerged as a part of the OMX Group, which owns and operates exchanges in the Nordic countries. In 2007, NASDQ acquired the OMX Group, creating the world's biggest exchange company, the NASDAQ OMX Group. This acquisition was useful for Baltic States as it created stable trading system with harmonized rules and market practices, which made Baltic region more attractive to investors. The Baltic Stock Exchange has a common list with all Baltic companies divided into four different segments, such as: Baltic Main List, Baltic Secondary List, Baltic Funds List and Baltic Bonds List. The system builds liquidity and better conditions for foreign investors who encourage Baltic financial markets to move into higher development zone.

Baltic markets are classified according to income levels, with highest earnings settled in Estonia and upper-middle income obtainable in Latvia and Lithuania. Despite the increasing level of development of Baltic States they are still ranked as frontier stock markets[1] because of small size.

Listed domestic companies, total

Country Name	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011
Estonia	14.0	14.0	13.0	15.0	16.0	18.0	18.0	16.0	15.0	15.0
Latvia	62.0	56.0	39.0	45.0	40.0	41.0	35.0	33.0	33.0	32.0
Lithuania	51.0	48.0	43.0	43.0	44.0	40.0	41.0	40.0	39.0	33.0

Market capitalization of listed companies (% of GDP)

Country Name	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011
Estonia	33.2	38.5	51.6	25.1	35.5	27.5	8.2	13.8	12.0	7.3
Latvia	7.7	10.2	12.0	15.8	13.6	10.8	4.8	7.0	5.2	3.8
Lithuania	10.3	18.9	28.7	31.5	33.9	25.9	7.7	12.1	15.6	9.5
Baltic	51.2	67.6	92.3	72.4	82.9	64.2	20.6	33.0	32.8	20.6

[1] Special subset of emerging markets in the S&P classification of the stock markets

Table[2] above provides a summary of the stock markets characteristics of Estonia, Latvia and Lithuania according to subsequent indicators of: number of listed companies, market capitalization, total value of traded stocks, and net inflows of foreign direct investment. Market capitalization of the Baltic Stock Exchange accounts to 6.76 billion US dollars for the end of December 2011. The biggest stock market is Lithuania, appraising for 60% of the region's market capitalization (4.08 billion US dollars). The numbers have significantly decreased after financial crisis of 2007-2008. Baltic markets show some recovery in 2009, unfortunately, followed by another downturn in 2011.

Market capitalization of listed companies (current billions US$)

Country Name	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011
Estonia	2.4	3.8	6.2	3.5	6.0	6.0	2.0	2.7	2.3	1.6
Latvia	0.7	1.1	1.7	2.5	2.7	3.1	1.6	1.8	1.3	1.1
Lithuania	1.5	3.5	6.5	8.2	10.2	10.1	3.6	4.5	5.7	4.1
Baltic	4.6	8.4	14.3	14.2	18.9	19.3	7.2	9.0	9.2	6.8

Stocks traded, total value (current billions US$)

Country Name	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011
Estonia	0.2	0.6	0.8	2.5	1.0	2.1	0.8	0.4	0.3	0.2
Latvia	0.1	0.1	0.1	0.1	0.1	0.1	0.0	0.0	0.0	0.1
Lithuania	0.2	0.2	0.5	0.7	2.1	1.0	0.5	0.3	0.3	0.2

Foreign direct investment, net inflows (BoP, current US$ billions)

Country Name	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011
Estonia	0.3	0.9	1.0	2.9	1.8	2.7	1.7	1.9	1.5	0.2
Latvia	0.3	0.3	0.6	0.7	1.7	2.3	1.4	0.1	0.4	1.6
Lithuania	0.7	0.2	0.8	1.0	1.8	2.0	2.0	0.0	0.7	1.2

The next table of traded stocks indicator demonstrates Latvia being extensively behind in the amount of traded stocks. This points thin trading in the market with minimum level of volume across all Baltic States. Regardless of the former fact, foreign direct investment is the highest in Latvia stock market reaching 1,56 billion of US dollars, while Estonian market barely approaches to 0.18 billion. Looking at the last three columns of the table it is clear that markets have improved their foreign investment situation and have recovered after the hit of financial crisis.

As reported by market capitalization measure, Estonia was far ahead from Latvia and Lithuania before 2004. After 2004 Lithuania and Estonia are competing with almost the same domination. The period of crisis 2007-2008 has significantly lowered market capitalization relatively to GDP. To sum up, all three markets experienced raise and decline in financial sector during the last 10 years but they managed to survive and recover even after most severe recessions.

[2] Figures in this chapter are taken from World Bank webpage (http://data.worldbank.org/)

2.2 Theory of Random Walk Hypothesis and Market Efficiency

Original idea of Efficient Market Hypothesis (EMH) was fully formulated by Eugene Fama in 1970. His dominant paper "Efficient Capital Markets: A review of Theory and Empirical Work" stated, that efficient market prices fully reflect all available information and represent the future price of the stock. If the current price is not the best predictor of future price, there might be an opportunity for investor to earn abnormal returns by using adequate strategies. Fama (1991) distinguished three types of efficiency depending on the assumption made on the available information set:

- *Weak-form* efficiency-holds if information contained in former prices is incorporated into the market prices;
- *Semi-strong form* efficiency-holds if publicly available information is incorporated into prices;
- *Strong-form* efficiency-holds if all information known to any market participant is incorporated into market prices.

In order to form empirically testable implications of the EMH, there should be specified the set of available information and the process of price formation. Within the framework of expected returns, the state that yields equilibrium continuously compounded rates of return is equilibrium state. (Granger, 1970) As expected returns are measured with respect to the observable risk of the security conditioned on a relevant information set, it is important to measure the risk of the associated security correctly. (Campbell, 1997) Expected price of a stock at time t+1 is defined by Fama as follows:

$$E\left(P_{j,t+1}|\Phi_t\right) = \left[1 + E\left(r_{j,t+1}|\Phi_t\right)\right]P_{j,t}$$

Where *E* is the expected value operator, $P_{j,t}$ is the price of security *j* at time t; $P_{j,t+1}$ is its price at t+1 (with reinvestment of any intermediate cash income from security), $r_{j,t+1}$ is the one period percentage return ($P_{j,t+1}$ - $P_{j,t}$)/ $P_{j,t}$; Φ_t is a general symbol for whatever set of information is assumed to fully reflect in price at *t*.

The conditional expectation notation is meant to imply that whatever expected return model is, the information in Φ_t is completely reflected in the formation of $P_{j,t+1}$ (Fama, 1970). So, the excess return in agreement with the EMH theory would be:

$$x_{j,t+1} = p_{j,t+1} - E(p_{j,t+1}|\Phi_t), \text{ thus we can conclude}$$

$$E\left(x_{j,t+1}\middle|\Phi_t\right) = 0$$

This expression illustrates that given information set, the abnormal returns from investing should be equal to zero ("fair game") and prices should follow random walk – $f\left(r_{j,t+1}\middle|\Phi_t\right) = f(r_{j,t+1})$.

Using statistical terms, EMH is the same as martingale hypothesis, which implies that the past sequence of series is relevant in forecasting the future. When the martingale hypothesis remains, the expected next period value of the series equals to its current value (anticipated on information set). The less restrictive sub-martingale hypothesis allows for future expected value to be greater or equal to its current value. Statistical formulation for expected price would be

$$E\left(P_{j,t+1}\middle|\Phi_t\right) \geq P_{j,t} \text{ thus implying } E\left(r_{j,t+1}\middle|\Phi_t\right) \geq 0.$$

In practice less restrictive model is more realistic than martingale hypothesis because of non-negative and non-constant dividends on stocks. (Fama, 1991)

Another statistical model is Random Walk Model (RWM), which is closely related to EMH, and assumes that successive price changes are independently and identically distributed. If prices or returns follow random walk, they are said to be not serially correlated and the error term is a white noise process.[3] The RWM does not tell that mean of the distribution is independent but rather the entire distribution of prices should be independent, based on the obtainable information set. The first definition of Random Walk Hypothesis looks like this:

$E[r_t] = E[r_{t+\tau}]$ and $cov(r_t, r_{t+\tau}) = 0 \; for\ all\ t\ and\ \tau > 0.$ RWH (1)

When RWH (1) is true, the returns are uncorrelated and best linear prediction of a future return is its unconditional mean, which here is assumed to be constant. This assumption was made by

[3] White noise process: a sequence of serially uncorrelated random variables with zero mean and finite variance.

Granger and Morgenstern (1970) and is relatively weak. The second assumption of RWH is stronger as it states that returns have stationary mean μ and the process of excess returns $\{r_t - \mu\}$ is a martingale difference. (Samuelson, 1965) A stationary mean in the definition appears to ensure that the sample autocorrelations are consistent estimates. Asset pricing models indeed do not require expected returns to be constant through time.

There are some specifications of RWM. It can be with drift or without drift depending on the value of expected price of the stock. A Random walk with drift implies that expected price changes may be not equal to zero.

$X_{t+1} = \delta + X_t + \varepsilon_{t+1}$, where ε_{t+1} is a white noise disturbance term.

RWM without drift has $\delta = 0$ in the equation above. Thus X_{t+1} is a martingale and a change in $X_{t+1} = X_{t+1} - X_t$ is a fair game for drift=0. This states that even if one period expected prices are i.i.d[4], prices themselves may not follow a random walk since the distribution of price changes according to current price level. RWM model is more restricted than martingale, because it requires higher conditional moments to be independent. If stock prices follow martingale and successive changes are found unpredictable, conditional variance may still be predictable from past variances. If the sequence of prices follows RWM, time varying conditional variances are not feasible (Fama, 1970).

From the perspective of technical trading rules, significant evidence of asset price or return predictability does not necessarily imply that a market is inefficient. (Taylor, 2005) In order to argue that market is truly inefficient, performance of superior trading rule should be compared with certain benchmark, taking into account all possible costs. Jensen (1970) defines weak-form efficient hypothesis of market by the following statement:

"No trading rule has an expected, risk adjusted, net return greater than that provided by risk-free investment. "(Taylor, 2005:175)

For evidences to be convincing, hypothesis requires economically and statistically significant performance of trading rule.

[4] i.i.d – independent and identically distributed

At the time, when successful trading strategy is found, there are other factors that need to be assessed before making precise conclusions upon the approach. Measuring the performance of the rule requires cost and risk adjustment, although for domestic equities risk altering is rather straightforward because only one risk factor has to be evaluated. On the other hand, cost evaluation might be more complicated. Further theory and empirical work on technical analysis of asset predictability is analyzed in Chapter 5.

3 Literature review

This chapter provides a plausible summary of accomplished reading, which helped to develop this paper. In the past century there was a huge amount of research dedicated to analyze whether financial markets are informationally efficient or not. Historically EMH is closely linked with random walk model which firstly was proposed by a French broker Jules Regnault (1863) and French mathematician Louis Bachelier (1900). As their studies were formally ignored and not considered as important dedication to financial markets theory, further attempts to prove random walk in financial series declined until the mid of 20th century.

In the early 1960s efficient market hypothesis was developed by Professor Eugene Fama, who studied this subject as his PhD research and published as a new type of characteristics of financial market. He suggested the first definition of the efficient market in 1969: "An efficient market is the market which adjusts rapidly to new information". This theory of Fama became widely accepted theory of stock markets. Samuelson (1970) contributed to the theory by adding proof of EMH while Fama refined and extended theory into three forms of financial market efficiency as mentioned in a previous chapter.

Most of developed equity markets, especially the NYSE and the LSE, are demonstrated to be efficient at least in a weak-form. US stock markets have been extensively examined in the past literature. Sharma and Kennedy (1977) and Solnik (1973) show that these capital markets are considered to be efficient, well organized and consistent with RWM. Porteba and Summers (1988) did the research on transitory components in equal-weighted and value weighted NYSE returns over the 1926-1985 period where findings suggest stock returns being positively correlated over the short period of time, and negatively correlated over the longer time horizon. Alternatively, Szakmary et al (1999) adopted filter rule to NASDAQ stocks and found that trading rules restricted to past stock's prices performed poorly, but those applied on past movements in the overall NASDAQ index tended to earn supernormal returns. However, even if the rules were successive in providing information about possible superior returns, taking into account transactions costs they became economically insignificant.

European equity markets generally are less efficient as stock prices exhibit some dependencies in their movements. Solnik (1973) tested validity of the RWM using largest European equity markets of French, German, British, Italian, Dutch, Belgium, Swiss, and Swedish and found that the deviation of European stock prices from RWM is more often than that of US stock prices. Worthington and Higgs (2003) used daily returns for sixteen developed markets and four emerging markets. Using multivariate statistical tests they showed that only five out of sixteen developed markets follow RWM. Using unit root tests and Johansen cointegration technique for world equity markets integration Chan (1997) found largest European markets[5] being efficient. His results were contradicted by Blasco et al. (1997) who found Spanish equity market not being efficient and explained it with theory of time-varying volatilities. Pandey et al (1998) examined pricing efficiency in west European markets using non-linear procedures and found high-dimensional determinism in equity indexes of Germany, Italy and the US, but none in French stock market.

Emerging and less developed countries are even more inefficient according to the empirical evidences as suggested by Errunza and Losq (1985). The inefficiency arises from the size of the market, trading volume, information disclosure quality, and transaction costs mostly. (Keane, 1983) Due to the description of less developed markets, they should not follow random walk model and be inefficient, however, empirical evidences are mixed irrespectively of which form of efficiency is examined. Some of the findings prove that efficiency cannot reject RWH in emerging markets, such as Branes (1986) on the Kuala Lumpur Stock exchange, Dickinson and Muragu (1994) on Nairobi Stock Exchange, Ojah and Karemera (1999) on Latin American stock market. On the other hand, weak form inefficiency was found in Russian, Czech and Polish equity markets by Worthington and Higgs (2003) and Abrosimova (2005). Mollah (2008) concluded that Botswana Stock Exchange is inefficient; Mobarek et al (2008) rejected RWH on Dhaka Stock Exchange of Bangladesh; and Harrison (2004) on Romanian stock market.

Past researches concerning Baltic States stock market efficiency were based on analysis of transition period. As pointed out in academic papers on transition economies[6], econometric modeling is a useful tool for analyzing efficiency, but it should be adjusted in a proper form. Therefore, it is not

[5] Denmark, France, Netherlands, Norway, Spain and Switzerland.
[6] see Hall (1993), Hall and O'Sullivan (1994), Hall and Koparanova (1995), Greenslade and Hall (1996), Ghysels and Cherkaou (1999), Basdevant (2000)

surprising that capital markets of transitional economies are not found weakly efficient using linear rules to forecast prices (Emerson et al. (1996), Macskasi (1996)). This condition especially holds in the early transition stages when financial market's institutional and informational structure is poorly defined.

Kvedaras and Basdevant (2002) analyzed Baltic capital markets of Estonia, Latvia and Lithuania. With the assistance of time variance ratios they show Estonia and Lithuania moving towards efficiency faster than Latvia, as the former apparently does not have structure that is satisfactory for effective performance. Academics performed analysis by combining the methodology of variance ratio robust to heteroskedasticity test and the state-space representation, which enabled them to use an efficient filtering technique – the Kalman filter – to get time varying autocorrelations. The main conclusion was that financial markets in the Baltic States are hardly approaching weak-form efficiency, at least when the linear price forecasting rules were used. Results do not suggest efficiency to be present in financial markets in the long run, but markets are developing and moving towards well-organized market structure.

