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Multiscale Volatility Transmission and Portfolio Construction Between the Baltic Stock Markets*

Dejan ŽIVKOV - Novi Sad School of Business, University of Novi Sad, Serbia (dejanzivkov@gmail.com) *corresponding author*

Slavica MANIĆ - Faculty of Economics in Belgrade, University of Belgrade, Serbia

Jasmina ĐURAŠKOVIĆ - Institute of Economic Sciences, Belgrade, Serbia

Abstract

This paper investigates volatility transmission and portfolio construction between the three Baltic stock indices at different time-horizons. Methodologies used for this study encompass parametric EGARCH model and the three non-parametric approaches – wavelet coherence, wavelet correlation and phase difference. Wavelet coherence indicated that risk integration between the Baltic stock markets is not so strong, while wavelet correlations confirmed this contention more precisely. Additional analysis showed that low wavelet correlations are also present between the Baltic indices and the German DAX index. These findings may suggest that the selected indices could be useful for the construction of risk-minimizing portfolios. In order to confirm (discard) this assumption, we constructed wavelet-based two-asset portfolios. The results provided evidence that hedging opportunities exist when the Baltic indices are combined between themselves, but also when they are coupled with the DAX index. This is particularly true for the longer time-horizons.

1. Introduction

It is well known that national stock markets are becoming increasingly integrated due to foreign investors' activities, the absence of the cross-border capital flow restrictions and the development of trading platforms in stock markets (see e.g. Didier et al., 2011; Emin, 2016; Tong et al., 2018). Having a clear picture about stock return linkages and their volatility transmissions is of utter importance for global investors, since they constantly observe changes in stock markets with the purpose to maximize their risk sharing benefits and accomplish optimal portfolio diversification (see e.g. Onay and Unal, 2012; Horvath and Petrovski, 2013; Aloui and Ben Hamida, 2015; Reboredo et al., 2015). Thorough understanding of stock volatilities is pertinent, since volatility reflects the uncertainty in the stock markets as well as the perception of risk among stock market participants. Numerous authors such as Jagric et al. (2006), Lin (2012), Vyrost et al. (2013) contended that international investors are particularly keen for emerging equity markets, because these countries have become a key ingredient of investors' diversification strategies in the last two decades. Analysis of volatility transmission among emerging markets is crucial due to their excessive volatility in nature (see e.g. Galo and Velucchi, 2008; Karilaid et al., 2014; Li and Giles, 2014; Balcilar et al., 2018).

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In that manner, recognizing any changes in international cross market interdependence can call for a portfolio reallocation.

Candelon et al. (2008) and Mofleh and Habib (2017) stressed that time horizon of investments is very important in the diversification strategy process, because the dynamics that govern short-term investment risks may be very different from long-term investment risks. Huang (2011) added that market connection could vary across time scales, and the assessed characteristics in frequency dimension can help in better comprehension of the complex patterns that exist between two financial variables. However, most researchers in their studies observed the interconnection between the markets only via empirical daily time-dimension, neglecting at the same time the frequency domain features. Conlon and Cotter (2012) explained that the sample reduction problem arises when researchers try to match the frequency of data with the different time-horizons.

This paper tries to understand the nature of volatility transmission between the three Baltic stock indices – OMXV, OMXR and OMXT, emphasizing the issue of risk co-movement at different time-horizons. Also, volatility transmission is an important issue in a context of diversification possibilities. Therefore, we try to answer whether these indices produce any risk-reducing benefits for investors with different term-horizons who combine the Baltic indices in a two-asset portfolio. Our interest for Baltic stock markets arises from several reasons. According to Brannas and Soultanaeva (2011), these markets have a common institutional setup in terms of a common owner and trading platform, which means that trade on all three markets can be performed with relative ease, thereby providing potentially rich diversification opportunities for interested investors. In spite of its relatively small size, the Baltic region is an appealing environment for various market investors due to number of factors. By first, these economies achieve relatively high rates of economic growth for a number of years (see e.g. Nakamura et al., 2012; Caporale et al., 2014; Kjosevski and Petkovski, 2017; Stankov et al., 2018). Also, they are all well-established EU members, and they all adopted euro as national currency. Table 1 presents the size of these markets along with the German stock market, which serves as a benchmark.

