Market Efficiency of Baltic Stock Markets: A Fractional Integration Approach

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Highlights
- Fractional integration technique as alternative method for testing Efficient Market Hypothesis (EMH)
- Weak form efficiency of Baltic stock markets
- Bull and Bear market phases of Baltic stocks
- Bear market volatility persists longer than bull market volatility

ABSTRACT

We investigate financial market efficiency in the time series of four daily Baltic stock market indices, namely: Baltic Benchmark Gross Index (OMXBBGI), all share index of Tallin-Lithuanian (OMXT), all share index of Riga (OMXR) and all share index of Vilnius (OMXV), based on historical data from 1 January, 2000 to 22 January 2016. We use fractional integration methods to test the hypothesis of market efficiency. Realizing that long-memory estimation could be spurious in the presence of structural breaks, we identify bull and bear market phases from each of the time series. Applying the fractional integration approach, we find that the random walk hypothesis of market efficiency is generally rejected in the overall, and at two bull and one bear sub-samples of the four Baltic stock indices. The volatility at the bear markets of these stocks persists more than the volatility at the bull markets. Our results therefore provide evidence for weak form of market efficiency in the Baltic stock markets, with some exceptions. As a way of policy, the results are relevant to portfolio managers and policy makers in a number of ways.

Keywords: Baltic stocks; Bull and bear phases; Efficient market hypothesis; Fractional cointegration; Fractional integration; Volatility.

JEL classification: C22

1. Introduction

The three countries by the coast line of the Baltic Sea, in the geographical centrum of Europe are the Lithuania, Latvia and Estonia. These countries obtained their independence from the Russian Empire in the 90s and became members of the North Atlantic Treaty Organisation (NATO) in March 2004, and later member states of the European Union (EU) in May 2004 (Kuisyte, 2014). Over the years, these countries have experienced high economic growth. This rapid economic growth was fuelled by Foreign Direct Investment (FDI) inflows which was abruptly terminated during the financial crisis period of 2008 to 2009 (Nikkinen et al., 2012). The Baltic stock markets are “niche” markets from global perspective. These are new markets with low market capitalizations and low trading volumes. Moreover, with the fact that these countries are emerging economies gingered the interest of researchers to study the level of financial market efficiency, with the mind of obtaining useful information relevant to decision makers and traders. The understanding of the efficiency or otherwise of the Baltic stock markets may be useful to investors in their portfolio diversification decisions and risk management (Maneschiöld 2006; Stasiukonytė and Vasiliauskaitė, 2008; Nikkinen et al., 2012). The first Baltic stock market commenced operation after the Second World War in 1993, as the Vilnius Stock Exchange (VSE) in Lithuania. Later, Riga Stock Exchange (RSE) in Latvia started trading in 1995 and Tallinn Stock Exchange (TSE) in Estonia commenced operation in 1996. The descriptive statistics of the financial market conditions of the Baltic States are given in Table 1. Of these three markets, VSE is the largest stock market based on the market capitalisation, and this is followed by the TSE, while the RSE is the smallest stock market. The three Baltic States have achieved substantial economic success since the independence period. In spite of these achievements, income levels are still low below those in developed or high income economies. In 1995, income levels in the Baltic States were over 20 percent of the level in the USA, with Latvia having the lowest income level of the three, and Estonia as the richest and best developed. In 2014, income level of the States was 43-50 percent of the level in the USA and 51-59 percent of the level in Sweden which is a neighbouring country (Staehr, 2015). Between 2008 and 2009, the three countries faced an economic crisis with deep recession of more than 14 percent, which is more in other Euro areas (Staehr, 2015).

Research regarding efficiency of Baltic stock markets is very scarce. Since efficient markets would imply that nothing but its own past information predicts the movements in the stock markets, suggesting that these markets are unaffected by, possible, other domestic and global macroeconomic and financial predictors affecting stock prices.

Table 1: Overview of Baltic Stock Markets

States	Variables	Mean (1995-2012	S.D. (1995-2012
Estonia	Market capitalization in $ Billions	2,841,496,277	1,789,988,815
	Portfolio-net inflows in $	-28,288,982	369,224,003
Latvia	Market capitalization in $ Billions	1,181,142,493	905,648,516
	Portfolio-net inflows in $	8,021,278	21,558,466
Lithuania	Market capitalization in $ Billions	3,860,776,732	3,153,798,169
	Portfolio-net inflows in $	12,554,087	63,023,488

Source: World Bank.
Portfolio equity includes net inflows from equity securities other than those recorded as direct investment and including shares, stocks, depository receipts (American or global), and direct purchases of shares in local stock markets by foreign investors

The aim of this paper is to analyse whether stock markets in the three Baltic economies can be dubbed as efficient. For this purpose, we investigate financial market efficiency in the time series of four daily Baltic stock market indices namely Baltic Benchmark Gross Index (OMXBBGI), all share index of Tallin-Lithuanian (OMXT), all share index of Riga (OMXR) and all share index of Vilnius (OMXV), based on historical data from 1 January, 2000 to 22 January 2016. We use fractional integration methods to test the hypothesis of efficiency instead of the standard practice of applying unit root testing, given that it is quite well-known that unit root tests have very low power against trend-stationarity (DeJong et al., 1992), structural breaks (Perron, 1989; Campbell and Perron, 1991), regime-switching (Nelson, Piger and Zivot, 2001), or fractional integration (Diebold and Rudebusch, 1991; Hassler and Wolters, 1995; Lee and Schmidt, 1996). Moreover, fractional integration tests are more general than the classical unit root tests in the sense, for example, that they allow for more flexible specifications, including the unit root case as a special case of interest when the number of differences is 1.

Fama (1965) formalized the argument that stock prices were following a random walk. In the literature, they defined the efficient market: “In an efficient market, at any point in time, the actual price of a security will be a good estimate of its intrinsic value” (Fama, 1965; in

Kuisyte, 2014).[1] Fama (1970) developed the efficient market hypothesis (EMH) which is widely applied in empirical financial time series analysis. The EMH stated that the prices of assets already contain past information and in the event of new information, the price quickly adjusts so that at any time, the security price will be equal to its real value. The weak form of market efficiency means that current stock prices reflect all information from market transactional data (see Cuestas et al., 2017). Government, investors and stakeholders are exposed to unhedged risk whenever they assume that countries are not related in their financial activities (Fazio, 2007). The countries in the same region often experience similar financial dependency, particularly in the time of extreme market movements. The Baltic stock markets are emerging markets in the same region that experience such financial dependency, and these markets are with low liquidity, low trading volumes and low absorption of information and news.