More recent work on European emerging markets is done by Smith (2011) with 15 emerging European markets being investigated including Estonia, Latvia and Lithuania. Smith performed four different methods of variance ratio testing, including bootstrapping technique on equity market indexes, and analyzed the effect on returns caused by global financial market crisis of 2007-2008. He concluded that the least efficient markets were Ukrainian, Maltese and Estonian. Latvian stock market was in the middle according to the relative levels of efficiency and Lithuania was ranked 13th. The author used fixed-length rolling sub-period window which enabled him to capture changes in efficiency and to compute relative efficiency in the markets. He found that degree of efficiency is very unstable across the markets. OMX Tallinn index showed that Estonia is relatively behind of other countries in efficiency analysis which decreased even more during economic downturn. On the other hand, the crisis had little effect on efficiency in Latvia stock market and greatly improved in the stock markets located in Lithuania.

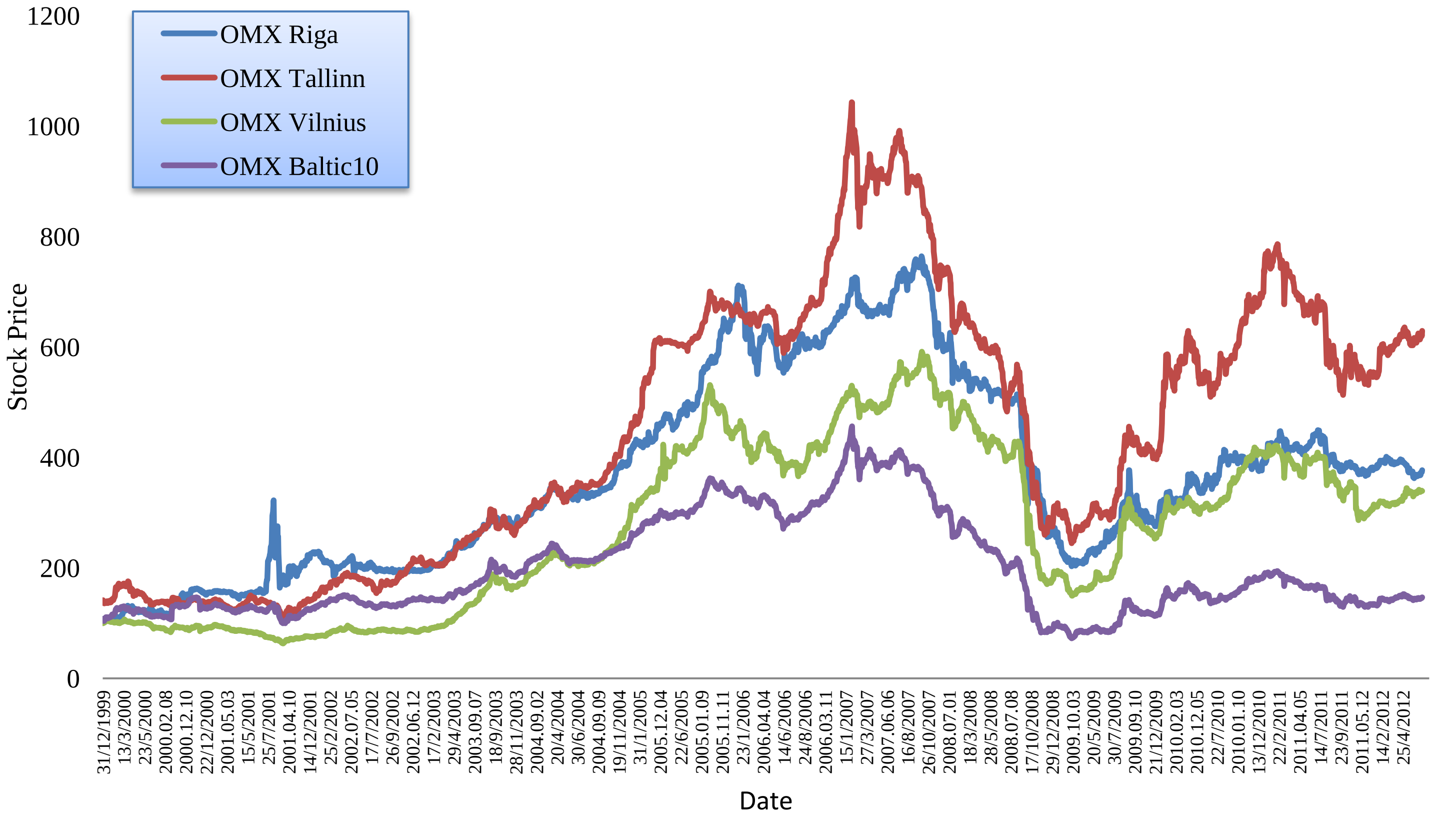
Final conclusions were reached that all 15 European markets are not efficient in absolute terms, but some are in relevant efficiency aspects proposed by Campbell, Lo, MacKinlay (1997, 24) Relative efficiency here represents measurement of efficiency of one market and compared to another one. This form of efficiency measurement is assumed to be better for investors as well as international investment funds because of two reasons: it can be applied at levels of individual stocks, group of stocks or market indexes; and it does not assume that emerging stock market is equally efficient over the sample period. (Lo, 2004:2005) Researchers rationalized evolving nature of market efficiency with the adaptive market hypothesis which enables evolutionary perspective to explain market efficiency and implies that it has a characteristic varying continuously through time and across the markets. The implications for empirical work are to apply tests that are capable to capture changes in efficiency over time. (Lo, 2004) This study uses classical approach of efficiency testing rather than time varying, as the period analyzed is considerably long and markets are assumed to be more developed than in early stages of their operation.

4 Data Presentation

4.1 Dataset analysis

The key data used in this study includes three daily price index series of Estonia, Latvia and Lithuania, and tradable OMX Baltic 10 stock index, compiled of ten most liquid stocks from the Baltic Exchange. Additionally, daily prices of highly developed UK and US market indexes[7] are included for benchmark comparison of results. The sample is taken from 1st January 2000 to 2nd July 2012, and encompasses closing prices of stocks. Sample size is based on the commencing of OMX Vilnius stock index. The stock market indexes are collected from DataStream. All indexes are listed in home currency, except for Lithuanian which is listed in Euros. The three main indexes representing Baltic States Stock Exchange are: OMX Tallinn, OMX Riga and OMX Vilnius.[8] Figure below shows series of Baltic stock price indexes during 2000-2012

Baltic Stock Market Index Daily Series 2000-2012



[1] UK market is represented by FTSE 100 and US market by S&P 500
[8] See appendix for full description of each index.

The NASDAQ OMX stock exchange in Tallinn, Riga and Vilnius formed the Baltic Market with the central idea to minimize the differences between the three Baltic financial markets, to facilitate cross-border trading and attract more investments to the region. The objective includes sharing the same trading system and harmonizing rules and market practices, reducing transaction costs and easing the use trading.[9] For the analysis to be more precise, there will also be used one more index: OMX Baltic 10. As mentioned before, it is a tradable index consisting of 10 the most actively traded stocks on the Baltic exchanges. In the case of emerging markets trading is not necessarily continuous all the time, thus more liquid index might provide substantial information about the efficiency in performing stocks. (Gilmore, 2003)

Thin or infrequent trading causes serious bias in empirical work, thus the longer period is taken the better outcome will be reached. (Lo and MacKinlay, 1988) This study uses 3261 observations of daily stock prices data. As analyses are conducted in returns, the former are calculated in log differences of price series: $R_t = \ln\left(\frac{P_t}{P_{t-1}}\right)$, where P_t represents price of stock index value and R_t continuously compounded return.[10]

There might be some discussion about reliability of Baltic Stock Exchange indexes. Some analysts argue that equity prices rather than indexes should be taken into account when market efficiency is analyzed. However, according to index calculation methodology the author assumes prices being reliable and accurate, which should not cause significant bias in the research. NASDAQ OMX provides a framework equation for Baltic Exchange index calculation:

$$I_t = \frac{\sum_{i=1}^{n} q_{i,t} * p_{i,t} * r_{i,t}}{\sum_{i=1}^{n} q_{i,t} * (p_{i,t-1} - d_{i,t}) * r_{i,t-1} * j_{i,t}} * I_{t-1},$$

where

I_t = Index level at time t

$q_{i,t}$ = Number of shares of company i applied in the index at time t

$p_{i,t}$ = Price in quote currency of a share in company i at time t

$d_{i,t}$ = Dividend only used for total return Indexes

$r_{i,t}$ = Foreign exchange rate of index quote currency to quote currency of company i at time t

$j_{i,t}$ = Adjustment factor for adjusting the share price of a constituent security due to corporate actions by the issuing company at time t

9 www.nasdaqomxbaltic.com

10 See appendix for return time series for each stock index.

4.2 Structural Break

When dealing with a rather long period of an econometric analysis, it would be beneficial to split the underlying investigation into two parts. In general, a structural break represents a point in time where the observed time-series significantly varies from its past. In order to make more accurate decision of where to cut off time series there were used two structural breakpoint tests of:

1. The Quandt-Andrews Unknown Breakpoint test (1988)
2. The Chow Test for Structural Breaks (1960)

The firstly mentioned break point test is superior as it finds the moment of break in time without any specifications and when it is not known to the researcher. The null hypothesis states that the parameters in the equation are stable, whereas rejecting the null indicates unstable parameters over time. To perform the test, an OLS regression has to be operated on the following equation:

$p_t = \alpha + \beta p_{t-1} + \epsilon_t$, regression on stock price is performed on previous lag value of market index. The output below represents results for Quandt (1960) and Andrews (1993) test with break points for OMX Riga stock index.

Quandt-Andrews unknown breakpoint test		
Null Hypothesis: No breakpoints within 15% trimmed data		
Number of breaks compared: 2282		
Statistic	Value	Prob.[1]
Maximum LR F-statistic (8/10/2007)	14.873	0.000
Maximum Wald F-statistic (8/10/2007)	29.745	0.000
Exp LR F-statistic	2.890	0.004
Exp Wald F-statistic	9.140	0.000
Ave LR F-statistic	**2.343**	**0.048**
Ave Wald F-statistic	**4.686**	**0.048**

The test indicates a breakpoint in October 2007. The p-value of 0.0000 confirms this, thus the null-hypothesis of no breakpoint can be rejected at 1% significance level. For OMX Tallinn and OMX Baltic 10 the break points were found in February 2007, OMX Vilnius has a split in March 2007.[11]

[11] See the Appendix for outputs of significant breakpoint results

In order to confirm the results of significant breaks in time series we now can use Chow test, as the moment of break is already found and can be tested. The following output confirms that OMX Riga indeed has a break in October 2007.

Significant p=0.000 rejects hypothesis of no specified breaks, thus the conclusion is reached of split being important in 2007.

Table 1. Chow Test for OMX Riga stock index

Chow Breakpoint Test: 6/02/2007			
Null Hypothesis: No breaks at specified breakpoints			
F-statistic	**21.05635**	**Prob. F(2,3257)**	**0.000**
Log likelihood ratio	41.89415	Prob. Chi-Square(2)	0.000
	42.11269	Prob. Chi-Square(2)	0.000

Chow tests confirmed the same results as Quandt-Andrews for other indexes as well. Author decided for simplicity to standardize the concrete dates for each stock index and take the average date of April 2007 to be the major break point of all index series. Thus two sub-samples might be identified as pre-crisis transition period 2000-2007, and post-crisis development period 2007-2012.The following analysis will be held on these two sub-periods and full sample to see if the break point provides not only statistical but economic significance too.

4.3 Descriptive Analysis of Data Series

First of all, it is important to look at fundamental statistics of each time series variable for full sample. The next table provides descriptive analysis of daily return series for six indexes (means, maximums, minimums, standard deviations, skewness, kurtosis, Jarque-Bera statistics and their p-values).

	OMX Baltic10	OMX Tallinn	OMX Riga	OMX Vilnius	FTSE 100	S&P 500
Mean	0.009686	0.045991	0.038339	0.037172	-0.004884	-0.000562
Median	0.024723	0.036705	0.000000	0.010020	0.000000	0.019533
Maximum	14.17492	12.09448	10.17979	11.86596	9.384339	10.95720
Minimum	-11.82307	-7.045882	-14.70522	-13.51500	-9.265572	-9.469514
Std. Dev.	1.240332	1.213473	1.549474	1.195244	1.292755	1.342393
Skewness	-0.174682	0.140517	-0.614916	-0.485320	-0.138361	-0.156266
Kurtosis	19.57863	10.64961	17.43694	26.03517	8.890533	10.56820
Jarque-Bera	37361.94	7961.667	28525.28	72225.90	4725.047	7795.876
Probability	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
Sum	31.58510	149.9758	125.0248	121.2182	-15.92611	-1.831712
Sum Sq. Dev.	5015.264	4800.403	7826.839	4657.267	5448.164	5874.585
Observations	3261	3261	3261	3261	3261	3261

Notes: Jarque-Bera statistics test for normality and the null hypothesis is rejected at 5% level in all markets.

The sample mean returns for Baltic States are positive and statistically significant indicating that markets were growing during the period of 2000-2012. FTSE 100 and S&P 500 stock indexes have negative average returns during the same period and substantially lower than Baltic markets. The maximum and minimum values of returns are approximately the same with slightly bigger increments for Baltic region. Volatility of returns does not provide significant differences between the indexes, except for Latvian stock index, which has highest volatility of 1.55%. Jarque-Bera test with null hypothesis of normal distribution is used for evaluation of distribution of returns. Generally the statistic is computed using skewness and kurtosis as follows:

$$JB^{12} = \frac{N}{6}(S^2 + \frac{(K-3)^2}{4})$$

Significant p-values indicate that returns are not normally distributed as hypothesis is strongly rejected. In a perfectly normal distribution case skewness approaches to zero and kurtosis to value of 3. The skewness for all indexes returns is negative, except for Estonia, and shows that the tails on the left side of probability density function are longer than those on the right side hence

[12]JB tests: where N is a number of observations, S denotes skewness and K denotes kurtosis.

indicating asymmetric distribution. (Brooks, 2009) In a Gaussian distribution analyzed by Kendall (1943), the kurtosis would be accepted with value 2.902; the findings above disclose much higher values of kurtosis indicating extreme leptokurtic distributions of returns. This leads to the first violation of random walk model as returns in random walk are assumed to be normally distributed. However, this is not the final case; a non-parametric test for homogenous distribution will give final conclusions later in the study.

Descriptive statistics for sub-period II (2007-2012)

	OMX Baltic10	OMX Tallinn	OMX Riga	OMX Vilnius	FTSE100	S&P500
Mean	0.075852	0.105075	0.102455	0.088572	-0.002652	0.001854
Median	0.073693	0.080414	0.030616	0.058805	0.000000	0.000000
Maximum	14.17492	7.342547	9.460949	11.86596	5.902563	5.573247
Minimum	-11.82307	-5.874106	-14.70522	-13.51500	-5.885338	-6.004513
Std. Dev.	0.924613	0.998460	1.568261	1.009282	1.117916	1.098078
Skewness	0.158305	0.136247	-1.247731	-0.694429	-0.208037	0.122167
Kurtosis	51.92921	10.00902	23.86319	40.09615	6.513620	5.890888
Jarque-Bera	184750.0	3796.645	34069.09	106339.8	966.0219	649.5065
Probability	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
Sum	140.4787	194.5991	189.7462	164.0360	-4.911283	3.433949
Sum Sq. Dev.	1582.437	1845.303	4552.431	1885.520	2313.260	2231.892
Observations	1852	1852	1852	1852	1852	1852

The same descriptive analysis is performed on two sub-samples in order to see if there are any significantly different results. By evaluating the first and second samples it is possible to recognize changes in stock return movements. While the means of returns in the first sub-period are positive and relatively large for all Baltic markets, the second period means of returns are negative and denote poor performance of indexes during and after a year 2007.