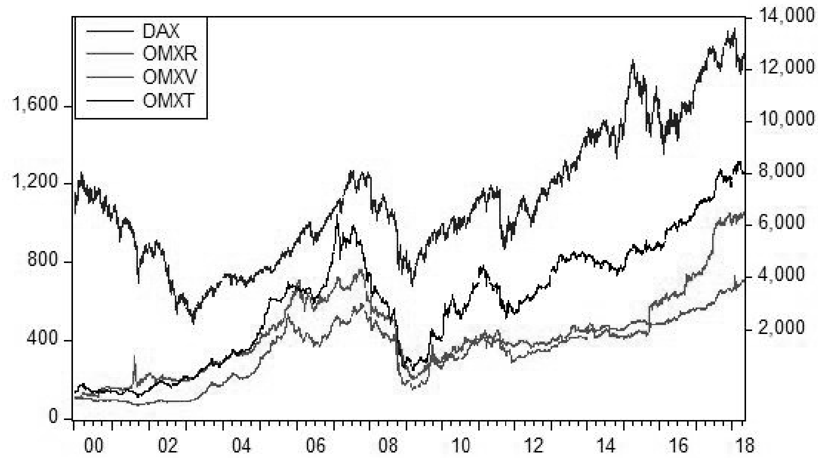
Table 1 The Size of The Baltic Stock Markets and the German Stock Market

	Lithuania	***Latvia***	***Estonia***	***Germany***
GDP in billions of USD♣	47.263	30.319	25.973	3,684.816
Market capitalization / GDP♦	9%	4.6%	11.2%	57.9%

♦ Stock market capitalization in 2017. Source: https://www.ceicdata.com/en/indicator.
♣ GDP in 2017. Source: International monetary fund.

In addition, in order to be more informative, this paper also considers volatility co-movement between Baltic stock markets and the German stock market, which provides a wider insight about the possible risk-reducing investment strategies. In this way, we can answer is it more optimal to combine the Baltic stock indices between themselves or perhaps the better solution is to combine them with the German DAX index. In other words, we try to find out whether or not strong volatility transmission links exist among the Baltic stock markets, and between these markets and the more developed German market at different time-horizons. This is important, because if prices of the Baltic stock markets closely co-move, there would be limited gains from the diversification point of view. In these conditions, investors would be exposed to unhedged risk, while risk reduction may prove difficult. Also, since returns and risks are the two sides of the same coin, Marfatia (2017) contended that having a clear picture about the integration of risks is at least as (or even more) important as understanding integration of returns. Figure 1 presents yearly dynamics of the selected indices, in which the growing path of these indices is clearly visible.

Figure 1 Empirical Dynamics of the Selected Stock Indices



Notes: Empirical dynamics of the selected indices is presented *via* daily data. Left Y axis denotes the value of the Baltic stock indices. Right Y axis marks the value of the German DX index.

In order to conduct time-frequency domain analysis, this paper combines the advantages of both parametric and nonparametric methods. In particular, at first stage, the EGARCH model is used to calculate conditional volatilities, which provide time-varying measures of risks (see e.g. Živkov et al., 2014). At the second stage, conditional volatilities are embedded into the wavelet framework in order to analyse the behaviour of the conditional volatility-series in the time-frequency domain. More specifically, the study utilizes two complementary approaches – wavelet coherence (WTC) and wavelet correlation, which can reveal interactions between time-series that can be hardly seen by any other traditional econometric tool. In addition, wavelet methodology does not rely on parameters nor on the estimation method, and it elegantly circumvents the problem of sample size reduction, that is, the computation is done without loss of valuable information. Number of recent studies utilized wavelet methodology to analyse various economic phenomena at different time-horizons (see e.g. Dajčman, 2012; Barunik and Vacha, 2013; Dajčman, 2013; Dewandaru et al., 2014; Lee and Lee, 2016; Njegić et al., 2017; Živkov, Malešević, Malešević and Malešević, 2018; Jiang et al., 2018; Si et al., 2018; Živkov et al., 2019). In order to do some additional analysis in terms of lead(lag) relationship, which can give an insight about the spillover effect between the Baltic stock markets, the paper considers the phase difference approach of Aguiar-Conraria and Soares (2011). The idea to use this method for the study was obtained from the following papers – Altar et al. (2017), Živkov, Balaban and Đurašković (2018). Phase difference allows researchers to see what is the direction of correlation (coherence) as well as the leading(lagging) role of particular variable, throughout the observed sample and at specific frequency band, which can be useful for asset-rebalancing purposes. To the best of the authors' knowledge, this is the first paper that provides a new look about volatility transmission as well as portfolio construction between the Baltic stock markets, taking into consideration both time and frequency aspects.