The wealth of a country is determined by the capitalization of her equity markets. The stability of market prices is then measured by the level of volatility observed. Volatility is a very prominent property of stocks which is observed from the data (see Mandelbrot, 1971a,b). Financial observers also need to look out for market efficiency; is it in the weak form or not? (see, e.g., Fama, 1970). An efficient market is therefore a trading platform whereby there are no possibilities of making abnormal returns from an active investment strategy, that is relevant information is incorporated into the prevailing asset price. Lim and Brooks (2011) provided a systematic review of the weak-form market efficiency literature that investigated return predictability from past price changes, with an exclusive focus on the stock markets. Their survey showed that the bulk of the empirical studies examined whether the stock market under study is or is not weak-form efficient. The paper categorized the emerging studies on time-

[1] Details of other approaches for investigating market efficiency are given in Fama and French (1992) and Engel (1995).

varying weak-form market efficiency based on the research framework adopted, namely non-overlapping sub-period analysis, time-varying parameter model and rolling estimation window. The paper further considered the case of Baltic economies in their empirical study on weak-form of market efficiency and found that market efficiency was negatively affected during the 2008-2009 global financial crisis. Smith (2012) investigated inefficiency in Baltic stock market. The author further stressed that the efficiency level posed a serious difficulty in forecasting future market developments and due to this fact, it is very difficult for investors to decide on how to diversify their portfolios.

Other studies such as Maneschiold (2006), Nielsson (2007), Dubinskas and Stunguriene (2010), Kazukauskas (2011) and Babalos et al. (2018), among others, investigated causal relationships between Baltic markets and other markets in the developed economy. Maneschiold (2006) applied bivariate and multivariate cointegration tests to study the long-run relationships among Baltic stock markets and major international stock markets which include stocks in the G7 countries like the United States, Japan, Germany, the United Kingdom, and France. The results indicated a common trend linking Latvia to European markets. Evidence further showed that the German market dominated the long-run relationship. Short-term Granger causality indicated causality running from European markets to Baltic markets. Nielsson (2007) explored the interdependency of the Nordic and Baltic stock markets between 1996 and 2006 and found little interdependency between the Nordic and Baltic stock indices. The results generally obtained low and insignificant response of shocks between each market while in the longer term, there is limited evidence of integration and only weak indication of convergence within the sampled period. Cointegration analysis was carried out by Dubinskas and Stunguriene (2010) to test for long-run dependency and trends in the Baltic and Russian markets in the pre-crisis period before 2008, in-crisis period, that is, September 2008 to May 2009, and in post-crisis period. Their results revealed a significant cointegrating relationship during all the three periods considered, while a strongest cointegrating factor was observed in the crisis period, and the weakest was observed in the post-crisis period. Kazukauskas (2011) also considered the long-run and short-run relationships between the Baltic and Swedish markets between 2000 and 2011 and found that VSE Granger caused TSE, whereas TSE did not Granger cause VSE, and there was no causality running from TSE to RSE or RSE to VSE (see Kuisyte, 2014). Babalos et al. (2018) investigated asymmetric causal relationship between developed European stock markets in Germany, France and the UK, with emerging markets in Estonia, Latvia and Lithuania. The study adopted both non-parametric and parametric causality tests, and the results indicated significant nonlinear returns and volatility spillovers from developed European markets to the Baltic markets.

Other authors have investigated the predictability of Baltic stock returns by means of Generalized Autoregressive Conditional Heteroscedasticity (GARCH) model of Bollerslev (1986), for example, Aktan et al. (2010) examined the characteristics of conditional volatility in the Baltic Stock Markets by using a broad range of symmetric and asymmetric GARCH models on daily returns from four Baltic stock indexes and found strong evidence that daily returns from Baltic Stock Markets can be successfully modelled by GARCH-type models. For all Baltic markets, we conclude that increased risk will not necessarily lead to a rise in the returns and all of the analyzed indexes exhibit complex time series characteristics involving asymmetry, long tails and complex autoregression in the returns. Brännäsa et al. (2012) investigated simultaneity and asymmetry of returns and volatilities in the Baltic stock markets using the modified Autoregressive Moving Average (ARMA)-Quadratic GARCH (QGARCH) model and found Riga and Tallinn to be dependent on each other, while Vilnius was uninfluenced by the other two markets.[2]

[2] Riga, Tallinn and Vilnius are the stock indices in the three Baltic States.,

This paper is the first investigating market efficiency of Baltic stock markets using fractional integration approach. In this context, market efficiency implies accepting the hypothesis that the series is I(1), as against the alternative that the series actually follows fractional integration which is the case of market inefficiency. However, the estimation of volatility models such as GARCH requires convergence of parameters for the existence of conditional variance equation used for persistence measure, thus, we used series-based approach in investigating volatility in this context. The presence of volatility persistence indicates the predictability of volatility of each Baltic stock market, which questions the validity of market efficiency (Capozza, et al., 2004; Barros et al. 2015). Fractional integration is then applied on the squared log-returns, with the estimate of persistence on the squared log-returns obtained in the range (0, 0.5), that is Long Range Dependence (LRD).[3] Also, none of these empirical papers on Baltic stock indices have identified subsamples of the historical indices, that is, the periods of bull and bear with the mind of checking for market efficiency as well as volatility at each of these subsamples. We address this issue in this paper. The bull and bear phases were then identified using the approach contained in Pagan and Soussonouv (2003). This is interesting, noting that it has been argued in recent years that fractional integration may be a spurious phenomenon caused by the presence of structural breaks or nonlinearities in the data (see, e.g., Diebold and Inoue, 2001; Kapetanios and Shin, 2011; etc.). The approach of Pagan and Soussonouv (2003) in identifying market phases also helps us to control for the sensitivity of the estimates of persistence due to structural breaks in the Baltic stock markets, especially given that our period of study covers the recent financial crisis.

By means of fractional integration techniques applied to bull and bear market phases, and to the overall sample, we found that Baltic stock markets cannot be dubbed as efficient,

[3] Both absolute and squared returns have always been widely employed as proxies for the volatility series (see Ding et al., 1993; Lobato and Savin, 1998; Bollerslev and Wright, 2000; Gil-Alana et al., 2015, among others).

that is, the future path of the stock price in these markets seems to be governed by its immediate past.