The measure of dispersion of spread has also increased for almost all markets notably. In the first period, skewness for Baltic 10 and Estonia are positive with long right tail in distribution, while Latvia and Lithuania contain negative skewness. In the second period, Baltic 10 stock index returns and OMX Vilnius have negative skewness, while Estonia together with Latvia possess positive skewness. This means markets are not performing in the same way and possess individual characteristics.

Descriptive statistics for sub-period II (2007-2012)

	OMX Baltic10	OMX Tallinn	OMX Riga	OMX Vilnius	FTSE100	S&P500
Mean	-0.077971	-0.032761	-0.046631	-0.030316	-0.007782	-0.003740
Median	0.000000	0.000000	0.000000	0.000000	0.000000	0.050058
Maximum	10.75852	12.09448	10.17979	11.00145	9.384339	10.95720
Minimum	-9.973461	-7.045882	-7.858646	-11.93777	-9.265572	-9.469514
Std. Dev.	1.557504	1.444981	1.521190	1.400683	1.492669	1.609025
Skewness	-0.138285	0.219541	0.283451	-0.287619	-0.090800	-0.258215
Kurtosis	9.703237	9.288358	8.371848	17.75096	8.897637	10.18405
Jarque-Bera	2640.579	2331.193	1711.783	12784.74	2042.486	3043.464
Probability	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
Sum	-109.7833	-46.12793	-65.65596	-42.68525	-10.95749	-5.265661
Sum Sq. Dev.	3413.126	2937.775	3255.826	2760.412	3134.880	3642.668
Observations	1408	1408	1408	1408	1408	1408

Test statistics for Jarque-Bera test are highly significant and hypothesis of normal distribution of returns is rejected at 5% and even at 1% of significance level. One might also notice extremely different number in the row of Sum returns for each index column. Before the crisis stock indexes of Baltic region have very high positive returns up to 194.599% while the UK and the US markets are situated just around the zero. In the second period of financial crisis, sum of returns move to another direction and is extremely negative. These results might indicate asset return predictability in Baltic region, these estimations and results are investigated in Chapter 5.

5 Fundamental Analysis and Empirical Results

5.1 Kolmogorov-Smirnov Goodness of Fit Test

Kolmogorov-Smirnov (K-S) test is a non-parametric test used to check if the observed distributions of variables fit theoretical or uniform distribution and how well a random sample of data fits that distribution. K-S goodness of fit test compares two distribution functions of a variable and provides results whether distributions are homogenous. For Random Walk Model to be true, distributions of returns are supposed to be homogenous. The table below summarizes the results for each of stock index return series.

One-Sample Kolmogorov-Smirnov Test

		Ret_Riga	Ret_Tallinn	Ret_Baltic10	Ret_Vilnius
Normal Parameters[a,,b]	Mean	0.030	0.010	0.000	-0.020
	Std. Deviation	2.160	2.125	2.124	2.098
Most Extreme Differences	Absolute	0.307	0.314	0.324	0.342
	Positive	0.300	0.303	0.323	0.323
	Negative	-0.307	-0.314	-0.324	-0.342
Kolmogorov-Smirnov Z		**17.549**	**17.948**	**18.494**	**19.508**
Asympt. Sig. (2-tailed)	**p-values**	**0.000**	**0.000**	**0.000**	**0.000**

Ho: Distributions are homogenous

Results from the table above show a 0.0000 probability for the Z value, clearly indicating that the frequency of distribution of the daily price indexes of Estonia, Latvia, Baltic10 and Lithuania do not fit by normal distribution. Results for sub-periods do not give any different results.

For weakly returns K-S test exhibit the same results thus the hypothesis of homogenous distribution for Baltic States Stock Markets is strongly rejected. These findings are consistent with Poshakwale (1996) and Mobarek (2000) analysis of emerging markets.

5.2 Runs Test

The runs test is another non-parametric technique to detect statistical dependencies between observations, which may not be detected by autocorrelations test. Runs test determines whether successive price changes are independent and unlike serial correlation it does not require returns to be normally distributed.[13] (Higgs, 2004) When the expected number of runs is significantly different from the observed number of runs, it means the market suffers from over- or under-reaction to information, providing an opportunity to make excess returns for traders. (Poshakwale, 1996) The main hypothesis for runs test is the following:

H_0: The observed series are random (The number of expected runs is about the same as the number of actual runs)

H_A: The observed series are not random (Significantly different counts of runs)

In this approach, each return is classified according to its position with respect to the mean of return. Hence, a positive change appears when the return is greater than the mean and a negative change, when return is below the mean. Zero change reflects return being equal to the mean. In order to get more accurate results, runs test was operated on different frequency of time series. Financial theory analysts and academics argue that using only daily returns might cause spurious results because of the serial correlation. To avoid errors and false interpretation there will be used daily and weekly return series of Baltic stock market indexes together with UK and US equity indexes for comparison matters.

The following tables represent results of runs test for period 2000-2012 and two sub-samples of 2000-2007 and 2007-2012.

Nonparametric Runs Test 2000-2012 Daily returns	**OMX Riga**			**OMX Tallinn**			**OMX Vilnius**		
Test Information	2000-2012	2000-2007	2007-2012	2000-2012	2000-2007	2007-2012	2000-2012	2000-2007	2007-2012
Runs about Median:	1693	945	740	1440	807	617	1456	784	666
Expected Runs about Median:	1632	927	701	1632	927	704	1632	927	702
P-Value for Clustering:	0.9838	0.7986	0.9806	0.0000	0.0000	0.0000	0.0000	0.0000	0.0268
P-Value for Mixtures:	0.0162	0.2014	0.0194	1.0000	1.0000	1.0000	1.0000	1.0000	0.9732
P-Value for non-randomness	**0.0323**	**0.4027**	**0.0387**	**0.0000**	**0.0000**	**0.0000**	**0.0000**	**0.0000**	**0.0537**
Runs Up or Down:	2206.000	1245.000	962.000	2026.000	1135.000	890.000	2103.000	1175.000	927.000
Expected Runs Up or Down:	2174.333	1234.333	939.000	2174.333	1234.333	939.000	2174.333	1234.333	939.000
P-Value for Trends:	0.9058	0.7218	0.9270	0.0000	0.0000	0.0010	0.0015	0.0005	0.2240
P-Value for Oscillation:	0.0942	0.2782	0.0730	1.0000	1.0000	0.9990	0.9985	0.9995	0.7760

[13] Non-parametric tests do not require variables to be normally distributed in order to test for interdependencies.

The first table above represents runs test on daily returns for 3 periods: full sample, 1st and 2nd sub-samples. The results are given for expected number of runs and actual number of runs. Statistical significance of *p*-values for randomness is shown in bold row. In the periods of *p*=0.000 null hypothesis of random walk in data is rejected strongly. For the three Baltic stock exchanges hypothesis are rejected at 5% in the full sample analysis 2000-2012. However, during the period of 2000-2007 hypothesis of randomness in data cannot be rejected for Latvian equity market as *p*=0.4027. Other markets reject random walk in the first sub-sample. In the last period of 2007-2012, Latvia and Estonia contain significant *p*-values, while Lithuania demonstrates randomness in data which cannot be rejected at 5%.

The test also provides information on data clustering, mixtures and trends. Mixtures appear as an absence of data points near the center line. A mixture may indicate a bimodal distribution due to a regular change of shift, machinery, or raw materials. Trends appear as an upward or downward drift in the data and may be due to special causes, such as tool wear. Estonia and Lithuania rejects probabilities of clustering and trending for both sub-periods, while Latvia contains mixtures in series.

Nonparametric Runs Test 2000-2012 Daily returns	**OMX Baltic 10**			**S&P 500**			**FTSE 100**		
Test Information	2000-2012	2000-2007	2007-2012	2000-2012	2000-2007	2007-2012	2000-2012	2000-2007	2007-2012
Runs about Median:	1406	751	643	1755	980	763	1691	957	734
Expected Runs about Median:	1632	927	702	1632	927	705	1632	927	705
P-Value for Clustering:	0.0000	0.0000	0.0007	1.0000	0.9931	0.9989	0.9811	0.9186	0.9383
P-Value for Mixtures:	1.0000	1.0000	0.9993	0.0000	0.0069	0.0011	0.0189	0.0814	0.0617
P-Value for non-randomness	**0.0000**	**0.0000**	**0.0015**	**0.0000**	**0.0137**	**0.0022**	**0.0379**	**0.1629**	**0.1234**
Runs Up or Down:	2048.000	1163.000	884.000	2207.000	1235.000	971.000	2173.000	1217.000	955.000
Expected Runs Up or Down:	2174.333	1234.333	939.000	2174.333	1234.333	939.000	2174.333	1234.333	939.000
P-Value for Trends:	0.0000	0.0000	0.0003	0.9126	0.5147	0.9785	0.4779	0.1696	0.8441
P-Value for Oscillation:	1.0000	1.0000	0.9997	0.0874	0.4853	0.0215	0.5221	0.8304	0.1559

Another table provides results for stock indexes of Baltic, US and UK markets. Baltic 10 index of mostly traded stocks gives almost identical results as OMX Tallinn, where hypothesis of randomness are strongly rejected at 5% and data is clustering. S&P 500 stock index rejects randomness in the period of 2000-2012, however it does not mean that index is inefficient as it has a history of trading for more than 40 years and this is only a small part of data. FTSE 100 stock index do not reject hypothesis of data being random, so this means UK stock index is mostly efficient comparing with the other prices. From these results it is clear that Latvia is performing efficient behavior of stock prices, while Lithuania and Estonia are much less efficient. These results are consistent with Smith (2011) conclusion while analyzing European emerging stock markets. He concluded OMX Riga being efficient stock price index and OMX Vilnius approaching efficiency as well, while OMX Tallinn is far beyond weak-form efficiency.

In order to make a relatively precise decision about outcome from runs test on Baltic stock markets the study also concerns weakly returns. Interesting results are delivered, as weakly returns of OMX Riga stock price index have strongly not rejected null hypothesis thus confirming major randomness in times series.

Nonparametric Runs Test 2000-2012 Weekly returns	**OMX Riga**			**OMX Tallinn**			**OMX Vilnius**		
Test Information	2000-2012	2000-2007	2007-2012	2000-2012	2000-2007	2007-2012	2000-2012	2000-2007	2007-2012
Runs about Median:	313	179	143	278	154	120	271	152	112
Expected Runs about Median:	326	186	141	326	186	141	326	186	141
P-Value for Clustering:	0.1537	0.2331	0.5946	0.0001	0.0004	0.0060	0.0000	0.0002	0.0003
P-Value for Mixtures:	0.8463	0.7669	0.4054	0.9999	0.9996	0.9940	1.0000	0.9998	0.9997
P-Value for non-randomness	**0.3074**	**0.4661**	**0.8107**	**0.0002**	**0.0009**	**0.0119**	**0.0000**	**0.0004**	**0.0005**
Runs Up or Down:	442.000	254.000	188.000	425.000	242.000	183.000	450.000	249.000	202.000
Expected Runs Up or Down:	433.000	246.333	186.333	433.000	246.333	186.333	433.000	246.333	186.333
P-Value for Trends:	0.7991	0.8283	0.5937	0.2281	0.2961	0.3178	0.9434	0.6292	0.9871
P-Value for Oscillation:	0.2009	0.1717	0.4063	0.7719	0.7039	0.6822	0.0566	0.3708	0.0129

Both periods 2000-2007 and 2007-2012 results are shown in the tables. OMX Tallinn and OMX Vilnius weakly returns have rejected null hypothesis at 95% confidence level, OMX Baltic 10 of mixed stocks has rejected null in the first sub-period but not in the second one. Developed stock markets of UK and US using weakly returns have not rejected hypothesis of randomness. Up to this point, it is possible to draw some conclusions about Latvian stock market as a follower of random walk model and being weak-form efficient, while other Baltic stock markets do not capture random walks in their structures.

Nonparametric Runs Test 2000-2012 Weekly returns	**OMX Baltic 10**			**S&P 500**			**FTSE 100**		
Test Information	2000-2012	2000-2007	2007-2012	2000-2012	2000-2007	2007-2012	2000-2012	2000-2007	2007-2012
Runs about Median:	275	152	126	339	187	154	339	195	145
Expected Runs about Median:	326	186	141	326	186	141	326	186	141
P-Value for Clustering:	0.0000	0.0002	0.0362	0.8463	0.5415	0.9402	0.8463	0.8256	0.6840
P-Value for Mixtures:	1.0000	0.9998	0.9638	0.1537	0.4585	0.0598	0.1537	0.1744	0.3160
P-Value for non-randomness	**0.0001**	**0.0004**	**0.0725**	**0.3074**	**0.9171**	**0.1196**	**0.3074**	**0.3487**	**0.6320**
Runs Up or Down:	454.000	259.000	196.000	444.000	248.000	196.000	447.000	251.000	197.000
Expected Runs Up or Down:	433.000	246.333	186.333	433.000	246.333	186.333	433.000	246.333	186.333
P-Value for Trends:	0.9748	0.9413	0.9154	0.8473	0.5816	0.9154	0.9039	0.7180	0.9353
P-Value for Oscillation:	0.0252	0.0587	0.0846	0.1527	0.4184	0.0846	0.0961	0.2820	0.0647

5.3 Autocorrelations Test

Serial dependence is most common test for RWM in a form of estimates of serial correlations for stock price indexes. (Granger, 1969) If there is any correlation in the residual series it is most likely the first order serial correlation between ϵ_t and ϵ_{t-1}. Kendal (1953), Moore (1964), Cootner (1962) and Fama (1965) calculated serial correlations for British and US data using daily and weekly observations. Kendal found some significant evidence of serial correlation while other researchers find very small correlation coefficient for first lag series. More recent investigations of stock behavior in emerging markets find significant dependence between the variables and their previous values.

Autocorrelation test evidences whether the coefficients of correlations are significantly different from zero. For large samples and higher order serial correlation Ljung-Box Q statistic is used. If there is no serial correlation in the residuals, the autocorrelations and partial autocorrelations at all lags should be nearly zero, and all Q-statistics should be insignificant with large p-values. (Chatfield, 1975)

Ljung-Box statistic $Q^{14} = T(T+2)\sum_{k=1}^{m}\frac{\tau_k^2}{T-k} \sim \chi_m^2$

The following autocorrelation test with 20 lags is performed on full sample and two sub-samples of daily return series.

[14] Ljung-Box statistic follows χ^2 (Chi) distribution with degrees of freedom m equal to the number of autocorrelations.