Beside introduction, the rest of the paper is structured as follows. Second section presents literature review. Third section explains used methodologies. Fourth section gives an overview of dataset and the preliminary findings. Fifth and sixth sections presents the results of volatility co-movements among the Baltic stock indices, and between the Baltic indices and the German DAX index, respectively. Seventh section explains how the risk minimizing portfolios are created and presents HEI_{Var} results. The last section concludes.

2. Literature Review and Related Studies

Over the recent years there has been long-standing interest in analysing the volatility transmission between stock markets. Égert and Kočenda (2007) researched co-movements among three stock markets indices in Central and Eastern Europe (BUX, PX-50, WIG-20) and Western European stock indices (DAX, CAC, UKX). They found no robust cointegration relationship for any of the stock index pairs, but they revealed that there is some indication of short-term spillover effects, regarding both stock returns and volatility. Gilmore et al. (2008) investigated short-term and long-term co-movements between developed European Union (EU) stock markets and the Czech, Polish and Hungarian stock markets. They used dynamic cointegration and principal components methods and concluded that there is no evidence of steadily increasing convergence of developed and emerging equity markets in EU, despite the decade-long process of alignment between these markets. Savva and Aslanidis (2010) measured the degree in stock market integration between the five Eastern European countries and the Euro-zone. They disclosed that the Czech, Slovenian and Polish markets have increased their correlation to the Euro-zone from 1997 to 2008, but they argued that this is not a broad-based phenomenon across Eastern Europe. Recent paper of Gjika and Horvath (2013) studied time-varying stock market co-movements in Central Europe via asymmetric dynamic conditional correlation multivariate GARCH model. They reported that the correlations have increased over time, and this applies for the correlations among all the Central European stock markets as well as for the correlations between the Central European markets vis-à-vis the euro area. Horvath et al. (2018) tried to determine the existence of contagion from the US stock market to six Central and Eastern European stock markets. They showed that during 1998-2014, unexpected negative events in the US market are followed by higher co-exceedance between the US and the Central and Eastern European stock markets. They asserted that contagion occurs also in tranquil times.

The literature that examines volatility spillovers in Baltic region is still scarce, but few papers considered these countries. For instance, Mateus (2004) supported the partial integration of the Baltic stock markets with respect to the world market during the period 1997–2002. Similar conclusion reached Maneschiöld (2006), who found that the Baltic markets exhibit a low degree of integration with developed international markets (US, Japan, Germany, UK, and France) during the period 1996–2005. Nielsson (2007) investigated the interdependence of the Nordic and Baltic stock markets, revealing the surprisingly little interdependence between these markets. He argued that the response of each market to a shock in another is insignificant in the short run. He reported a limited evidence of an integration and only weak indication of convergence within the sample period in the longer term. Soultanaeva (2008) studied the spillover effect of the political events from the Russian stock market to the Baltic stock markets. She concluded that the reaction of the Baltic stock markets to political news and events in Russia mitigated over time, while the Baltic stock market reaction depends primarily on the rate of information arrival as well as on differences in investors' interpretations of news announcements and opinions. Kuusk et al. (2011) addressed the issue of the financial contagion from the US stock market to the Baltic stock markets during the recent financial crisis. They found evidence to support the contagion hypothesis and suggested that linkages between the USA and the Baltic stock markets have become stronger after the collapse of Lehman Brothers bank in USA in 2008. Nikkinen et al. (2012) examined the interdependence between developed European stock markets and the three Baltic markets with particular attention to the global financial crisis (GFC) of 2008–2009. They uncovered that Baltic stock markets were apparently segmented before the crisis, whereas they were highly integrated during the crisis. Alexakis et al. (2016) studied a contagion effect between Baltic markets and developed European markets during the global financial crisis and the Euro zone Sovereign Debt Crisis (ESDC). They observed the EUROSTOXX50 stock index, which credibly describes the dynamics of the developed markets. Their results disclosed that Latvia and Lithuania were contagious during the GFC, but these countries were not affected by the harmful effects of the ESDC. On the other hand, Estonia was not impacted so strongly by GFC, but this effect was more significant during ESDC.