The rest of the paper is therefore structured as follows: Section 2 briefly describes the methodology while Section 3 presents the data and the main empirical results. Section 4 concludes the manuscript.

2. Methodology

2.1. Long-Memory Approach

This paper is based on the concept of fractional integration. For this purpose we need to define first an integrated of order 0 (or I(0)) process, which is a covariance stationary process with a spectral density function that is positive and finite at the zero frequency. Then, a process is said to be integrated of order d (and denoted by I(d)) if it can be represented as:

$$(1 - \mathrm{L})^{\mathrm{d}} \mathrm{x}_{\mathrm{t}} \;=\; u_{\mathrm{t}}, \qquad \mathrm{t} \;=\; 1, 2, \ldots, \tag{1}$$

with $x_t = 0,\ t \leq 0$, L is the lag operator (i.e., $Lx_t = x_{t-1}$), and where u_t is $I(0)$. Fractional integration takes place when d is a fractional value. In this context, d plays a crucial role since it will be an indicator of the degree of dependence of the time series. Thus, the higher the value of d is, the higher the level of association will be between the observations. In addition, the process admits an infinite Moving Average representation such that, assuming, for instance that u_t is white noise,

$$x_t \;=\; \sum_{k=0}^{\infty} a_k\, u_{t-k}, \tag{2}$$

with $a_k \;=\; \dfrac{\Gamma(k+d)}{\Gamma(k+1)\Gamma(d)}$ where Γ(x) means the Gamma function. Thus, the impulse responses are also affected by the magnitude of d, and the higher the value of d is, the higher the responses will be.

In this context, if $d > 0$ in (1), x_t displays the property of long memory, so-named because of the strong degree of association between observations far distant in time. Moreover, if $0 < d < 0.5$, x_t is covariance stationary, and if $0.5 \leq d < 1$, x_t becomes nonstationary, in the sense that the variance of the partial sums increase in magnitude with d; Nevertheless, in both cases (i.e. with $d < 1$), the series will be mean reverting, with shocks having temporary effects, and disappearing in the long run (i.e., $a_k \rightarrow 0$ as $k \rightarrow \infty$). On the other hand, if $d \geq 1$, the shock will be permanent, lasting forever unless strong policy measures are adopted.

In the following section we estimate the differencing parameter d by using both parametric and semiparametric approaches. For the former we use a Whittle estimate in the frequency domain as proposed in Dahlhaus (1989) along with a parametric Lagrange Multiplier (LM) test due to Robinson (1994) that has the advantage that it remains valid even in nonstationary contexts ($d \geq 0.5$). The results were practically identical in the two cases. The test of Robinson (1994) considers the following null hypothesis:

$$H_o : d = d_o \qquad (3)$$

for any real value d_o, in the model given by equation (1), where x_t can be the errors in a regression model of form:

$$y_t = \beta^T z_t + x_t, \quad t = 1, 2, \dots, \qquad (4)$$

where y_t is the time series we observe and z_t is a (kx1) vector of deterministic terms that might include a constant and a time trend. This test has a standard null limit distribution and its functional form can be found in any of the numerous empirical applications of the tests, (see, e.g., Gil-Alana and Robinson, 1997; Gil-Alana and Moreno, 2012 and Abbritti et al., 2016 among others). Additionally, we use a semiparametric approach (Robinson, 1995) that is also based on the Whittle function and that uses only a band of frequencies degenerating to zero. This method is implicitly defined by:

$$\hat{d} = arg\ min_d \left(log\ \overline{C(d)} - 2\,d\ \frac{1}{m} \sum_{j=1}^{m} log\ \lambda_j \right), \qquad (5)$$

$$for\ \ d \in (-1/2\,,\ 1/2); \quad \overline{C(d)} = \frac{1}{m} \sum_{j=1}^{m} I(\lambda_j)\, \lambda_j^{2d}, \quad \lambda_j = \frac{2\,\pi\, j}{T}, \quad \frac{1}{m} + \frac{m}{T} \to 0,$$

where m is the bandwidth parameter, and $I(\lambda_j)$ is the periodogram of the time series of interest. Under finiteness of the fourth moment and other mild conditions, Robinson (1995) proved that:

$$\sqrt{m}\,(\hat{d} - d_o) \to_d N(0, 1/4) \quad as\ T \to \infty,$$

where d_o is the true value of d and with the only additional requirement that $m \to \infty$ slower than T.

Given that our paper looks at developing financial markets data over a period which also includes the recent financial crisis, it is not illogical to assume that there are likely to be regime changes in the stock markets of the Baltic countries. Understandably, parameter estimates across these regimes cannot be expected to remain the same. Hence, we supplement our long memory estimations for the full-sample by repeating the econometric analysis across the bull and bear phases of the stock market. The following sub-section discusses how we identify these two regimes.

2.2 Algorithm for identifying the Market Phases

Pagan and Sossounov (2003) proposed an algorithm for identifying bull and bear phases of financial market, where both phases are defined based on the troughs and peaks in the time series. For example, the bull phase lies between an immediate trough and the next peak, while the bear phase lies between an immediate peak and the next trough of the time series. The algorithm follows the following steps:

(1a). Determine the initial turning points in raw data by choosing local peaks (troughs) as occurring when they are the highest (lowest) values in a window of eight days on either side of the date.

(1b). Enforce alternation of turns by selecting the highest of the multiple peaks (or the lowest of the multiple troughs).

(2a). Eliminate turns within six days of beginning and end of the series.

(2b). Eliminate peaks (or troughs) at both ends of the series which are lower or higher.

(2c). Eliminate cycles whose duration is less than 16 days.

(2d). Eliminate phases whose duration is less than four days unless fall or rise exceeds 20%.

3. Data and empirical results

The data considered in the paper are four daily Baltic indices: Baltic Benchmark Gross Index (OMXBBGI), all share index of Tallin-Lithuanian (OMXT), all share index of Riga (OMXR) and all share index of Vilnius (OMXV).[4] These data were collected from the NASDAQ OMX Baltic internet website http://www.nasdaqbaltic.com/, and the time series span between 1 January, 2000 and 22 January 2016. In order to reduce the magnitude of the data points and obtain data that are much closer to normality, we then computed the log-transformed series which are used in computing the fractional integration estimates. Then, squared log-returns are obtained by taking the squares of the first difference of each of the log transformed series. The natural logarithmic values of the series and the squared returns have been plotted in Figure 1, and we observe similar movements in the four price indices.