OMX Riga									
Lag	Autocorrelation (2000-2012)	Q	Prob	Autocorrelation (2000-2007)	Q	Prob	Autocorrelation (2007-2012)	Q	Prob
1	0.045	64.89	0.000	0.1	18.60	0.000	**-0.038**	19.91	0.158
2	0.104	41.83	0.000	0.169	71.47	0.000	**0.008**	20.85	0.353
3	0.025	43.84	0.000	0.039	74.25	0.000	**0.000**	20.85	0.555
4	-0.076	62.90	0.000	-0.118	100.03	0.000	**-0.024**	28.81	0.578
5	-0.032	66.28	0.000	-0.079	111.49	0.000	**0.027**	39.20	0.561
6	-0.046	73.15	0.000	-0.126	141.12	0.000	**0.060**	89.41	0.177
7	-0.035	77.16	0.000	-0.056	147.02	0.000	**-0.011**	91.26	0.244
8	0.003	77.19	0.000	-0.021	147.87	0.000	**0.030**	104.25	0.236
9	0.042	83.07	0.000	0.037	150.44	0.000	**0.045**	133.38	0.148
10	0.075	101.24	0.000	0.124	179.32	0.000	**-0.001**	133.38	0.205
11	0.067	116.13	0.000	0.146	218.94	0.000	**-0.046**	164.04	0.127
12	0.074	134.02	0.000	0.100	237.73	0.000	**0.032**	178.40	0.121
13	0.099	166.44	0.000	0.110	260.29	0.000	**0.081**	272.72	0.011
14	0.050	174.65	0.000	0.028	261.74	0.000	0.077	357.77	0.001
15	-0.028	177.18	0.000	-0.038	264.46	0.000	-0.017	361.80	0.002
16	-0.054	186.86	0.000	-0.073	274.50	0.000	-0.033	377.00	0.002
17	-0.063	199.98	0.000	-0.103	294.50	0.000	-0.013	379.43	0.003
18	-0.022	201.61	0.000	-0.083	307.52	0.000	0.058	427.58	0.001
19	-0.038	206.36	0.000	-0.077	318.75	0.000	0.012	429.62	0.001
20	-0.023	208.09	0.000	-0.037	321.32	0.000	-0.007	430.34	0.002

The table above represents Ljung-Box test for higher order autocorrelations for OMX Riga stock price index. There are three columns of correlation coefficients for different time periods. For the full sample Q statistics are significant at lag all lags and thus serial dependence is not rejected in returns. Looking at the first sample for period 2000-2007 all coefficients are significant and thus reject hypothesis of independence. The last column of serial correlation coefficients represents interesting results of insignificant autocorrelations and hypothesis cannot be rejected. Findings suggest that OMX Riga Stock price index possess enough randomness in the second sub-period of 2007-2012 and gives substantial evidence of market efficiency. These results are consistent with those obtained from runs test in a previous chapter.

The results for other Baltic Stock market indexes of autocorrelations are represented in Appendix as they all reject hypothesis of random walk model. Returns of OMX Tallinn, OMX Vilnius and OMX Baltic 10 consist significant serial correlations in full sample and sub-samples thus from this dependence test they do not follow random walk model and are not weak-form efficient.

5.4 Unit root testing

It is important to test whether data is stationary or not. Unit root is a necessary but not sufficient condition for a random walk. In financial time series, price series usually are not stationary. Using non-stationary data might lead to spurious regressions because of the shocks that do not gradually die away and cause. (Brooks, 2008) However, the first differences of prices commonly have constant variance, constant mean and constant autocovariances. Three different tests are used to test the null hypothesis of unit root: Augmented-Dickey-Fuller (ADF) test, the Phillips-Peron (PP) test, and the Kwiatowski, Phillips, Schmidt and Shin (KPSS) test.

Analysis will be started with well known ADF test, where the null hypothesis of non-stationarity in time series will be estimated on the form of following regression equation:

$$\Delta p_{it} = \alpha_0 + \alpha_1 t + \rho_0 p_{it-1} + \sum_{i=1}^{q} \rho_i \Delta p_{it-1} + \varepsilon_{it}$$

where p_{it} stands for price for the i-th market at time t, Δp_{it}=p_{it}-p_{it-1}, ρ are the coefficients to be estimated, q is the number of lagged terms, t is the trend term which might be included or not, α_1 estimated coefficient on trend, α_0 is the constant, and ε_{it} is white noise.

There might be some discussions about how many lags of dependent variable should be included in the test, thus the number is arbitrary. Including too few lags will not remove all of the autocorrelation, thus biasing the results, while using too many will increase the coefficient standard errors. (Brooks, 2008) According to the theory, for financial data it is advised to determine the number of lags by the frequency of time series. (Brooks, 2008) Therefore, if data is monthly the lag number should be around 12, if quarterly - 4 lags. For weakly and more frequent data there should be a higher number of lags included for superior precision. In this study there will be used 36 lags for daily data. Test is performed without including trend and intercept parameter as it does not seem to be necessary. The outputs in the next page correspond to ADF, PP and KPSS statistical tests for all stock index return series.

The tests of unit root were performed on daily return levels of indexes of Estonia, Latvia, Lithuania and Baltic-10 index. MacKinnon’s critical values are used in order to determine the significance of the test statistic associated with ρ_0. Test performed in levels provides presence of unit root in time series, however, the first differences remove any non-stationarity and data rejects unit root for all series. The PP tests incorporate an automatic correction to the non-augmented Dickey-Fuller procedure to allow for autocorrelated residuals. Lastly, KPSS which under null hypothesis have reverse assumption – no unit root in the data. If the results are significant, than hypothesis of no unit root is rejected and non stationarity concluded. If hypothesis is not rejected, that means data is stationary. This test is useful in order to compare it with ADF/PP to check if the outcome of unit root test is superior, which in this case is proved to be reliable.

Null Hypothesis: RET_Baltic10 has a unit Lag Length: 0 (Automatic - based on SIC,				Null Hypothesis: RET_Baltic10 has a unit Bandwidth: 25 (Newey-West automatic) using				Null Hypothesis: RET_Baltic10 is stationary Bandwidth: 26 (Newey-West automatic) using Bartlett kernel			
		t-	Prob.*			Adj. t-	Prob.*			LM-	
Augmented Dickey-Fuller test		-48.1	**Reject**	**Phillips-Perron test statistic**		-51.611	**Reject**	**Kwiatkowski-Phillips-Schmidt-Shin**		0.28300	Do not Reject
Test	1% level	-2.5657		Test	1% level	-2.5657		Asymptotic	1% level	0.73900	Do not Reject
	5% level	-1.9409			5% level	-1.9409			5% level	0.46300	Do not Reject
	10% level	-1.6166			10% level	-1.6166			10% level	0.34700	Do not Reject
*MacKinnon (1996) one-sided p-values.				*MacKinnon (1996) one-sided p-values.				*Kwiatkowski-Phillips-Schmidt-Shin (1992, Table			

Null Hypothesis: RET_Tallinn has a unit Lag Length: 0 (Automatic - based on SIC,				Null Hypothesis: RET_Tallinn has a unit Bandwidth: 22 (Newey-West automatic) using				Null Hypothesis: RET_Tallinn is stationary Bandwidth: 23 (Newey-West automatic) using Bartlett kernel			
		t-	Prob.*			Adj. t-	Prob.*			LM-	
Augmented Dickey-Fuller test		-49.389	**Reject**	**Phillips-Perron test statistic**		-52.037	**Reject**	**Kwiatkowski-Phillips-Schmidt-Shin**		0.23694	Do not Reject
Test	1% level	-2.5657		Test	1% level	-2.5657		Asymptotic	1% level	0.739	Do not Reject
	5% level	-1.9409			5% level	-1.9409			5% level	0.463	Do not Reject
	10% level	-1.6166			10% level	-1.6166			10% level	0.347	Do not Reject
*MacKinnon (1996) one-sided p-values.				*MacKinnon (1996) one-sided p-values.				*Kwiatkowski-Phillips-Schmidt-Shin (1992, Table			

Null Hypothesis: RET_Riga has a unit root Lag Length: 3 (Automatic - based on SIC,				Null Hypothesis: RET_Riga has a unit root Bandwidth: 21 (Newey-West automatic) using				Null Hypothesis: RET_Riga is stationary Bandwidth: 20 (Newey-West automatic) using Bartlett kernel			
		t-	Prob.*			Adj. t-	Prob.*			LM-	
Augmented Dickey-Fuller test		-28.786	**Reject**	**Phillips-Perron test statistic**		-55.049	**Reject**	**Kwiatkowski-Phillips-Schmidt-Shin**		0.39268	Do not Reject
Test	1% level	-2.5657		Test	1% level	-2.5657		Asymptotic	1% level	0.739	Do not Reject
	5% level	-1.9409			5% level	-1.9409			5% level	0.463	Do not Reject
	10% level	-1.6166			10% level	-1.6166			10% level	0.347	Do not Reject
*MacKinnon (1996) one-sided p-values.				*MacKinnon (1996) one-sided p-values.				*Kwiatkowski-Phillips-Schmidt-Shin (1992, Table			

Null Hypothesis: RET_Vilnius has a unit Lag Length: 7 (Automatic - based on SIC,				Null Hypothesis: RET_Vilnius has a unit Bandwidth: 27 (Newey-West automatic) using				Null Hypothesis: RET_Vilnius is stationary Bandwidth: 28 (Newey-West automatic) using Bartlett kernel			
		t-	Prob.*			Adj. t-	Prob.*			LM-	
Augmented Dickey-Fuller test		-16.2	**Reject**	**Phillips-Perron test statistic**		-54.663	**Reject**	**Kwiatkowski-Phillips-Schmidt-Shin**		0.23412	Do not Reject
Test	1% level	-2.5657		Test	1% level	-2.5657		Asymptotic	1% level	0.739	Do not Reject
	5% level	-1.9409			5% level	-1.9409			5% level	0.463	Do not Reject
	10% level	-1.6166			10% level	-1.6166			10% level	0.347	Do not Reject
*MacKinnon (1996) one-sided p-values.				*MacKinnon (1996) one-sided p-values.				*Kwiatkowski-Phillips-Schmidt-Shin (1992, Table			

5.5 Variance ratio analysis

Monte Carlo simulations have proved that Variance Ration test is more reliable than traditional tests of unit root (ADF, PP) and serial correlation tests (Box-Pierce). There are two types of tests that are applicable for calculating variance ratio: single variance ratio tests by Lo and MacKinlay (1988) and multiple variance ratio tests by Chow and Denning (1993). Lo and MacKinlay shows that variance ratio statistic is derived from the assumption of linear relations in observation interval regarding the variance of increments: if the return series follows a random walk process, variance of *q*th-differenced variable will be *q* times larger as first-differenced variable.

$Var\left(p_t - p_{t-q}\right) = qVar(p_t - p_{t-1})$, where q>0,

Variance ratio is defined by the following equation:

$$VR(q) = \frac{\left(\frac{1}{q}\right)Var\left(p_t - p_{t-q}\right)}{Var(p_t - p_{t-1})} = \frac{\sigma^2(q)}{\sigma^2(1)}$$

For hypothesis of Random Walk Model to be true, variance ratio must be equal or very slightly deviated from the unity. If VR (q) statistic is significantly different from unity, the hypothesis should be rejected with evidences of autocorrelations in return series (ρ)

$VR(q) = \frac{V(q)}{qV(1)} = 1 + \rho_\tau$, when ρ_τ is significantly different from zero, the return series are not independent.

Two test statistics were produced by Lo and MacKinlay (1988) under the null of homoscedastic and heteroscedastic increments random walk respectively. If null hypothesis is not rejected, performed test statistic has an asymptotic standard normal distribution. Academics' procedure is developed for individual variance ratios testing with specific aggregation interval *q*, but RWH requires all ratios for all lags to be equal to 1. Chow and Denning's (1993) multiple variance ratios generate procedure for multiple comparison of the set of ratios with unity. They use maximum value of Z-statistic for particular period in time. This study uses two techniques of Univariate and multivariate variance ratio calculations. The table below provides information of variance ratios for OMX Baltic10 and OMX Tallinn stock indexes with probabilities calculated using asymptotic normal results defined by Lo and MacKinlay (1988).

The null hypothesis verifies that return series is a martingale difference for each stock index estimated. Variance ratios estimates are provided for full sample and also divided into two sub-samples. Since there is specified more than one test period, there are two sets of results. The “Joint tests” are the tests of the joint null hypothesis for all periods, while “Individual tests” are the variance ratio tests applied to individual periods.

Variance Ratio Test for OMX Baltic10				
Null Hypothesis: Cumulated RET_BALTIC10 is a martingale				
Sample: 5/01/2000 3/07/2012				
Heteroskedasticity robust standard error estimates				
Joint Tests		Value	df	Probability
Max |z| (at period 32)*		**6.662149**	**3260**	**0.0000**
Individual Tests				
Period	Var. Ratio	Std. Error	z-Statistic	Probability
2	1.171409	0.042041	4.077227	0.0000
4	1.360148	0.075552	4.76688	0.0000
8	1.563128	0.111659	5.043283	0.0000
16	1.992141	0.153442	6.465913	0.0000
32	2.376286	0.206583	6.662149	0.0000
Sample: 3/01/2000 7/02/2007				
Joint Tests		Value	df	Probability
Max |z| (at period 16)*		**6.723966**	**1852**	**0.0000**
Individual Tests				
Period	Var. Ratio	Std. Error	z-Statistic	Probability
2	1.193253	0.04211	4.589236	0.0000
4	1.412786	0.07404	5.575138	0.0000
8	1.590521	0.103524	5.704182	0.0000
16	1.936945	0.139344	6.723966	0.0000
32	2.125681	0.187801	5.994025	0.0000
Sample: 8/02/2007 2/07/2012				
Joint Tests		Value	df	Probability
Max |z| (at period 32)*		**5.047885**	**1408**	**0.0000**
Individual Tests				
Period	Var. Ratio	Std. Error	z-Statistic	Probability
2	1.15592	0.058314	2.673823	0.00750
4	1.321833	0.104972	3.06589	0.00220
8	1.541429	0.155953	3.471752	0.00050
16	1.997337	0.214701	4.645234	0.00000
32	2.457641	0.288763	5.047885	0.00000

Variance Ratio Test for OMX Tallinn				
Null Hypothesis: Cumulated RET_ESTONIA is a martingale				
Sample: 5/01/2000 3/07/2012				
Heteroskedasticity robust standard error estimates				
Joint Tests		Value	df	Probability
Max |z| (at period 32)*		**7.679981**	**3260**	**0.0000**
Individual Tests				
Period	Var. Ratio	Std. Error	z-Statistic	Probability
2	1.145483	0.030204	4.816708	0.0000
4	1.297714	0.054216	5.491246	0.0000
8	1.488527	0.080346	6.080316	0.0000
16	1.837752	0.112742	7.430705	0.0000
32	2.203954	0.156765	7.679981	0.0000
Sample: 3/01/2000 7/02/2007				
Joint Tests		Value	df	Probability
Max |z| (at period 32)*		**6.187123**	**1852**	**0.0000**
Individual Tests				
Period	Var. Ratio	Std. Error	z-Statistic	Probability
2	1.135838	0.033109	4.102781	0.0000
4	1.272128	0.060417	4.504157	0.0000
8	1.44559	0.089207	4.994981	0.0000
16	1.749825	0.12692	5.907845	0.0000
32	2.100149	0.177813	6.187123	0.0000
Sample: 8/02/2007 2/07/2012				
Joint Tests		Value	df	Probability
Max |z| (at period 32)*		**5.341619**	**1408**	**0.0000**
Individual Tests				
Period	Var. Ratio	Std. Error	z-Statistic	Probability
2	1.144779	0.044558	3.249201	0.00120
4	1.296895	0.079435	3.73756	0.00020
8	1.505802	0.117683	4.298019	0.00000
16	1.863727	0.164605	5.247259	0.00000
32	2.217009	0.227835	5.341619	0.00000

Here, the Chow-Denning maximum |z| statistic is associated with the period 32 individual test. For OMX Baltic10 and OMX Tallinn Z values are high and very significant, thus null hypothesis is rejected for all joint and individual tests at 1% significance level. However, if there would be a crucial requirement to compare the performance of variance ratio across the transition period and post-crisis, there is a slight increase in probabilities during the second period in both indexes although they are not significant. According to these results both stock price indexes are not martingale processes.