3. Methodologies

3.1 EGARCH Specification

The goal of this study is to measure time-scale volatility co-movements between Baltic stock indices as well as between these indices and the DAX index. In the latter process, these volatilities are used for portfolio construction purposes. In order to properly recognize the features of volatilities, such as volatility clustering and asymmetric effect that might exist in the selected stock markets, EGARCH(1,1) model is considered. This assumption is based on previous papers (see e.g. Kanas, 2012; Živkov et al., 2016; Chaker and Hel, 2015; Erragragui et al., 2018), who reported that it is not unlikely to found these characteristics in daily stock time-series. The mean equation specification is determined based on Akaike information criterion, and ARMA(1,2) prove to be an optimal lag order for all the Baltic indices, while for the DAX index it is an ARMA(1,0). Equations (1) and (2) present the mean and EGARCH model specifications, respectively:

$$r_{t,i} = C_i + AR_{t-n,i} + MA_{t-m,i} + \varepsilon_{t,i}; \quad \varepsilon_{t,i} = h_{t,i} z_{t,i}; \quad z_{t,i} \sim iid, \tag{1}$$

$$\ln(h_{t,i}) = c_i + \alpha_i \left| \frac{\varepsilon_{t-1,i}}{\sqrt{h_{t-1,i}}} \right| + \beta_i \ln(h_{t-1,i}) + \gamma_i \frac{\varepsilon_{t-1,i}}{\sqrt{h_{t-1,i}}}, \tag{2}$$

where r stands for stock returns, calculated as $r_{t,i} = 100 \times \log(P_{t,i}/P_{t-1,i})$, whereby $P_{t,i}$ is the stock closing price for the particular stock index (i) at time (t). Common white noise is presented by $Z_{t,i}$ conditional on the information (I) at time t-1, which follow Normal distribution $Z_{t,i}|I_{t-1} \sim N(0,1)$. Conditional variance is labelled by $h_{t,i}$, β term captures the persistence of volatility and α gauges an ARCH effect. Symbol γ stands for the coefficient that measures asymmetric response of volatility to positive and negative shocks.

3.2 Wavelet Methodology and Wavelet Correlations

Simply speaking, wavelet technique is a nonlinear and energy preserving transformation method, which projects original time-series onto a sequence of basic functions, which are called wavelets (see Tsai and Chang, 2018). Wavelet theory knows two basic wavelet functions: the father wavelet (ϕ) and the mother wavelet (ψ). The father wavelets augment the representation of the smooth or low frequency parts of a signal with an integral equal to 1, and the mother wavelets are helpful in describing the details of high frequency components with an integral equal to 0. Father and mother wavelet functions are generated in the following way:

$$\phi_{J,k}(t) = 2^{-J/2}\phi\left(\frac{t-2^J k}{2^J}\right), \qquad \psi_{j,k}(t) = 2^{-j/2}\psi\left(\frac{t-2^j k}{2^j}\right). \tag{3}$$

Expression (3) indicates that the scale or dilation factor is 2^J, whereas the translation or location parameter is 2^Jk. For our research purposes, we use the non-orthogonal wavelets, known as the maximum overlap discrete wavelet transformation (MODWT), which is based on a highly redundant non-orthogonal transformation. Decomposed signals in MODWT framework are given in the following way:

$$s_{J,k} \approx \int f(\mathrm{t})\phi_{J,k}(t)dt \tag{4}$$

$$D_{j,k} \approx \int f(\mathrm{t})\psi_{j,k}(t)dt, \qquad j = 1,2,\dots,J. \tag{5}$$

where symbols $S_j(t)$ and $D_j(t)$ denote the fluctuation and scaling coefficients, respectively, at the j-th level wavelet that reconstructs the signal in terms of a specific frequency (trending and fluctuation components). According to the above, an empirical time-series y(t) can be expressed in terms of those signals as:

$$y(t) = S_J(t) + D_J(t) + D_{J-1}(t) + \cdots + D_1(t). \tag{6}$$

We perform multiresolution analysis with 7 levels of time scales using MODWT with Daubechies least asymmetric (LA) wavelet filter of length L= 8, which is also known as LA(8) wavelet filter.