[4]OMXBBGI consists of a portfolio of the largest capitalized and most traded stocks in Lithuania, Latvia and Estonia, representing all sectors on the NASDAQ OMR Baltic market. OMXT, OMXR and OMXV include all the stocks listed on both the main and secondary lists. The indexes reflect the current status of the market in these three countries (see Kuisyte, 2014).

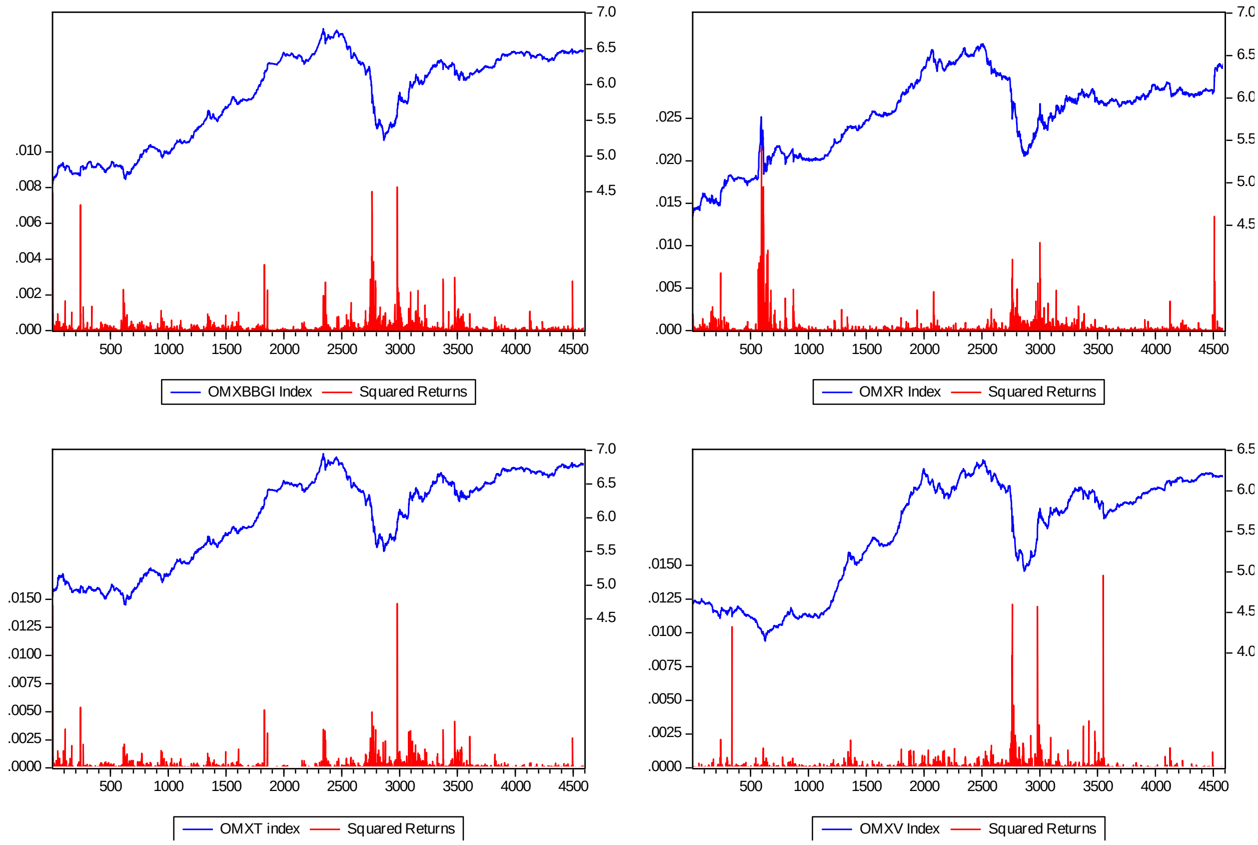

Figure 1: Plots of Stock Indices and Squared Log-Returns

In Table 2, we present descriptive measurements on the indices and log-return series, in the upper and lower panel of the result tables, respectively. In the upper panel, mean values for each index is closed to the median value, and the minimum and maximum values are far apart, that is 100 and 882.4, respectively for OMXBBGI index. The lowest standard deviation value occur in the case of OXMV index, while the highest occur in the case of OMXT index. Only OMXV is negatively skewed, and kurtosis are low peaked and thin tailed (platykurtic). The Jarque-Bera (JB) test statistics are significant at 5% level in the four cases supporting the non-normality of the series. Null hypotheses of classical unit root tests (Augmented Dickey Fuller, ADF and Philips-Perron, PP) are not rejected in any case. By considering the squared log-returns in the lower panel of the table, mean, median, and other descriptive measures are generally low to justify that they originate from price difference. Skewness values are very high and positive in the four cases. Kurtosis values are extremely high, and JB test sternly rejected null hypotheses of normality in all cases. Similarly, we carried out unit root tests on the returns, and the results indicated rejection of null hypothesis of unit roots in squared returns.

Table 2: Data description and Unit Root tests

	Prices			
	OMXBBGI	OMXR	OMXT	OMXV
Mean	404.3	365.2	490.3	287.8
Median	440.3	377.4	545.0	315.0
Maximum	882.4	764.5	1043.3	591.4
Minimum	100	100	110.73	63.18
Std. Dev.	208.570	159.131	266.131	155.014
Skewness	0.045	0.368	0.036	-0.055
Kurtosis	1.714	2.399	1.561	1.535
Jarque-Bera	**318.5**	**173.0**	**397.6**	**413.7**
ADF	0.9149[3]	0.9378[0]	1.2487[1]	-1.0633[1]
PP	0.6273[32]	0.6349[24]	0.8614[28]	-1.6874[34]
	Squared Returns			
	OMXBBGI	OMXR	OMXT	OMXV
Mean	8.86E-05	1.14E-04	1.86E-04	9.73E-05
Median	1.15E-05	1.46E-05	2.05E-05	1.18E-05
Maximum	0.0080	0.0146	0.0216	0.0143
Minimum	0.0000	0.0000	0.0000	0.0000
Std. Dev.	3.54E-04	4.43E-04	8.47E-04	4.89E-04
Skewness	12.79	18.02	12.65	17.51
Kurtosis	228.07	511.69	213.94	396.79
Jarque-Bera	9834473	49845529	8650655	29957509
Probability	0.0000	0.0000	0.0000	0.0000
ADF	**-11.550[11]**	**-13.504[11]**	**-8.353[7]**	**-19.012[5]**
PP	**-65.713[37]**	**-69.546[34]**	**-75.962[43]**	**-59.205[37]**

In bold, significant tests at 5% level. In square brackets are the optimal lag length for augmentation in the case of ADF test, and bandwidth number in the case of PP test.