Next, previous test is repeated by using bootstrapping and heteroskedasticity robust. The p-values for the individual variance ratio tests are generally consistent with the previous results, albeit with probabilities that are slightly lower than before, which is noticeable for both stock indexes in the second sub-sample.[15] It is vastly important to look at other two stock indexes of Latvia and Lithuania. The table below presents results with Lo and MacKinlay (1980) asymptotic probabilities and Chow-Denning maximum Z- statistic.

The estimates are given for each interval of 2, 4, 8, 16 and 32 days, corresponding to one-day and less frequent calendar periods. For each estimate table presents estimates of the variance ratio VR (q) and the test statistics for the null hypothesis of homoscedastic, Z(q) and heteroscedastic, $Z^*(q)$ increments random walk. Consider the results for Latvian stock exchange. With the maximum Z value at period 4 probability is significantly high, thus hypothesis of martingale process cannot be rejected for full sample of daily returns of OMX Riga. Looking at the results of first and second sub-samples separately they are very different. During the period 2000-2007 random walk model can be rejected at 10% significance level, which is also consistent with autocorrelations test. Further, second sub-sample of 2007-2012 data provides results, where variance ratio is very close to unity, thus there is very little serial dependencies in observations. Findings are compared with Wald bootstrapping technique[16] and consistent results are obtained, only with lower values of probabilities. We may conclude that the Latvian equity market is coherent with Random Walk model and according to Variance Ratio Test is weak-form efficient.

Further, let's reflect on Lithuanian stock market performance with respect to variance ratio analysis. Considering the full sample period results argue against random walk hypothesis as null is strongly rejected with p=0.000. On the contrary, first sub-sample of 2000-2007 has insignificant z-values in period 4 and 8 where hypothesis of martingale cannot be rejected at 5%. However, the Chow-Denning statistic provides us with p=0.001, which strongly rejects null for joint test. The

[15] See appendix for bootstrap variance ratio outputs
[16] See appendix for output.

same conclusions are applicable for second sub-sample. The bootstrapping technique employed for OMX Vilnius has also rejected random walk hypothesis for Lithuanian stock price index.

Overall, variance ratio analyses confirmed results that have been obtained from Autocorrelations and Runs tests. Even if they do not have the same results for unit root testing, it has significant implications on efficiency in Baltic stock markets. Estonia and Lithuania seems to have persistent serial dependencies between asset returns in both sub-samples, while Latvia performs significant improvement in the second period of financial crisis and afterwards. So far, examination of market stock indexes has provided strong evidences of asset returns predictability in OMX Tallinn, OMX Vilnius and OMX Baltic10 indexes. Further steps toward final conclusion will be testing cointegration level of all Baltic region markets and applying technical strategy in order to see whether return predictability is really significant in this study period.

Variance Ratio Test for OMX Riga					**Variance Ratio Test for OMX Vilnius**				
Null Hypothesis: Cumulated RET_LATVIA is a martingale					Null Hypothesis: Cumulated RET_LITHUANIA is a martingale				
Sample: 5/01/2000 3/07/2012					**Sample: 5/01/2000 3/07/2012**				
Heteroskedasticity robust standard error estimates					Heteroskedasticity robust standard error estimates				
Joint Tests		Value	df	Probability	Joint Tests		Value	df	Probability
Max |z| (at period 4)*		**2.000766**	**3260**	**0.2074**	**Max |z| (at period 32)***		**6.638004**	**3260**	**0.0000**
Individual Tests					Individual Tests				
Period	Var. Ratio	Std. Error	z-Statistic	Probability	Period	Var. Ratio	Std. Error	z-Statistic	Probability
2	1.045661	0.051801	0.881469	0.3781	2	1.128155	0.047242	2.712746	0.0067
4	1.184866	0.092398	2.000766	0.0454	4	1.244854	0.090603	2.702481	0.0069
8	1.136284	0.136603	0.997668	0.3184	8	1.404453	0.135532	2.984201	0.0028
16	1.279527	0.191299	1.461203	0.1440	16	1.868715	0.181138	4.795881	0.0000
32	1.287877	0.261151	1.10234	0.2703	32	2.516301	0.228427	6.638004	0.0000
Sample: 3/01/2000 7/02/2007					**Sample: 3/01/2000 7/02/2007**				
Joint Tests		Value	df	Probability	Joint Tests		Value	df	Probability
Max |z| (at period 4)*		**2.383372**	**1852**	**0.0829**	**Max |z| (at period 32)***		**4.329526**	**1852**	**0.0001**
Individual Tests					Individual Tests				
Period	Var. Ratio	Std. Error	z-Statistic	Probability	Period	Var. Ratio	Std. Error	z-Statistic	Probability
2	1.103744	0.082588	1.256174	0.2091	2	1.118407	0.034826	3.399978	0.0007
4	1.348585	0.146257	2.383372	0.0172	4	1.183822	0.102834	1.787564	0.0738
8	1.249522	0.214554	1.162982	0.2448	8	1.273484	0.165585	1.651625	0.0986
16	1.38686	0.299774	1.290505	0.1969	16	1.623499	0.220227	2.831165	0.0046
32	1.263878	0.409527	0.644348	0.5193	32	2.157435	0.267335	4.329526	0.0000
Sample: 8/02/2007 2/07/2012					**Sample: 8/02/2007 2/07/2012**				
Joint Tests		Value	df	Probability	Joint Tests		Value	df	Probability
Max |z| (at period 32)*		**1.234777**	**1408**	**0.7055**	**Max |z| (at period 32)***		**5.177858**	**1408**	**0.0000**
Individual Tests					Individual Tests				
Period	Var. Ratio	Std. Error	z-Statistic	Probability	Period	Var. Ratio	Std. Error	z-Statistic	Probability
2	0.963076	0.045435	-0.812682	0.41640	2	1.134698	0.076059	1.770972	0.07660
4	0.953716	0.084717	-0.546336	0.58480	4	1.285729	0.135589	2.107319	0.03510
8	0.975641	0.130786	-0.186248	0.85230	8	1.493845	0.198391	2.489249	0.01280
16	1.122581	0.185352	0.661341	0.50840	16	2.034555	0.265571	3.89558	0.00010
32	1.311242	0.252063	1.234777	0.21690	32	2.754532	0.338853	5.177858	0.00000

*Probability approximation using studentized maximum modulus with parameter value 5 and infinite degrees of freedom

5.6 Cointegration and Granger Causality

A set of variables is defined as cointegrated if a linear combination of them is stationary. (Brooks, 2008) There are quite a few non-stationary series that move together over time, therefore showing existence of some influences on the series. Cointegration may also be seen as a long-term phenomenon as it is possible that cointegrating variables deviate from their relationship in the short term but their connection returns in the long run. Graphical analysis of trends and patterns in which stock markets are moving can also be helpful to indicate significant correlations. Engle and Granger (1987) note that a linear combination of two or more non-stationary series can be stationary in which case it is said series are cointegrated. Single equation cointegration test is used on stock market indexes with both Engle-Granger and Phillips-Ouliaris test methods. The output below represents statistical significance of statistics and probabilities together with null hypothesis.

Sample: 5/01/2000 3/07/2012

Null hypothesis: Series are not cointegrated

Cointegrating equation deterministics: C

Automatic lags specification based on Schwarz criterion (maxlag=28)

Sub-sample 1					**Sub-sample 2**					**Full sample**				
Dependent	tau-statistic	Prob.*	z-statistic	Prob.*	**Dependent**	tau-statistic	Prob.*	z-statistic	Prob.*	**Dependent**	tau-statistic	Prob.*	z-statistic	Prob.*
OMX_Riga	-3.171218	0.1789	-21.9958	0.1110	**OMX_Riga**	-2.801322	0.3305	-14.18121	0.3690	**OMX_Riga**	-2.952602	0.2618	-17.21881	0.2402
OMX_Tallinn	-1.70754	0.8426	-11.60285	0.5114	**OMX_Tallinn**	-2.133647	0.6728	-7.839327	0.7455	**OMX_Tallinn**	-2.942988	0.2659	-18.24695	0.2053
OMX_Vilnius	-1.171507	0.9488	-6.004169	0.8500	**OMX_Vilnius**	-2.999509	0.2429	-15.64014	0.3012	**OMX_Vilnius**	-3.46137	0.0983	-23.50464	0.0863

*MacKinnon (1996) p-values.

Statistical results show that three series are not cointegrated significantly during the full sample period as well as through two sub-samples. However, analyzing them separately with each other author found noteworthy results on relationship between stock price indexes. The most of cointegration exists between OMX Vilnius and OMX Tallinn stock prices indexes during the full sample, but when data is divided into sub-periods cointegration significance disappears. Phillips-Ouliaris test method gave the same results of no significant integrating relationship, thus the repetitive outcomes of outputs are not presented in the study.

Given the absence of cointegrating relationship, we turn to Granger causality analysis, using returns without an error correction term. Granger causality is a commonly used test in VAR analyses in order to test causalities among variables. By causality we usually refer to a relation where an event X causes another event Y**,** and thus increments changes in X accordingly. Granger causality is a bit different and refers to the correlation between the current value of one variable and the past values of others. In other words, it shows whether dynamical movements in Y can be explained by X. In particular, the test shows whether a movement in Y can best be described by its own past or whether it can be better explained by the past movements of another variable, namely X. Causality test can show four possible outcomes for two variables:

1. X does not Granger cause Y, Y does not Granger cause X

2. X does not Granger cause Y, Y does Granger cause X

3. X does Granger cause Y, Y does not Granger cause X

4. X does Granger cause Y, Y does Granger cause X

Granger Causality Test for OMX Tallinn, OMX Riga, OMX Vilnius			
Null Hypothesis: for sample 2000-2012	**Obs.**	**F-Statistic**	**Prob.**
RET_LATVIA does not Granger Cause RET_ESTONIA	3259	0.43379	0.6481
RET_ESTONIA does not Granger Cause RET_LATVIA		7.36342	**0.0006**
RET_LITHUANIA does not Granger Cause RET_ESTONIA	3259	2.09610	0.1231
RET_ESTONIA does not Granger Cause RET_LITHUANIA		16.3291	**0.0000**
RET_LITHUANIA does not Granger Cause RET_LATVIA	3259	12.5268	**0.0000**
RET_LATVIA does not Granger Cause RET_LITHUANIA		2.10085	0.1225
Null Hypothesis: for sub-sample 2000-2007	**Obs.**	**F-Statistic**	**Prob.**
RET_LATVIA does not Granger Cause RET_ESTONIA	1850	0.54829	0.5780
RET_ESTONIA does not Granger Cause RET_LATVIA		0.50322	0.6047
RET_LITHUANIA does not Granger Cause RET_ESTONIA	1850	3.62899	**0.0267**
RET_ESTONIA does not Granger Cause RET_LITHUANIA		9.04010	**0.0001**
RET_LITHUANIA does not Granger Cause RET_LATVIA	1850	3.28017	**0.0378**
RET_LATVIA does not Granger Cause RET_LITHUANIA		4.69081	**0.0093**
Null Hypothesis: for sub-sample 2007-2012	**Obs.**	**F-Statistic**	**Prob.**
RET_LATVIA does not Granger Cause RET_ESTONIA	1406	0.80336	0.4480
RET_ESTONIA does not Granger Cause RET_LATVIA		12.3286	**0.0000**
RET_LITHUANIA does not Granger Cause RET_ESTONIA	1406	1.62725	0.1968
RET_ESTONIA does not Granger Cause RET_LITHUANIA		6.11554	**0.0023**
RET_LITHUANIA does not Granger Cause RET_LATVIA	1406	15.5146	**0.0000**
RET_LATVIA does not Granger Cause RET_LITHUANIA		0.58515	0.5572

Full sample results are consistent with second period results as they provide stronger influence on stock indexes behavior during the second period. According to this Estonian stock index does Granger cause Latvian stock market, but Latvian market does not cause Estonian. A single direction relationship is common for Latvian and Lithuanian markets as well. Estonia Granger causes Lithuania, but not otherwise. The last row of first table shows that Lithuanian stock market has significant impact on Latvian. Apparently, Estonian stock index has strong influence on both Latvian and Lithuanian stock markets but is not affected by itself, Lithuanian stock market has some influence on Latvian, and finally, Latvian does not Granger cause any of the former equity markets.

The second part of the table represents first sub-period, where testing outcome is different. There exists mutual causality between Estonian and Lithuanian, and Latvian and Lithuanian stock markets. However, there is no Granger causality between Latvian and Estonian financial markets as hypothesis cannot be rejected at high levels of *p*-value. In the third table of different period results are different thus proving Estonia does have causality on Latvian market. Further, test finds significant causality for Lithuanian and Estonian stock price indexes. It appears that Granger causality runs both ways and is significant at 5% significance level. These results differ in the second sub-period, where Lithuania does not cause Estonian stock market anymore. The relationship between Lithuania and Latvia financial stock markets is significant during the period 2000-2007, although in the second period Latvian stock index does not cause Lithuanian stock index anymore.

6 Technical Analysis and Empirical Results

6.1 History and Empirical Work on Trading Rules

Random walk model testifies that returns cannot be predicted from their own lagged values. However, technical analysis is still considered to be a viable and efficient approach to individual stock selection and market analysis.

Trading rule basically is a method for converting history of prices into investment decisions. These strategies started to emerge more than a century ago when Bachelier (1900) wrote the seminal paper of his development in a number of statistical models about price prediction, including Brownian motion. Andreou, Pitts and Spanos (2001) continued the research on how these models capture empirical irregularities inherent in economic data. Researchers Pruitt and White (1988) and Dunis (1989) directly support the application of trading rules and argue that moving averages, filters and patterns seems to generate significant abnormal returns. Lukac and Brorsen (1990) investigated futures market trading where rules generated abnormal returns.

Brock, Lakonishok, and Lebaron (1992) examined the predictability of technical trading rules such as moving average rule and trading range breakout rule in US (Dow Jones Industrial Average) equity markets during the period 1897-1986. Brock et al. finds significant, positive values of the mean return and probability differences of standard deviation. The first and second moments of DJIA returns were found predictable to some degree and technical rules were informative. Authors drew four particularly interesting conclusions for the moving average rule:

- “Buy signals consistently generate higher returns than Sell signals”. For their findings 12% for Buy returns and -7% for Sell returns in DJIA
- “returns following sell signals are negative, which is not explainable by any equilibrium models:”
- “returns following buy signals are less volatile than returns following sell signals”
- “returns from these strategies are not consistent with popular models”, such as ARCH

Further research studies have been done for DJIA stock index by Bessembinder and Chan (1995a.) and found that negative expected returns on Sell days only occur before 1939. They claim that realistic transaction costs remove any abnormal profits. Sullivan, Timmermann, and White (1999) discussed the problem of data-snooping which occur when researcher copy technical rules from financial literature that have best historical returns. Sullivan et al reanalyzed data of Brock et al. and concluded that there indeed was significant evidence of informative trading rules in DJIA until 1986.