Applying afore-mentioned multi-resolution analysis, we can present the dependence structure of a stochastic process between Baltic conditional volatilities on a scale-by-scale basis, that is, we can compute the wavelet correlations. Assuming a bivariate stochastic process $\mathbb{Z}_t = (x_t, y_t)$ of two time-series, x(t) and y(t), whereby $\widehat{D}_{j,t} = \left(\widehat{D}_{x,j,t}, \widehat{D}_{y,j,t}\right)$ is a scale J wavelet coefficient computed from $\mathbb{Z}_t$. Each wavelet coefficient is obtained by applying the MODWT process in $\mathbb{Z}_t$. The time-dependent wavelet variance for scale J of each time-series is then presented as $\sigma^2_{x,j,t} = Var(\widehat{D}_{x,j,t})$ and $\sigma^2_{y,j,t} = Var(\widehat{D}_{y,j,t})$, whereas time-dependent wavelet covariance for scale J is $\gamma_{x,y,j,t} = COV(\widehat{D}_{x,j,t}, \widehat{D}_{y,j,t})$. Combining wavelet variances and wavelet covariance, we can calculate the wavelet correlation[1] coefficients as follows:

$$\rho_{x,y,j,t} = \frac{COV(\widehat{D}_{x,j,t}, \widehat{D}_{y,j,t})}{\left(Var(\widehat{D}_{x,j,t})Var(\widehat{D}_{y,j,t})\right)^{1/2}} \tag{7}$$

3.3 Wavelet Coherence

In order to put more credibility in our results, we use another wavelet tool called wavelet coherence[2]. WTC provides information about the strength of the correlation throughout the wavelet scales and the observed sample. It can gauge the local linear correlation between two stationary time-series at each scale, and it is equivalent to the squared correlation coefficient in a linear regression (see Vacha and Barunik, 2012). Torrence and Webster (1999) asserted that WTC can be presented as a squared absolute value of the smoothed cross wavelet spectra normalized by the product of the smoothed individual wavelet power spectra of each selected time-series. The cross wavelet transform of two time-series, x(t) and y(t), is defined as $W_{xy}(u,s) = W_x(u,s)W^*_y(u,s)$, wherein W_x and W_y are the wavelet transforms of x and y, respectively. Symbol u represents a position index, s denotes the scale, while the symbol * indicates to a complex conjugate. The squared wavelet coherence coefficient is presented in equation (8):

$$R^2(u,s) = \frac{\left|\mathbb{S}\left(s^{-1}W_{xy}(u,s)\right)\right|^2}{\mathbb{S}(s^{-1}|W_x(u,s)|^2)\mathbb{S}\left(s^{-1}\left|W_y(u,s)\right|^2\right)} \tag{8}$$

where $\mathbb{S}(.)$ stands for the smoothing operator. The squared wavelet coherence coefficient ranges $0 \leq R^2(u,s) \leq 1$, whereby values near zero point to weak correlation, while values near one indicate to strong correlation. According to Grinsted et al. (2004), theoretical distribution for the wavelet coherence is not known, hence statistical significance is tested by Monte Carlo methods.

3.4 The Wavelet Power Spectrum

The wavelet power spectrum of a time-series x(t) is simply given by $|W_x(u,s)|^2$, which is so-called auto-wavelet power spectrum (see Jiang et al., 2015). It represents a measure of the local variance (volatility) for x(t) at each frequency. According to Hudgins et al. (1993), the cross-wavelet transform of two time-series x(t) and y(t) is defined as $W_{xy}(u,s) = W_x(u,s)W^*_y(u,s)$, their cross-wavelet power spectrum is accordingly written as $\left|W_{xy}(u,s)\right|^2 = |W_x(u,s)|^2\left|W^*_y(u,s)\right|^2$ and it presents a measure of the local covariance between x(t) and y(t) at each frequency. In the wavelet power spectrum plots,

[1] Wavelet correlations are calculated via 'waveslim' package in 'R' software.
[2] Wavelet coherence is calculated via 'WaveletComp' package in 'R' software.

wavelet power is represented by black and white shades, whereby darker shades indicate to a high power, while lighter shades correspond to a low power.