We then estimate the fractional differencing parameter d in the following model,

$$y_t = \beta_0 + \beta_1 t + x_t; \qquad (1 - L)^d x_t = u_t, \qquad t = 1, 2, ... \qquad (3)$$

where y_t is the observed time series, β_0 and β_1 are the coefficients respectively for an intercept and a linear time trend, and x_t is I(d), implying thus that the disturbances u_t are I(0). We start by analysing the whole sample period.

In Table 3, we present the estimates of d (and their 95% confidence intervals) for the three standard cases examined in the literature of: i) no deterministic terms (i.e., $\beta_0 = \beta_1 = 0$ in (3); an intercept (β_0 unknown and $\beta_1 = 0$), and with an intercept and a linear time trend (β_0 and β_1 unknown), and report the results based on the Whittle approach in the frequency domain for the two cases of uncorrelated (white noise) and autocorrelated errors. For the latter case, we use a non-parametric model that is based on the exponential spectral model of Bloomfield (1973). This model is non-parametric in the sense that it is exclusively defined in terms of its spectral density function that is given by:

$$f(\lambda; \tau) \; = \; \frac{\sigma^2}{2\pi} \exp\left(2\sum_{j=1}^{p} \tau_j \cos(\lambda\, j) \right),$$

where p indicates the number of short run parameters. Bloomfield (1973) showed that this specification approximates highly ARMA parameterized models with a few number of parameters.

Focussing on the case of an intercept (which is the most realistic one according to the t-values of the deterministic terms, unreported), the estimated values of d are significantly higher than 1 in the four logged series examined, ranging from 1.04 (OMXR with autocorrelated errors) to 1.13 (OMXT with white noise) and thus, the random walk hypothesis, associated to the efficiency in the market is decisively rejected in the four cases examined. On the other hand in Table 4, for the case of squared log-returns, which are used as proxy for the volatility, the estimates of d are in all cases in the range (0, 0.5) implying long memory and mean reverting behaviour. The lowest values refer here to OMXT (0.18 and 0.17 for uncorrelated and autocorrelated errors, respectively) while the highest value (0.32) corresponds to OMXV.

Table 3: Estimates of d for the whole sample (in logs)

i) Uncorrelated (White noise) errors									
	No regressors			An intercept			A linear time trend		
OMXBBGI	1.01	(0.99,	1.03)	**1.12**	**(1.10,**	**1.14)**	1.12	(1.10,	1.14)
OMXR	1.01	(0.98,	1.03)	**1.06**	**(1.04,**	**1.08)**	1.06	(1.04,	1.08)
OMXT	1.01	(0.98,	1.03)	**1.13**	**(1.10,**	**1.15)**	1.13	(1.10,	1.15)
OMXV	1.01	(0.98,	1.03)	**1.12**	**(1.10,**	**1.15)**	1.12	(1.10,	1.15)
ii) Autocorrelated (Bloomfield) errors									
	No regressors			An intercept			A linear time trend		
OMXBBGI	1.00	(0.99,	1.05)	**1.10**	**(1.08,**	**1.15)**	1.10	(1.07,	1.15)
OMXR	1.01	(0.98,	1.05)	**1.04**	**(1.00,**	**1.09)**	1.04	(1.00,	1.09)
OMXT	1.00	(0.97,	1.03)	**1.11**	**(1.08,**	**1.16)**	1.11	(1.07,	1.17)
OMXV	1.01	(0.97,	1.04)	**1.10**	**(1.08,**	**1.17)**	1.10	(1.08,	1.17)

In bold, the significant cases according to the deterministic terms. In parenthesis, the 95% confidence intervals for the estimated value of d.

Table 4: Estimates of d for the squared returns

i) Uncorrelated (White noise) errors									
	No regressors			An intercept			A linear time trend		
OMXBBGI	0.27	(0.25,	0.29)	**0.27**	**(0.25,**	**0.29)**	0.27	(0.25,	0.29)
OMXR	0.27	(0.25,	0.29)	**0.27**	**(0.2,**	**0.29)**	0.27	(0.26,	0.29)
OMXT	0.18	(0.16,	0.20)	**0.18**	**(0.16,**	**0.20)**	0.18	(0.16,	0.20)
OMXV	0.32	(0.29,	0.35)	**0.32**	**(0.29,**	**0.35)**	0.32	(0.29,	0.35)
ii) Autocorrelated (Bloomfield) errors									
	No regressors			An intercept			A linear time trend		
OMXBBGI	0.25	(0.23,	0.31)	**0.25**	**(0.23,**	**0.31)**	0.25	(0.23,	0.32)
OMXR	0.25	(0.23,	0.29)	**0.25**	**(0.22,**	**0.29)**	0.25	(0.22,	0.29)
OMXT	0.17	(0.14,	0.22)	**0.17**	**(0.13,**	**0.22)**	0.17	(0.13,	0.22)
OMXV	0.32	(0.28,	0.36)	**0.32**	**(0.28,**	**0.36)**	0.32	(0.28,	0.36)

In bold, the significant cases according to the deterministic terms. In parenthesis, the 95% confidence intervals for the estimated value of d.

Table 5: Semiparametric estimates of d for the whole sample (in logs)

m	OMXBBGI	OMXR	OMXT	OMXV
30	1.298	1.094	1.273	1.202
40	1.278	1.179	1.236	1.225
50	1.217	1.143	1.118	1.129
60	1.157	1.077	1.150	1.189
70	1.188	1.022	1.151	1.234
80	1.204	1.035	1.128	1.188
90	1.165	1.028	1.120	1.196
100	1.184	1.056	1.140	1.203
200	1.243	1.193	1.186	1.305
300	1.205	1.032	1.145	1.195
400	1.175	1.065	1.122	1.165
500	1.146	1.097	1.107	1.136

m is the bandwidth number.