Technical analysis of trading rules quickly spread to other financial markets. Bessembinder and Chan (1995) applied BLL trading rule for Hong Kong, Japan, Korea, Malaysia, Thailand, and Taiwan stock markets from 1975 to 1991. Results indicated strong predictability for emerging markets in Malaysia, Thailand, and Taiwan which is consistent with Dawson (1991) and Yong (1991) results who find several patterns in the Malaysian stock market. (Taylor, 2005)

Hudson, Dempsey, and Keasy (1996) applied Brock et al. method for UK FT-30 stock index series from 1935 to 1994. Significant results of informative rules were found until 1981; however, any profits obtained from trading rules were eliminated by transaction costs.

6.2 Moving Average Trading Rule Application to Baltic Stock Indexes

6.2.1 Methodology

A comparison of two moving averages defines one of the most frequently mentioned trading rules in the financial literature. Two averages of short length (S) and long length (L) are calculated at time *t* from the most recent price observations, including p_t.

$$a_{t,S} = \frac{1}{S}\sum_{j=0}^{S-1} p_{t-S+j} \; Short\ Lenght\ Average$$

$$a_{t,L} = \frac{1}{L}\sum_{j=1}^{L} p_{t-L+j} \; Long\ Lenght\ Average$$

The relative difference between the averages is considered, with the formula given below

$$R_t = \frac{a_{t,S} - a_{t,L}}{a_{t,L}}$$

where most common values are $S \leq 5$ and $L \geq 50$.

When short term average is above (below) the long-term average, recent prices are higher (lower) than older prices and it may be thought that prices are following upward or downward trend respectively. (Taylor, 2005) In case of similar averages, information is not precise enough to make a good decision about the trend. Brock et al. (1992) classified the decision making strategy for *t+1* period, which is the time from close on day *t* until the close on *t+1*, as

$$Buy\ if\ R_t > B, \qquad Neutral\ if -B \leq R_t \leq B, \qquad Sell\ if\ R_t < -B$$ [17]

When the bandwidth is set to zero, all days are either Buys or Sells.

The rule is performed on four stock indexes of OMX Tallinn, OMX Riga, OMX Vilnius and OMX Baltic10 daily returns during the period 2000-2012. The parameters are selected to make relevant comparisons of the performance of the strategy. For short moving average, S, value of 1 is chosen, while for long moving average, L, three different values of 50, 100 and 200 are selected.

[17] The bandwidth according to which the position of trading is determined, here 1%

The returns are calculated as before, in logarithmic form, and other parameters are calculated as required by Brock (1992).

The null hypothesis states that rule is not informative and alternative – the rule is informative and thus stock market index is not efficiently performing. An obvious test of the null hypothesis requires calculation of standard deviation S_I and S_J respectively from the Buy and Sell returns, followed by comparison statistic with standard normal distribution

$$z = (\bar{r}_I - \bar{r}_J)(\frac{s_I^2}{n_I} + \frac{s_J^2}{n_J})^{-0.5}$$

Buy and Sell probabilities are also estimated in the study.

6.2.2 Estimations

The table below represents first results for OMX Vilnius stock price index.

OMX Vilnius									
S	**L**	**%B**	**Z**	**L**	**%B**	**Z**	**L**	**%B**	**Z**
1	50	1	**6.231**	100	1	**5.458**	200	1	**5.005**
	Buy	**Sell**	**Neutral**	**Buy**	**Sell**	**Neutral**	**Buy**	**Sell**	**Neutral**
Count	1637	1146	433	1615	1226	325	1840	1091	134
Sum r	290.372	-142.714	-27.695	249.893	-133.141	5.010	253.549	-119.669	-3.231
Sum r*r	2191.506	2050.217	409.700	2196.987	2266.205	173.615	2227.097	2150.899	177.467
Mean	0.177	-0.125	-0.064	0.155	-0.109	0.015	0.138	-0.110	-0.024
Variance	1.308	1.775	0.944	1.337	1.838	0.536	1.192	1.961	1.334
St. Dev	1.144	1.332	0.972	1.156	1.356	0.732	1.092	1.400	1.155
Mean p.a	46.119	-32.378	-16.630	40.230	-28.235	4.008	35.828	-28.519	-6.268
Trades	61	57		37	45		24	15	
Av.duration	26.836	20.105		43.649	27.244		76.667	72.733	

The table includes parametres used for optimization of trading rule, required statistical values of mean, variance, sum of squared returns, number of buy and sell days. The first notice on the difference between Buy days and Sell days provides impression about the strategy. Brock et. al (1992) also found significant different between averages. Form OMX Vilnius the mean of Buy days 17.7% and the mean for Sell days -12.5% for L=50 indicates strong divergence between the averages. This is consistent with Brock (1992) conclusion, where he states that Buy signals consistently generate higher returns than Sell signals. Moreover, longer length averages of L=100 and L=200 have the same characteristics for Buy/Sell return differences. Neutral position generates negative returns for shorter average but positive in the longer-length case. Standard deviations of 1.14% and 1.33% reports that returns following buy signals are less volatile than returns following sell signals, which is also consistent with Brock results. Number of trades for the index is slowly declining as the length of moving average increases. The overall conclusion for OMX Vilnius is drawn form Z-statistic value, which is highly significant. Thus for Lithuania index hypothesis of market efficiency is rejected for all parameters as the rule was found informative.

OMX Tallinn									
S	**L**	**%B**	**Z**	**L**	**%B**	**z**	**L**	**%B**	**z**
1	50	1	**5.584**	100	1	**4.993**	200	1	**4.611**
	Buy	**Sell**	**Neutral**	**Buy**	**Sell**	**Neutral**	**Buy**	**Sell**	**Neutral**
Count	1623	1160	433	1759	1140	267	1977	957	132
Sum r	283.190	-116.303	-34.122	249.893	-116.145	8.259	253.224	-107.452	7.495
Sum r*r	2140.041	2198.570	350.223	2143.928	2225.962	207.007	2389.013	1946.177	70.902
Mean	0.174	-0.100	-0.079	0.142	-0.102	0.031	0.128	-0.112	0.057
Variance	1.289	1.887	0.804	1.199	1.944	0.777	1.193	2.023	0.538
St. Dev	1.135	1.374	0.897	1.095	1.394	0.882	1.092	1.422	0.733
Mean p.a	45.366	-26.068	-20.489	36.937	-26.489	8.043	33.302	-29.193	14.764
Trades	59	65		35	38		25	17	
Av.duration	27.508	17.846		50.257	30.000		79.080	56.294	

The following table represents the same calculations performed on OMX Tallinn stock market index. Number of buying and selling days is very similar to OMX Vilnius case but in the case of L=100 and L=200 Estonia present higher difference between two signals. Buy signals also have positive and significant mean (17.4%) while sell signals have significantly negative mean (-10%) for L=50, and the difference is reduces by increasing parameter L. Significant Z-statistic indicates that the rule is informative, thus Estonian stock index also provides evidence of inefficient performing during 2000-2012.

OMX Riga									
S	**L**	**%B**	**Z**	**L**	**%B**	**z**	**L**	**%B**	**z**
1	50	1	**2.152**	100	1	**0.864**	200	1	**2.190**
	Buy	**Sell**	**Neutral**	**Buy**	**Sell**	**Neutral**	**Buy**	**Sell**	**Neutral**
count	1538	1084	594	1763	1033	370	1983	912	171
sum r	161.431	-41.562	-1.913	106.667	6.238	1.004	150.117	-52.913	-5.512
sum r*r	3851.827	3301.573	624.848	4297.141	2766.197	640.951	4957.550	2054.358	297.091
mean	0.105	-0.038	-0.003	0.061	0.006	0.003	0.076	-0.058	-0.032
variance	2.495	3.047	1.054	2.435	2.680	1.737	2.496	2.252	1.747
st dev	1.580	1.746	1.026	1.560	1.637	1.318	1.580	1.501	1.322
mean p.a	27.290	-9.969	-0.837	15.731	1.570	0.705	19.683	-15.085	-8.381
trades	94	89		76	64		32	37	
av.duration	16.362	12.180		23.197	16.141		61.969	24.649	

Third case of moving average rule analysis takes into account OMX Riga stock index return performance. Here results are more uncommon. The number of signals for Buy and Sell days are about the same comparing with previous indexes, however, the difference between Buy and Sell averages is significantly lower.[18] According to standard deviation measure, buy returns are still less volatile than sell returns. Comparing z-statistics for OMX Riga stock index we get: for L=50 rule is not informative at 5% level as p=0.0603 but the rule is still informative at 10% significance level; for L=100 hypothesis are cannot be rejected at any reasonable level; for L=200 rule can be rejected at 5% but not at 1% significance level. To sum up, OMX Riga stock market shows much higher efficiency level comparing with other indexes, which is consistent with fundamental analysis.

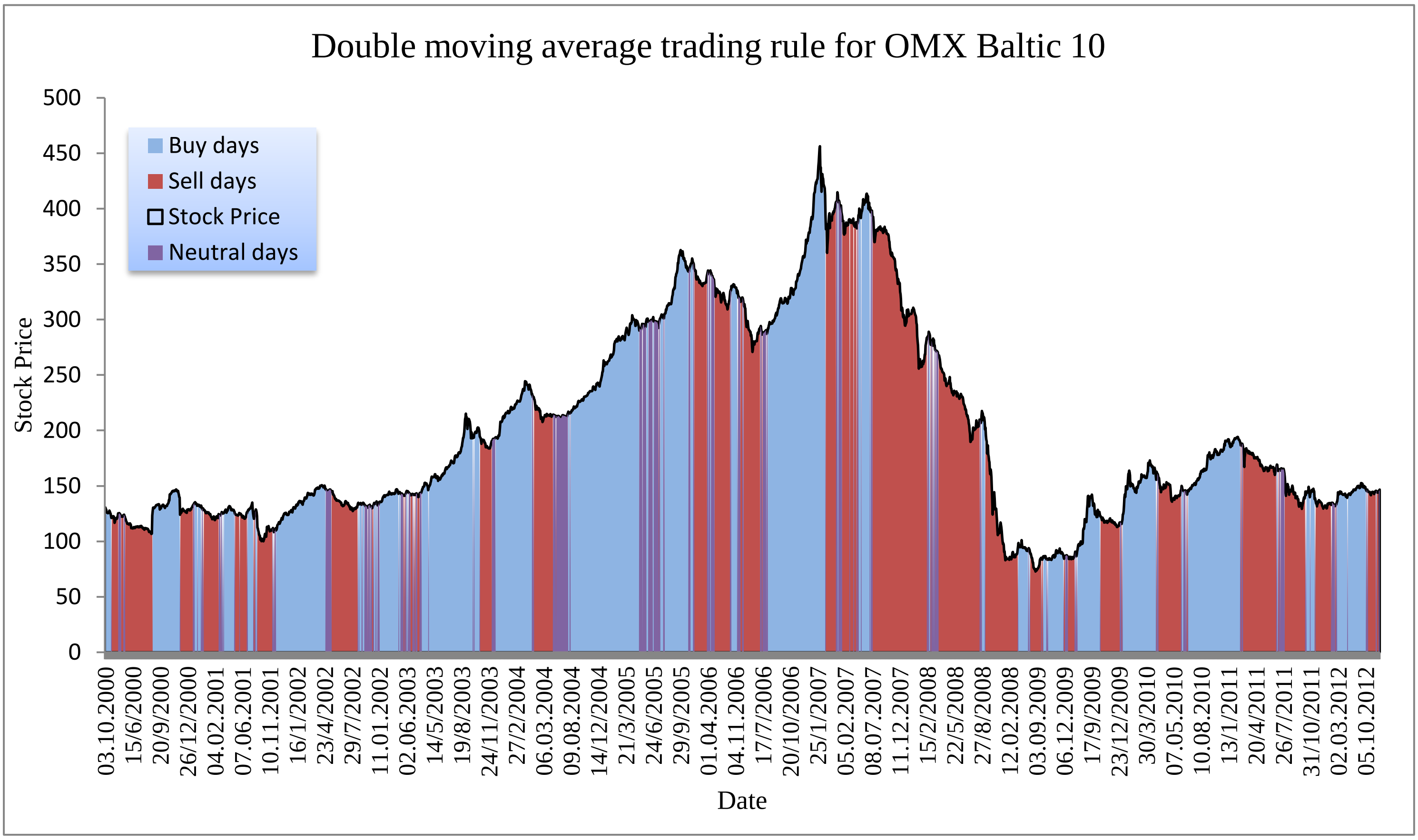
OMX Baltic 10									
S	**L**	**%B**	**Z**	**L**	**%B**	**z**	**L**	**%B**	**z**
1	50	1	**5.668**	100	1	**4.879**	200	1	**4.222**
	Buy	**Sell**	**Neutral**	**Buy**	**Sell**	**Neutral**	**Buy**	**Sell**	**Neutral**
count	1506	1289	419	1505	1414	247	1748	1124	191
sum r	210.575	-177.308	101.507	195.143	-161.444	129.228	146.042	-147.928	12.333
sum r*r	1794.133	2707.377	15204.335	2493.393	2829.865	14929.609	2028.223	2463.766	145.546
mean	0.140	-0.138	0.242	0.130	-0.114	0.523	0.084	-0.132	0.065
variance	1.173	2.083	36.315	1.641	1.990	60.415	1.154	2.177	0.762
st dev	1.083	1.443	6.026	1.281	1.411	7.773	1.074	1.475	0.873
mean p.a	36.354	-35.764	62.988	33.712	-29.686	136.029	21.722	-34.218	16.788
trades	68	67		37	38		28	20	
av.duration	22.147	19.239		40.676	37.211		62.429	56.200	

The last table represents moving average rule performance on OMX Baltic 10. The results are similar to those for OMX Vilnius and OMX Riga with large difference between buy signals and sell signals and hence hypothesis of rule being uninformative is strongly rejected at 1% significance level with p=0.0000. The index built from common stocks appears to be available for profit exlpitation.

Moving average rule is significant if there can be found a long period of days following the same movement of price. In case of frequent trading there are costs applied which reduce abnormal profits to minimum and trading rule looses its significance. The figure below represents trading rule performed on Latvian stock index with long average equal 50. Blue plot in figure represents Buy days; purple indicates Neutral days and red denotes Sell days. The longest period of Buy -173

[18] For L=50, 10.5% and -3.8%; for L=100, 6.1% and 0.6%; and for L=200, 7.6% and -5.8% respectively.

days and for Sell – 157 days. The black line represents stock price on that day. It is clear from graph that moving average rule suggests buying stock while it is climbing upwards and selling when it is descending.



When the rule is significant and instantaneously gives a good strategy to exploit market profitability there should be included analysis of transaction costs. Brock et. al (1992) argued that super normal returns which are seemed to be earned by trading rule vanish after costs being taken into account. For this reason, the breakeven cost for trading rule was calculated that ensures the average daily profit is in excess of risk-free interest payments. Moreover, wealth analysis is completed in order to evaluate realistic performance of trading rules for Baltic market stock indexes. The table below represents how differs the final wealth of 1000 Euros invested in stock market after the transaction costs have been applied.

	Wealth OMX Vilnius			Wealth OMX Riga			Wealth OMX Tallinn			Wealth OMX Baltic 10		
L	**50**	**100**	**200**	**50**	**100**	**200**	**50**	**100**	**200**	**50**	**100**	**200**
Initial W	€ 1,000.00	€ 1,000.00	€ 1,000.00	€ 1,000.00	€ 1,000.00	€ 1,000.00	€ 1,000.00	€ 1,000.00	€ 1,000.00	€ 1,000.00	€ 1,000.00	€ 1,000.00
Final W	€ 17,537.09	€ 11,304.29	€ 12,574.01	€ 5,058.91	€ 2,926.64	€ 4,486.94	€ 15,407.84	€ 11,855.36	€ 12,581.69	€ 7,648.86	€ 5,499.22	€ 4,307.77
Switches	220	161	77	336	261	133	222	137	81	251	140	93
Breakeven C%	1.74%	2.21%	4.62%	0.50%	0.26%	1.18%	1.49%	2.29%	3.95%	1.43%	2.37%	3.18%
Actual C %	1.00%	1.00%	1.00%	1.00%	1.00%	1.00%	1.00%	1.00%	1.00%	1.00%	1.00%	1.00%
Revised W	€ 1,921.76	€ 2,241.35	€ 5,799.41	€ 172.78	€ 212.40	€ 1,178.77	€ 1,654.84	€ 2,991.83	€ 5,574.29	€ 613.81	€ 1,346.57	€ 1,691.71
Min	€870.17	€897.04	€969.30	€948.54	€793.17	€907.73	€860.61	€937.08	€951.59	€959.22	€917.14	€900.72
Max	€18,636.06	€11,971.95	€12,574.01	€6,246.70	€3,603.20	€5,004.12	€17,367.07	€12,414.46	€14,351.22	€8,672.11	€5,540.96	€5,057.85

The actual transaction cost here is assumed to be 1% as it varies for markets in the region of 0.02%-0.5%[19] and in the past period there have been higher transaction costs due to more sophisticated process of trading. There is no risk premium assumed in the calculations. The breakeven cost given in the table is calculated with the formula:

$C^* = \frac{(r_I - r_J)}{2\left(\frac{1}{D_t} + \frac{1}{D_J}\right)}$ and it assumes that capital is required to finance trades.[20]

When trading costs are lower than breakeven cost, traders are assumed to outperform the benchmark strategy. The revised wealth after transaction costs have been applied is calculated as follows

$$W^* = Final\ W \times (1 - C^*)^{switches}$$

As the table illustrates, investing 1000 € into the market would accumulate positive returns, in some cases very significant, especially in OMX Vilnius and OMX Tallinn, when long average is large enough. The number of switches shows how many times the strategy changes from Buying, Selling or Neutral. As the number of transaction increases the cost also increases consequently lowering the profits. According to these estimations markets might be exploited with ability to earn abnormal profits. These conclusions are not in favor of market efficiency, but they are not final and not negotiable.

[19]Manually matched equity transaction - 0.03% of transaction value but not less than EUR 0.30 and not more than EUR 140 for each transaction side that the Exchange member is. 0.045% of the value per trade for each party to the trade, except trades in debt securities; 0.03% of the value of the trade, but no more than LTL 500 per each party to the trade, where the trade is reported as “Standard” or the “Exchange Granted Trade”, except trades in debt securities.

[20] Formula represents the average of means divided by the fraction of average duration of Buy and Sell trades.

The flaws, such as data snooping, are not included and examined properly in the research, which might be a significant bias to the results. The problem of data snooping can be avoided by using genetic algorithm methodology as some of the analysts have applied it to past returns. (Taylor, 2005) The method also does not include any risk adjustment to investment strategies and other applicable operation costs, such as membership costs, handling and admission fees. There also might be any external causes diluting possibility to earn superior returns form Baltic Stock Markets.

7 Final conclusions

This study examines the validity of efficient market hypothesis on Baltic equity markets, using four stock price index series. The period of analysis is carefully observed and divided into two parts according to economic and statistical significance. The first period 2000-2007 of analysis reflects transitional movements in stock prices, where equity markets do not have well built structure and proper trading conditions but are growing and developing rapidly. The second sub-period 2007-2012 indicates how stock markets in Estonia, Latvia and Lithuania are affected by financial crisis and how they are recovering over the past 3 years. Statistical tests prove that results are different for some index series in sub-samples.

Testing methodology is divided into two parts – statistical and technical. The first one is responsible for finding predictive patterns in asset return series, while the second one is responsible for utilizing the predictability in advantageous way. Non-parametric runs test indicates significant serial dependence in OMX Tallinn, OMX Vilnius and OMX Baltic 10 index series during the period 2000-2012. The same test finds significant predictability in OMX Riga return series during the first period 2000-2007, however, in the second time interval Latvian equity market does not reject random walk hypothesis and shows increased efficiency. Autocorrelations test provides the same outcome. All indexes possess significantly high autocorrelations, thus martingale hypothesis is rejected in the first sub-sample, while in the second one the same conclusions apply to Estonian and Lithuanian markets, except for Latvia. The required condition for random walk model of unit roots was rejected for Baltic stock market return series in full sample as well as in sub-samples. Variance ratios are entirely consistent with autocorrelations and runs tests. Two variance ratio tests reject hypothesis of finite variances for OMX Tallinn, OMX Vilnius and OMX Baltic10 stock market indexes. On the contrary, neither asymptotic probabilities nor bootstrapping rejects variance ratio being unity for Latvian stock index. As the graph of four Baltic stock market indexes present some visible similarities in trending, cointegration tests of single equation does not reject hypothesis of series being not integrated. Nevertheless, Granger causality test certifies some stock movements being dependent on other equity prices.

The last part of study is dedicated to technical analysis of moving average trading rule. As the predictable patterns from statistical analyses are found, the trading rule is employed in order to exploit the serial dependencies between returns. High significance of trading strategy is found for OMX Tallinn, OMX Vilnius and OMX Baltic10 stock indexes, but none for Latvian stock market. The positive profits are obtained from moving average trading rule, thus some bias in findings may exist. A variety of costs and operational difficulties have to be overcome for successful traders who are assess risks carefully and earn abnormal returns.

The can be some comments made on data collection and analysis. The data set used for this study may also be modified in order to get more superior results. Stock price indexes not always fully reflect all price movements of equities, so if the prices of stocks are used instead of indexes, findings might be more precise. Nevertheless, results are based on reliable sources of data and methodology chosen according to previous experiences and to reflect local significant factors of Baltic Exchange.

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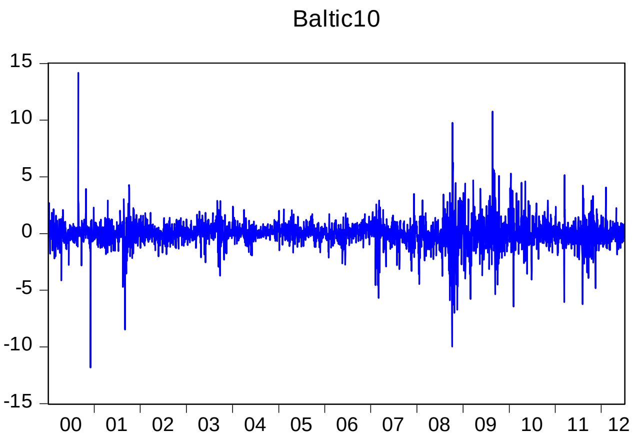
APPENDIX I:

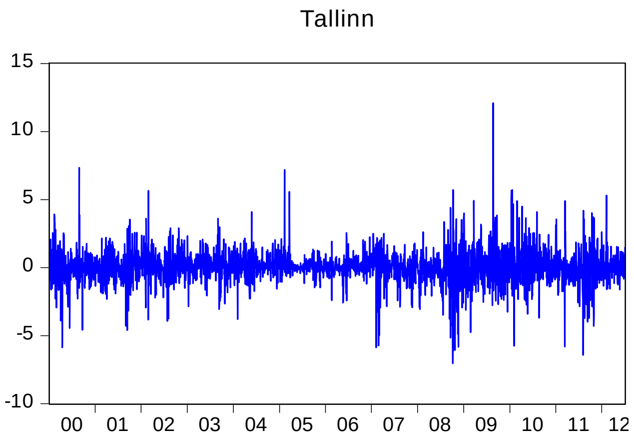
Description of Stock Indices Used

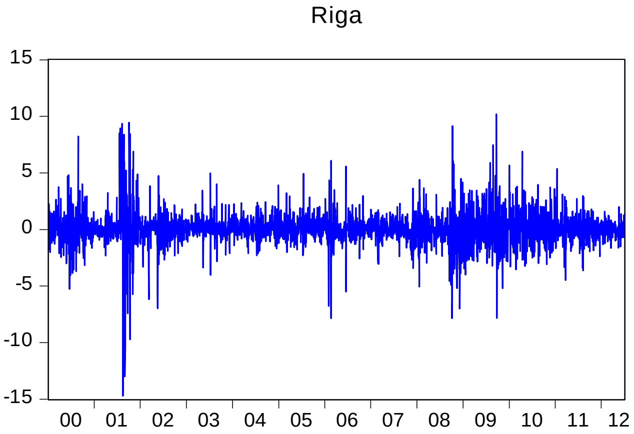
NASDAQ OMX uses a common classification of indexes for the Nordic and Baltic markets. All indexes are chain-linked, meaning that they are always calculated based on the price level of the previous trading day. The indexes are market weighted, calculated based on the change in the total market value from one point in time to another of all the shares included in the index.

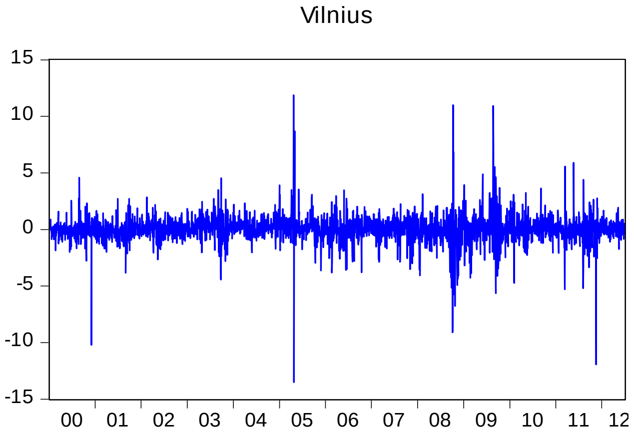
1. **OMX Baltic 10** (OMXB10) – PI, GI. OMXB10 is a tradable index consisting of the 10 most actively traded stocks on the Baltic exchanges. The limited number of constituents guarantees that all the underlying shares of the index have excellent liquidity, which results in an index that can be used as a good basis for derivatives. The weight of the constituent stocks is based on the market value adjusted by the free float and is capped to 15%. The composition of the OMXB10 index is revised twice a year, on January 1 and July 1. The base date for OMXB10 index is December 31, 1999 with a base value of 100. The index is calculated in Euro and is available as PI and GI. The index values are disseminated in real time with one second interval.
2. **OMX Tallinn** (OMXT) – GI. OMX Tallinn is an all-share index which includes all the shares listed on the Main and Secondary lists on the NASDAQ OMX Tallinn with exception of the shares of the companies where a single shareholder controls at least 90% of the outstanding shares. The aim of the index is to reflect the current status and changes on the Tallinn market. The base date for the OMXT is June 3, 1996, with a base value of 100. The index is available as Gross Index. The index values are disseminated with 60 seconds interval.
3. **OMX Riga All Share** (OMXR) – GI. OMX Riga is an all-share index consisting of all the shares listed on the Main and Secondary lists on the NASDAQ OMX Riga with exception of the shares of the companies where a single shareholder controls at least 90% of the outstanding shares. The aim of the index is to reflect the current status and changes on the Riga market. The base date for the OMXR is December 31, 1999, with a base value of 100. The index is available as Gross Index. The index values are disseminated with 60 seconds interval.
4. **OMX Vilnius All Share** (OMXV) – GI. OMX Vilnius is an all-share index which includes all the shares listed on the Main and Secondary lists on the NASDAQ OMX Vilnius with exception of the shares of the companies where a single shareholder controls at least 90% of the outstanding shares. The aim of the index is to reflect the current status and changes on the Vilnius market. The base date for the OMXV is December 31, 1999, with a base value of 100. The index is available as GI. The index values are disseminated with 60 seconds interval.

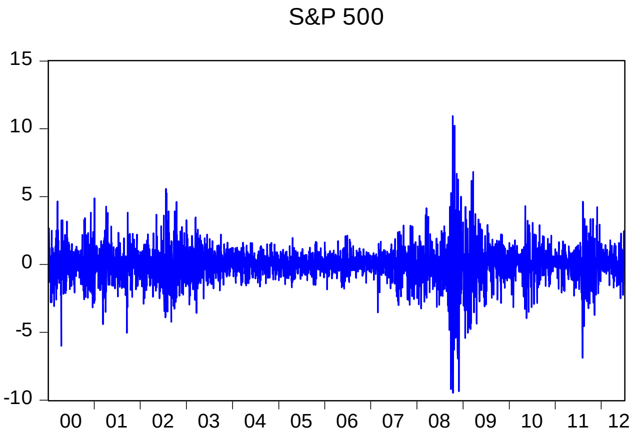
Return time series for stock market indexes 2000-2012

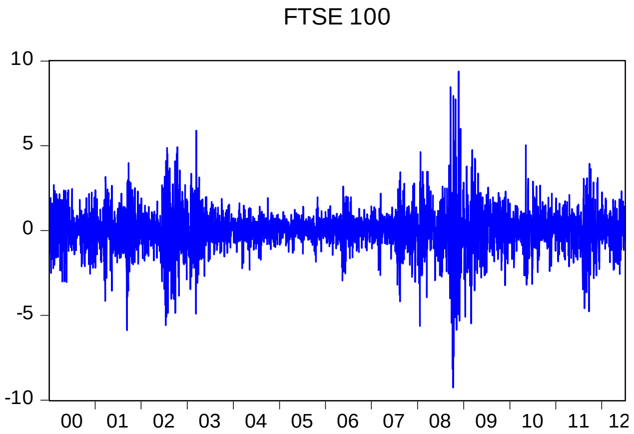












Structural breakpoint outputs

Quandt-Andrews unknown breakpoint test		
OMX Tallinn		
Null Hypothesis: No breakpoints within 15% trimmed data		
Number of breaks compared: 2282		
Statistic	Value	Prob.
Maximum LR F-statistic (6/02/2007)	21.056	0.0000
Maximum Wald F-statistic (6/02/2007)	42.113	0.0000
Exp LR F-statistic	4.298	0.0004
Exp Wald F-statistic	14.114	0.0000
Ave LR F-statistic	**2.902**	**0.0206**
Ave Wald F-statistic	**5.805**	**0.0206**

Note: probabilities calculated using Hansen's (1997) method

Quandt-Andrews unknown breakpoint test		
OMX Vilnius		
Null Hypothesis: No breakpoints within 15% trimmed data		
Number of breaks compared: 2282		
Statistic	Value	Prob.
Maximum LR F-statistic (4/03/2007)	14.082	0.0000
Maximum Wald F-statistic (4/03/2007)	28.164	0.0000
Exp LR F-statistic	2.642	0.0063
Exp Wald F-statistic	8.217	0.0005
Ave LR F-statistic	**2.902**	**0.0206**
Ave Wald F-statistic	**5.804**	**0.0206**

Note: probabilities calculated using Hansen's (1997) method

Quandt-Andrews unknown breakpoint test		
OMX Baltic 10		
Null Hypothesis: No breakpoints within 15% trimmed data		
Number of breaks compared: 2282		
Statistic	Value	Prob.
Maximum LR F-statistic (7/02/2007)	30.513	0.0000
Maximum Wald F-statistic (7/02/2007)	61.026	0.0000
Exp LR F-statistic	8.792	0.0000
Exp Wald F-statistic	23.298	0.0000
Ave LR F-statistic	**4.203**	**0.0035**
Ave Wald F-statistic	**8.405**	**0.0035**