Table 6: Semiparametric estimates of d for the squared returns in the whole sample

m	OMXBBGI	OMXR	OMXT	OMXV
30	0.210	0.279	0.382	0.240
40	0.243	0.268	0.281	0.162
50	0.231	0.260	0.326	0.170
60	0.230	0.323	0.365	0.191
70	0.271	0.359	0.327	0.183
80	0.279	0.306	0.303	0.207
90	0.292	0.274	0.331	0.208
100	0.313	0.281	0.366	0.239
200	0.353	0.277	0.333	0.283
300	0.314	0.216	0.242	0.279
400	0.264	0.192	0.214	0.283
500	0.265	0.181	0.217	0.308

m is the bandwidth number.

Tables 5 and 6 also focuses on the estimates of d on the log-prices and the squared log-returns, but using now using the semiparametric Whittle approach proposed in Robinson

(1995). Similarly to the parametric approach, the estimates of d are all above 1 for the log-prices series, while the differencing parameter ranges between 0 and 0.54 for the squared return series.

Then, we identified the market phases, that is, the periods of bull and bear in the four indices, based on the algorithm set up by Pagan and Sossounov (2003).[5] After following the procedure, we obtained three distinct market phases, which are 2 bull and 1 bear periods from the beginning to the end of the time series sample. Table 7 therefore summarized the timings of the market phase as well as the size of each sub-samples. We then computed the same type of analysis in Table 3-6 on the different subsamples identified.

Table 7: Bull and Bear Market Phases for Baltic Stocks

Stocks	Phases	Market	Period	Sample size
OMXBBGI	1st	1st Bull	1 January 2000 – 7 February 2007	2341
	2nd	1st Bear	8 February 2007 - 9 March 2009	524
	3rd	2nd Bull	10 March 2009 - 17 August 2015	1625
OMXT	1st	1st Bull	23 September 2001 – 6 February 2007	1709
	2nd	1st Bear	7 February 2007 – 9 March 2009	525
	3rd	2nd Bull	10 March 2009 - 17 August 2015	1625
OMXR	1st	1st Bull	1 January 2000 – 5 October 2007	2509
	2nd	1st Bear	8 October 2007 – 9 March 2009	356
	3rd	2nd Bull	10 March 2009 - 14 January 2016	1729
OMXV	1st	1st Bull	18 September 2001 – 8 October 2007	1884
	2nd	1st Bear	9 October 2007 – 10 March 2009	356
	3rd	2nd Bull	11 March 2009 - 16 July 2015	1602

We follow the algorithm proposed by Pagan and Sossounov (2003).

[5] Though Pagan and Soussounov (2003) algorithm for detecting bull and bear market phases is basically a forward-looking filter, the true state of financial market is usually observed with a lag. Hence, ideally the algorithm should be applied on rolling windows to account for forward-looking bias. However, note that unlike macroeconomic data, stock market data is available at a higher frequency and is also not subject to revisions. In addition, since, we perform the tests of efficiency ex post, we do not believe this is a major concern to us. Of course, in case of forecasting over an out-of-sample period, it would make more sense to apply the algorithm on rolling window. We are grateful to a referee for raising this concern though.

We then present the results for the first bull period in Tables 8 and 9; Tables 10 and 11 refer to the first bear period, while Tables 12 and 13 concentrate on the second bull period.

Starting with the results for the first bull period and using the parametric approach (Table 8), the estimates of d are all above 1 and the unit root is rejected in favour of d > 1 in all cases except for the OMXR. For this series, the unit root null cannot be rejected, and focussing on the semiparametric method (Table 9), this is precisely the unique series where we observe values which are below 1 for some bandwidth numbers. Note that this result (the one presented in Table 8(i) for OMXR)) suggests that the random walk model cannot be rejected for this subsample. If we concentrate now on the bear period, the results are very similar, in the sense that the estimated values of d are significantly higher than 1 for OMXBBGI, OMXT and OMXV, while the random walk model (i.e., d = 1 with white noise errors) cannot be rejected for the OMXR (Table 10(i)). Similarly, this series presents the lowest values with the semiparametric method (in Table 11).

Table 8: Estimates of d for the log BULL 1 PERIOD

i) Uncorrelated (White noise) errors									
	No regressors			An intercept			A linear time trend		
OMXBBGI	1.01	(0.98,	1.04)	**1.13**	**(1.10,**	**1.16)**	1.13	(1.10,	1.16)
OMXR	1.00	(0.98,	1.03)	**1.05**	**(0.99,**	**1.08)**	1.05	(1.02,	1.08)
OMXT	1.01	(0.97,	1.04)	**1.16**	**(1.13,**	**1.20)**	1.16	(1.13,	1.20)
OMXV	1.01	(0.97,	1.03)	**1.13**	**(1.10,**	**1.18)**	1.13	(1.10,	1.16)
ii) Autocorrelated (Bloomfield) errors									
	No regressors			An intercept			A linear time trend		
OMXBBGI	1.02	(0.97,	1.07)	**1.09**	**(1.05,**	**1.14)**	1.09	(1.05,	1.14)
OMXR	1.01	(0.97,	1.07)	**1.06**	**(0.98,**	**1.14)**	1.08	(1.02,	1.14)
OMXT	1.00	(0.95,	1.06)	**1.07**	**(1.01,**	**1.13)**	1.07	(1.02,	1.13)
OMXV	1.00	(0.96,	1.06)	**1.10**	**(1.05,**	**1.14)**	1.09	(1.05,	1.14)

Table 9: Semiparametric estimates of d for the logged BULL1 data

	OMXBBGI	OMXR	OMXT	OMXV
30	1.309	0.750	1.301	1.163
40	1.240	0.668	1.194	1.244
50	1.224	0.715	1.198	1.166
60	1.147	0.801	1.160	1.168
70	1.183	0.894	1.171	1.186
80	1.161	0.976	1.138	1.227
90	1.159	1.035	1.140	1.251
100	1.179	1.081	1.153	1.274
200	1.144	0.904	1.093	1.132
300	1.124	1.054	1.088	1.102
400	1-103	1.100	1.093	1.107
500	1.115	1.132	1.103	1.103