Note: probabilities calculated using Hansen's (1997) method

Chow Breakpoint Test: 6/02/2007			
Null Hypothesis: No breaks at specified breakpoints			
F-statistic	**21.056**	**Prob. F(2,3257)**	**0.000**
Log likelihood ratio	41.894	Prob. Chi-Square(2)	0.000
Wald Statistic	42.113	Prob. Chi-Square(2)	0.000

Chow Breakpoint Test: 4/03/2007			
Null Hypothesis: No breaks at specified breakpoints			
F-statistic	**14.082**	**Prob. F(2,3257)**	**0.000**
Log likelihood ratio	28.077	Prob. Chi-Square(2)	0.000
Wald Statistic	28.164	Prob. Chi-Square(2)	0.000

Chow Breakpoint Test: 7/02/2007			
Null Hypothesis: No breaks at specified breakpoints			
F-statistic	**30.513**	**Prob. F(2,3257)**	**0.000**
Log likelihood ratio	60.535	Prob. Chi-Square(2)	0.000
Wald Statistic	61.026	Prob. Chi-Square(2)	0.000

Autocorrelations Test

OMX Tallinn									
Lag	Autocorrelation (2000-2012)	Q	Prob	Autocorrelation (2000-2007)	Q	Prob	Autocorrelation (2007-2012)	Q	Prob
1	0.143	66.94	0.0000	0.138	35.10	0.0000	0.145	29.50	0.0000
2	0.058	77.82	0.0000	0.053	40.31	0.0000	0.048	32.80	0.0000
3	0.043	83.78	0.0000	-0.006	40.38	0.0000	0.064	38.52	0.0000
4	0.033	87.31	0.0000	0.033	42.38	0.0000	0.033	40.10	0.0000
5	0.028	89.93	0.0000	0.017	42.93	0.0000	0.037	42.01	0.0000
6	0.049	97.65	0.0000	0.019	43.59	0.0000	0.060	47.12	0.0000
7	0.043	103.67	0.0000	0.052	48.63	0.0000	0.029	48.35	0.0000
8	0.038	108.34	0.0000	0.010	48.81	0.0000	0.050	51.86	0.0000
9	0.038	113.03	0.0000	0.031	50.55	0.0000	0.038	53.90	0.0000
10	0.063	125.96	0.0000	0.029	52.13	0.0000	0.077	62.23	0.0000
11	0.039	130.83	0.0000	0.050	56.78	0.0000	0.025	63.13	0.0000
12	0.037	135.40	0.0000	0.008	56.89	0.0000	0.047	66.22	0.0000
13	0.027	137.73	0.0000	0.010	57.08	0.0000	0.020	66.77	0.0000
14	0.035	141.84	0.0000	-0.003	57.10	0.0000	0.053	70.77	0.0000
15	0.017	142.75	0.0000	0.034	59.25	0.0000	0.010	70.92	0.0000
16	0.016	143.62	0.0000	-0.028	60.76	0.0000	0.043	73.58	0.0000
17	0.000	143.62	0.0000	-0.016	61.23	0.0000	-0.004	73.61	0.0000
18	0.011	143.98	0.0000	0.009	61.40	0.0000	0.015	73.95	0.0000
19	-0.006	144.09	0.0000	-0.026	62.64	0.0000	0.013	74.19	0.0000
20	-0.020	145.36	0.0000	0.002	62.65	0.0000	-0.033	75.77	0.0000

OMX Vilnius									
Lag	Autocorrelation (2000-2012)	Q	Prob	Autocorrelation (2000-2007)	Q	Prob	Autocorrelation (2007-2012)	Q	Prob
1	0.127	52.89	0.0000	0.112	23.34	0.0000	0.134	25.47	0.0000
2	0.029	55.56	0.0000	-0.018	23.97	0.0000	0.056	29.96	0.0000
3	0.045	62.25	0.0000	0.026	25.27	0.0000	0.053	34.00	0.0000
4	0.006	62.37	0.0000	-0.045	29.07	0.0000	0.037	35.97	0.0000
5	0.004	62.41	0.0000	0.002	29.08	0.0000	0.001	35.97	0.0000
6	0.101	96.04	0.0000	0.105	49.62	0.0000	0.095	48.87	0.0000
7	0.068	111.01	0.0000	0.053	54.79	0.0000	0.074	56.65	0.0000
8	0.075	129.44	0.0000	0.045	58.58	0.0000	0.092	68.62	0.0000
9	0.064	142.72	0.0000	0.054	64.06	0.0000	0.066	74.87	0.0000
10	0.064	156.19	0.0000	0.022	64.98	0.0000	0.089	86.02	0.0000
11	0.032	159.57	0.0000	0.036	67.37	0.0000	0.025	86.94	0.0000
12	0.061	171.56	0.0000	0.054	72.91	0.0000	0.061	92.25	0.0000
13	0.081	192.80	0.0000	0.001	72.92	0.0000	0.130	116.39	0.0000
14	0.058	203.95	0.0000	0.039	75.79	0.0000	0.066	122.61	0.0000
15	0.027	206.30	0.0000	0.017	76.32	0.0000	0.031	123.98	0.0000
16	0.058	217.18	0.0000	-0.004	76.36	0.0000	0.096	137.14	0.0000
17	0.024	219.00	0.0000	0.020	77.13	0.0000	0.021	137.76	0.0000
18	0.036	223.28	0.0000	0.055	82.81	0.0000	0.021	138.40	0.0000
19	0.042	229.00	0.0000	0.025	84.03	0.0000	0.051	142.19	0.0000
20	0.013	229.59	0.0000	-0.001	84.03	0.0000	0.022	142.86	0.0000

OMX Baltic 10									
Lag	Autocorrelation (2000-2012)	Q	Prob	Autocorrelation (2000-2007)	Q	Prob	Autocorrelation (2007-2012)	Q	Prob
1	0.171	95.18	0.0000	0.197	71.72	0.0000	0.154	33.38	0.0000
2	0.075	113.31	0.0000	0.1	90.17	0.0000	0.052	37.21	0.0000
3	0.061	125.37	0.0000	0.019	90.86	0.0000	0.07	44.06	0.0000
4	0.023	127.09	0.0000	0.028	92.27	0.0000	0.019	44.58	0.0000
5	0.019	128.22	0.0000	-0.005	92.33	0.0000	0.027	45.63	0.0000
6	0.061	140.39	0.0000	0.006	92.39	0.0000	0.08	54.78	0.0000
7	0.053	149.48	0.0000	0.042	95.68	0.0000	0.053	58.75	0.0000
8	0.080	170.61	0.0000	0.054	101.13	0.0000	0.087	69.52	0.0000
9	0.047	177.81	0.0000	0.042	104.36	0.0000	0.045	72.41	0.0000
10	0.079	198.41	0.0000	0.059	110.84	0.0000	0.082	82.07	0.0000
11	0.023	200.19	0.0000	0.041	113.99	0.0000	0.011	82.23	0.0000
12	0.037	204.76	0.0000	0.052	118.97	0.0000	0.023	83.02	0.0000
13	0.055	214.54	0.0000	-0.021	119.82	0.0000	0.078	91.75	0.0000
14	0.058	225.41	0.0000	0.028	121.32	0.0000	0.065	97.81	0.0000
15	0.024	227.33	0.0000	0.043	124.78	0.0000	0.016	98.18	0.0000
16	0.044	233.61	0.0000	-0.004	124.82	0.0000	0.063	103.87	0.0000
17	-0.005	233.70	0.0000	-0.029	126.42	0.0000	-0.005	103.90	0.0000
18	-0.006	233.81	0.0000	-0.029	127.95	0.0000	0.008	104.00	0.0000
19	-0.003	233.85	0.0000	-0.026	129.25	0.0000	0.011	104.18	0.0000
20	-0.040	238.99	0.0000	-0.043	132.69	0.0000	-0.037	106.19	0.0000

Variance ratio analysis with Lo MacKinlay probabilities

Variance Ratio Test for OMX Riga				
Null Hypothesis: Cumulated RET_LATVIA is a martingale				
Sample: 5/01/2000 3/07/2012				
Heteroskedasticity robust standard error estimates				
Test probabilities computed using wild bootstrap: dist=twopoint,				
reps=1000, rng=kn, seed=273095911				
Joint Tests		Value	df	Probability
Max |z| (at period 4)		**2.000766**	**3260**	**0.1040**
Individual Tests				
Period	Var. Ratio	Std. Error	z-Statistic	Probability
2	1.045661	0.051801	0.881469	0.3930
4	1.184866	0.092398	2.000766	0.0370
8	1.136284	0.136603	0.997668	0.3060
16	1.279527	0.191299	1.461203	0.1110
32	1.287877	0.261151	1.10234	0.2030
Sample: 3/01/2000 7/02/2007				
Joint Tests		Value	df	Probability
Max |z| (at period 4)		**2.383372**	**1852**	**0.0520**
Individual Tests				
Period	Var. Ratio	Std. Error	z-Statistic	Probability
2	1.103744	0.082588	1.256174	0.2220
4	1.348585	0.146257	2.383372	0.0160
8	1.249522	0.214554	1.162982	0.2080
16	1.38686	0.299774	1.290505	0.1450
32	1.263878	0.409527	0.644348	0.4740
Sample: 8/02/2007 2/07/2012				
Joint Tests		Value	df	Probability
Max |z| (at period 32)		**1.234777**	**1408**	**0.4960**
Individual Tests				
Period	Var. Ratio	Std. Error	z-Statistic	Probability
2	0.963076	0.045435	-0.812682	0.4490
4	0.953716	0.084717	-0.546336	0.5800
8	0.975641	0.130786	-0.186248	0.8580
16	1.122581	0.185352	0.661341	0.4980
32	1.311242	0.252063	1.234777	0.2050

Variance Ratio Test for OMX Vilnius				
Null Hypothesis: Cumulated RET_LITHUANIA is a martingale				
Sample: 5/01/2000 3/07/2012				
Heteroskedasticity robust standard error estimates				
Test probabilities computed using wild bootstrap: dist=twopoint,				
reps=1000, rng=kn, seed=273095911				
Joint Tests		Value	df	Probability
Max |z| (at period 32)		**6.638004**	**3260**	**0.0000**
Individual Tests				
Period	Var. Ratio	Std. Error	z-Statistic	Probability
2	1.128155	0.047242	2.712746	0.0060
4	1.244854	0.090603	2.702481	0.0040
8	1.404453	0.135532	2.984201	0.0040
16	1.868715	0.181138	4.795881	0.0000
32	2.516301	0.228427	6.638004	0.0000
Sample: 3/01/2000 7/02/2007				
Joint Tests		Value	df	Probability
Max |z| (at period 32)		**4.329526**	**1852**	**0.0000**
Individual Tests				
Period	Var. Ratio	Std. Error	z-Statistic	Probability
2	1.118407	0.034826	3.399978	0.0000
4	1.183822	0.102834	1.787564	0.0500
8	1.273484	0.165585	1.651625	0.0940
16	1.623499	0.220227	2.831165	0.0040
32	2.157435	0.267335	4.329526	0.0000
Sample: 8/02/2007 2/07/2012				
Joint Tests		Value	df	Probability
Max |z| (at period 32)		**5.177858**	**1408**	**0.0030**
Individual Tests				
Period	Var. Ratio	Std. Error	z-Statistic	Probability
2	1.134698	0.076059	1.770972	0.0780
4	1.285729	0.135589	2.107319	0.0330
8	1.493845	0.198391	2.489249	0.0240
16	2.034555	0.265571	3.89558	0.0030
32	2.754532	0.338853	5.177858	0.0030

Variance ratio analysis with bootstrapping

Variance Ratio Test for OMX Baltic10				
Null Hypothesis: Cumulated RET_BALTIC10 is a martingale				
Sample: 5/01/2000 3/07/2012				
Heteroskedasticity robust standard error estimates				
Test probabilities computed using wild bootstrap: dist=twopoint, reps=1000, rng=kn, seed=273095911				
Joint Tests		Value	df	Probability
Max |z| (at period 32)		**6.662149**	**3260**	**0.0000**
Individual Tests				
Period	Var. Ratio	Std. Error	z-Statistic	Probability
2	1.171409	0.042041	4.077227	0.0000
4	1.360148	0.075552	4.76688	0.0000
8	1.563128	0.111659	5.043283	0.0000
16	1.992141	0.153442	6.465913	0.0000
32	2.376286	0.206583	6.662149	0.0000
Sample: 3/01/2000 7/02/2007				
Joint Tests		Value	df	Probability
Max |z| (at period 16)		**6.723966**	**1852**	**0.0000**
Individual Tests				
Period	Var. Ratio	Std. Error	z-Statistic	Probability
2	1.193253	0.04211	4.589236	0.0000
4	1.412786	0.07404	5.575138	0.0000
8	1.590521	0.103524	5.704182	0.0000
16	1.936945	0.139344	6.723966	0.0000
32	2.125681	0.187801	5.994025	0.0000
Sample: 8/02/2007 2/07/2012				
Joint Tests		Value	df	Probability
Max |z| (at period 32)		**5.047885**	**1408**	**0.0000**
Individual Tests				
Period	Var. Ratio	Std. Error	z-Statistic	Probability
2	1.15592	0.058314	2.673823	0.0090
4	1.321833	0.104972	3.06589	0.0030
8	1.541429	0.155953	3.471752	0.0010
16	1.997337	0.214701	4.645234	0.0000
32	2.457641	0.288763	5.047885	0.0000

Variance Ratio Test for OMX Tallinn				
Null Hypothesis: Cumulated RET_ESTONIA is a martingale				
Sample: 5/01/2000 3/07/2012				
Heteroskedasticity robust standard error estimates				
Test probabilities computed using wild bootstrap: dist=twopoint, reps=1000, rng=kn, seed=273095911				
Joint Tests		Value	df	Probability
Max |z| (at period 32)		**7.679981**	**3260**	**0.0000**
Individual Tests				
Period	Var. Ratio	Std. Error	z-Statistic	Probability
2	1.145483	0.030204	4.816708	0.0000
4	1.297714	0.054216	5.491246	0.0000
8	1.488527	0.080346	6.080316	0.0000
16	1.837752	0.112742	7.430705	0.0000
32	2.203954	0.156765	7.679981	0.0000
Sample: 3/01/2000 7/02/2007				
Joint Tests		Value	df	Probability
Max |z| (at period 32)		**6.187123**	**1852**	**0.0000**
Individual Tests				
Period	Var. Ratio	Std. Error	z-Statistic	Probability
2	1.135838	0.033109	4.102781	0.0000
4	1.272128	0.060417	4.504157	0.0000
8	1.44559	0.089207	4.994981	0.0000
16	1.749825	0.12692	5.907845	0.0000
32	2.100149	0.177813	6.187123	0.0000
Sample: 8/02/2007 2/07/2012				
Joint Tests		Value	df	Probability
Max |z| (at period 32)		**5.341619**	**1408**	**0.0000**
Individual Tests				
Period	Var. Ratio	Std. Error	z-Statistic	Probability
2	1.144779	0.044558	3.249201	0.0000
4	1.296895	0.079435	3.73756	0.0000
8	1.505802	0.117683	4.298019	0.0000
16	1.863727	0.164605	5.247259	0.0000
32	2.217009	0.227835	5.341619	0.0000