Table 10: Estimates of d for the log BEAR 1 PERIOD

i) Uncorrelated (White noise) errors			
	No regressors	An intercept	A linear time trend
OMXBBGI	0.99 (0.92, 1.06)	**1.12 (1.07, 1.18)**	1.12 (1.07, 1.18)
OMXR	0.99 (0.92, 1.07)	**0.99 (0.93, 1.06)**	0.99 (0.93, 1.06)
OMXT	0.98 (0.93, 1.05)	**1.15 (1.10, 1.22)**	1.15 (1.10, 1.22)
OMXV	0.99 (0.91, 1.06)	**1.09 (1.04, 1.17)**	1.10 (1.04, 1.17)
ii) Autocorrelated (Bloomfield) errors			
	No regressors	An intercept	A linear time trend
OMXBBGI	0.97 (0.89, 1.08)	**1.12 (1.04, 1.23)**	1.13 (1.04, 1.23)
OMXR	0.96 (0.86, 1.11)	**1.02 (0.92, 1.12)**	1.02 (0.92, 1.13)
OMXT	0.97 (0.89, 1.09)	**1.16 (1.06, 1.27)**	1.16 (1.06, 1.28)
OMXV	0.96 (0.87, 1.11)	**1.10 (1.01, 1.20)**	1.09 (1.01, 1.20)

Table 11: Semiparametric estimates of d for the logged BEAR1 data

	OMXBBGI	**OMXR**	**OMXT**	**OMXV**
30	1.318	1.093	1.223	1.184
40	1.123	1.172	1.095	1.202
50	1.159	1.059	1.111	1.235
60	1.191	0.982	1.155	1.077
70	1.136	0.999	1.121	1.105
80	1.146	1.010	1.157	1.113
90	1.126	1.021	1.147	1.114
100	1.141	1.034	1.171	1.116
200	1.095	---	1.131	---
300	---	---	---	---
400	---	---	---	---
500	---	---	---	---

Table 12: Estimates of d for the log BULL 2 PERIOD

i) Uncorrelated (White noise) errors			
	No regressors	An intercept	A linear time trend
OMXBBGI	1.00 (0.97, 1.04)	**1.08 (1.05, 1.11)**	1.08 (1.05, 1.11)
OMXR	1.00 (0.96, 1.04)	**0.96 (0.93, 0.99)**	0.96 (0.93, 0.99)
OMXT	1.01 (0.97, 1.04)	**1.07 (1.04, 1.11)**	1.07 (1.04, 1.11)
OMXV	1.00 (0.97, 1.04)	**1.10 (1.06, 1.13)**	1.10 (1.06, 1.13)
ii) Autocorrelated (Bloomfield) errors			
	No regressors	An intercept	A linear time trend
OMXBBGI	1.00 (0.95, 1.06)	**1.06 (1.01, 1.11)**	1.06 (1.01, 1.11)
OMXR	1.00 (0.95, 1.06)	**1.03 (0.98, 1.08)**	1.02 (0.98, 1.08)
OMXT	1.00 (0.96, 1.06)	**1.05 (0.99, 1.10)**	1.05 (0.99, 1.10)
OMXV	1.10 (0.96, 1.06)	**1.07 (1.03, 1.12)**	1.07 (1.03, 1.12)

Table 13: Semiparametric estimates of d for the logged BULL2 data

	OMXBBGI	OMXR	OMXT	OMXV
30	1.102	1.028	1.080	1.062
40	1.077	1.027	1.063	1.104
50	1.082	1.010	1.066	1.108
60	1.119	1.034	1.076	1.187
70	1.176	1.075	1.136	1.257
80	1.184	1.040	1.151	1.201
90	1.183	1.043	1.180	1.196
100	1.202	1.033	1.198	1.209
200	1.092	0.999	1.066	1.084
300	1.077	1.008	1.059	1.098
400	1.048	0.980	1.051	1.084
500	1.063	0.993	1.064	1.079

Finally, focusing on the second bull period (Tables 12 and 13), the same happens once more, with the lowest estimates of *d* corresponding to OMXR and followed by OMXT. For the former series, the unit root is rejected in favour of mean reversion when using uncorrelated errors; however, under autocorrelation, the unit root null cannot be rejected. For OMXBBGI and OMXV, this hypothesis is rejected in all cases in favour of d > 1.

Next we focus on the volatility, as earlier mentioned, measured in terms of the squared returns. Starting with the first bull period (Tables 14 and 15), evidence of long memory (i.e., d > 0) is obtained in the four series, the values being especially higher in the case of the OMXR series. However, these values are much higher in the four cases when examining the first bear period in Tables 16 an 17; here, in some cases they are even above 0.50 implying nonstationarity (see, e.g., OXXV with autocorrelation, with an estimated value of d of 0.62); finally, the results for the second bull period are similar to those in the first period, being in the interval (0, 0.5) in all cases. Thus, the main difference observed between the bull and the bear periods refer specifically to the volatility issue, presenting a much higher degree of dependence in case of the bear period. This result is in agreement to the works of a number of authors who found that volatility is always higher during bear periods than in the bull periods (Maheu and McCurdy (2000), Gomez Biscarri and Perez de Gracia (2004), Gonzalez et al. (2005), Guidolin and Timmermann, 2005, Nishina et al. (2006), Tu (2006), etc.).

Table 14: Estimates of d for the squared returns BULL 1 PERIOD

i) Uncorrelated (White noise) errors			
	No regressors	An intercept	A linear time trend
OMXBBGI	0.05 (0.02, 0.08)	**0.05 (0.02, 0.08)**	0.04 (0.01, 0.07)
OMXR	0.25 (0.22, 0.27)	**0.24 (0.22, 0.27)**	0.24 (0.22, 0.27)
OMXT	0.08 (0.04, 0.12)	**0.07 (0.03, 0.11)**	0.06 (0.03, 0.10)
OMXV	0.20 (0.16, 0.24)	**0.20 (0.17, 0.24)**	0.20 (0.17, 0.24)
ii) Autocorrelated (Bloomfield) errors			
	No regressors	An intercept	A linear time trend
OMXBBGI	0.10 (0.06, 0.14)	**0.09 (0.05, 0.14)**	0.08 (0.04, 0.14)
OMXR	0.23 (0.21, 0.26)	**0.23 (0.20, 0.26)**	0.23 (0.20, 0.26)
OMXT	0.09 (0.04, 0.14)	**0.08 (0.04, 0.14)**	0.07 (0.03, 0.13)
OMXV	0.12 (0.08, 0.17)	**0.13 (0.09, 0.18)**	0.11 (0.07, 0.17)

Table 15: Semiparametric estimates of d for the squared return BULL1 data

	OMXBBGI	OMXR	OMXT	OMXV
30	0.065	0.411	0.257	0.332
40	0.145	0.488	0.329	0.207
50	0.116	0.500	0.324	0.230
60	0.138	0.500	0.252	0.258
70	0.126	0.500	0.192	0.253
80	0.120	0.500	0.172	0.223
90	0.105	0.500	0.167	0.215
100	0.077	0.500	0.182	0.169
200	0.076	0.403	0.096	0.164
300	0.089	0.423	0.096	0.144
400	0.065	0.249	0.076	0.168
500	0.075	0.248	0.063	0.172

Table 16: Estimates of d for the squared returns BEAR 1 PERIOD

i) Uncorrelated (White noise) errors									
	No regressors			An intercept			A linear time trend		
OMXBBGI	0.52	(0.45,	0.60)	**0.52**	**(0.45,**	**0.60)**	0.51	(0.45,	0.60)
OMXR	0.35	(0.29,	0.42)	**0.35**	**(0.29,**	**0.42)**	0.35	(0.29,	0.42)
OMXT	0.33	(0.27,	0.40)	**0.33**	**(0.27,**	**0.40)**	0.33	(0.27,	0.42)
OMXV	0.52	(0.45,	0.60)	**0.52**	**(0.45,**	**0.60)**	0.52	(0.45,	0.60)
ii) Autocorrelated (Bloomfield) errors									
	No regressors			An intercept			A linear time trend		
OMXBBGI	0.44	(0.35,	0.60)	**0.44**	**(0.36,**	**0.61)**	0.44	(0.35,	0.60)
OMXR	0.41	(0.30,	0.58)	**0.42**	**(0.31,**	**0.58)**	0.41	(0.29,	0.58)
OMXT	0.31	(0.23,	0.42)	**0.31**	**(0.24,**	**0.45)**	0.32	(0.32,	0.51)
OMXV	0.62	(0.44,	0.86)	**0.62**	**(0.44,**	**0.86)**	0.62	(0.62,	0.86)

Table 17: Semiparametric estimates of d for the squared return BEAR1 data

	OMXBBGI	OMXR	OMXT	OMXV
30	0.455	0.402	0.471	0.342
40	0.309	0.482	0.270	0.416
50	0.321	0.380	0.249	0.500
60	0.340	0.352	0.230	0.500
70	0.417	0.370	0.283	0.500
80	0.450	0.400	0.312	0.500
90	0.371	0.433	0.274	0.500
100	0.418	0.426	0.299	---
200	0.500	---	0.340	---
300	---	---	---	---
400	---	---	---	---
500	---	---	---	---

Table 18: Estimates of d for the squared returns BULL 2 PERIOD

i) Uncorrelated (White noise) errors			
	No regressors	An intercept	A linear time trend
OMXBBGI	0.18 (0.15, 0.21)	**0.17 (0.15, 0.20)**	0.15 (0.12, 0.19)
OMXR	0.11 (0.09, 0.14)	**0.11 (0.09, 0.13)**	0.10 (0.07, 0.12)
OMXT	0.14 (0.11, 0.17)	**0.13 (0.10, 0.16)**	0.10 (0.07, 0.14)
OMXV	0.16 (0.13, 0.20)	**0.16 (0.13, 0.20)**	0.15 (0.11, 0.19)
ii) Autocorrelated (Bloomfield) errors			
	No regressors	An intercept	A linear time trend
OMXBBGI	0.22 (0.18, 0.26)	**0.21 (0.16, 0.26)**	0.17 (0.13, 0.23)
OMXR	0.25 (0.20, 0.29)	**0.23 (0.19, 0.28)**	0.22 (0.17, 0.27)
OMXT	0.16 (0.13, 0.21)	**0.15 (0.12, 0.19)**	0.10 (0.06, 0.16)
OMXV	0.12 (0.08, 0.16)	**0.11 (0.08, 0.16)**	0.08 (0.03, 0.13)

Table 19: Semiparametric estimates of d for the squared return BULL2 data

	OMXBBGI	OMXR	OMXT	OMXV
30	0.348	0.374	0.288	0.239
40	0.432	0.331	0.288	0.297
50	0.410	0.309	0.278	0.292
60	0.473	0.293	0.325	0.346
70	0.355	0.285	0.266	0.306
80	0.368	0.242	0.285	0.328
90	0.346	0.234	0.286	0.277
100	0.325	0.194	0.267	0.279
200	0.244	0.243	0.193	0.173
300	0.230	0.190	0.167	0.163
400	0.187	0.173	0.133	0.131
	0.175	0.174	0.137	0.135

4. Concluding remarks

The purpose of this paper is to investigate the levels of financial market efficiency in the three Baltic States, namely, the Lithuania, Latvia and Estonia. Against this backdrop, the objective of this paper is to analyse whether stock markets in the three Baltic economies can be dubbed as efficient. For this purpose, we investigate financial market efficiency in the time series of four daily Baltic stock market indices, namely: Baltic Benchmark Gross Index (OMXBBGI), all share index of Tallin-Lithuanian (OMXT), all share index of Riga (OMXR) and all share index of Vilnius (OMXV), based on historical data from 1 January, 2000 to 22 January 2016. We use fractional integration methods to test the hypothesis of efficiency instead of relying on the standard practice of applying unit root testing, given that it is quite well-known that unit root tests have very low power against trend-stationarity, structural breaks, regime-switching, or fractional integration. However, realizing that long-memory estimation could be spurious in the presence of structural breaks, we identified bull and bear market phases from each of the time series to accommodate for regime changes in the estimation of the long-memory parameter.

We find that the random walk hypothesis of market efficiency is rejected in the overall sample and in the majority of the cases, at the two bull and one bear sub-samples of the four Baltic stock indices. Some major cases of exceptions are the OMXR data for the first bull and bear periods. Note that, the relatively less explosive behavior of the OMXR could possibly associated with its comparatively lower degree of market capitalization, as outlined earlier (in Table 1). In addition, we find that the volatility at the bear regime of these stock markets have more persistence than the volatility at the bull phases. Due to the fact that long range dependence exists in the squared log-returns and the hypothesis of unit integration, I(1) is rejected, in general, in the indices, we can then conclude that Baltic stock markets are in states of market inefficiency. In other words, the future path of the stock prices in these markets are predictable.

Note that, since these markets are inefficient, there is possibility of traders to make abnormal returns at Baltic stock markets, as revealed in the findings. In terms of drawing policy conclusions, given that we test for the weak-form of market efficiency and hence, do not include any predictors in the model, we can merely speculate that policy-makers can use the information on lagged stock prices to predict the future path of growth and inflation, since it is widely recognized that stock markets are leading indicators (Stock and Watson, 2003).

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