3.5 Phase Difference

Since wavelet coherence measures the squared correlation, the direction of coherence cannot be observed directly. Therefore, the direction of the correlation as well as the lead-lag relationship between observed variables is determined by phase arrows in WTC plots. Following Torrence and Webster (1999), the wavelet coherence phase difference has the following form:

$$\phi_{xy}(u,s) = tan^{-1}\left(\frac{\Im\{S(s^{-1}W_{xy}(u,s))\}}{\Re\{S(s^{-1}W_{xy}(u,s))\}}\right), \tag{9}$$

where $W_{xy}(u,s) = W_x(u,s)\overline{W_y}(u,s)$ is the cross wavelet transform of two time-series, x(t) and y(t), whereas W_x and W_y are the wavelet transforms of x and y, respectively. Symbols u and s have exact same meaning as in equation (8). $\Im$ and $\Re$ are the imaginary and real parts of the smooth power spectrum, respectively. Vacha and Barunik (2012) explained that right (left) pointing arrows in WTC plots indicate that the time-series are in-phase (anti-phase) or are positively (negatively) correlated. If arrows point to the right and up, the second variable is lagging and if they point to the right and down, the second variable is leading. Reversely, if arrows point to the left and up, the second variable is leading and if arrows point to the left and down, the second variable is lagging.

Due to the fact that phase arrows behave erratically at lower coherence areas, this paper also applies phase difference method of Aguiar-Conraria et al. (2011)[3], which is capable of determining the average phase-position at specific frequency band, throughout the observed sample. According to these authors, if $\phi_{xy} \in (\pi/2, 0) \cup (0, -\pi/2)$ then the series move in phase. If phase difference is in realm $(\pi/2, 0)$ then the time-series y leads x. The time-series x leads y if $\phi_{xy} \in (-\pi/2, 0)$. An anti-phase situation, that is, negative correlation, happens if we have a phase difference in an area $\phi_{xy} \in (-\pi/2, \pi) \cup (-\pi, \pi/2)$. If $\phi_{xy} \in (\pi/2, \pi)$ then x is leading. Otherwise, time-series y is leading if $\phi_{xy} \in (-\pi, -\pi/2)$. Phase difference of zero indicates that the time-series move together, analogous to positive correlation, at the specified frequency.

4. Dataset and Preliminary Findings

The present study uses daily data for three Baltic stock indices – OMXV (Vilnius index; Lithuania), OMXR (Riga index; Latvia) and OMXT (Tallinn index; Estonia) as well as German DAX index. The time-span ranges from January 4, 2000 to April 28, 2018. The data are collected from Datastream. Public holidays and non-working days in any particular year are excluded from the entire sample and daily dates are synchronized between the pairs of the stock markets. This entails some loss of information, but in order to maintain consistency in comparing data across countries and to avoid false inference, this step is necessary. Using wavelet signal-decomposing technique, this paper observes interdependence between stock market volatilities at seven different scale levels, which

[3] The results were obtained by applying ASToolbox of Aguiar-Conraria and Soares (2011).

corresponds to following time-horizons – scale 1 (2-4 days), scale 2 (4-8 days), scale 3 (8-16 days), scale 4 (16-32 days), scale 5 (32-64 days), scale 6 (64-128 days) and scale 7 (128-256 days). First four scales are treated as short-term observations, fifth and sixth scales correspond to midterm, while seventh scale represents the long-term. Utilizing wavelet coherence and phase difference approaches, the study can investigate the dynamic nexus of volatility transmissions in different frequency levels, which could serve well for various economic agents who have different term objectives.

In order to measure volatility transmission between the stock indices, the conditional variances of every index are calculated and extracted from the EGARCH models. With the aim to avoid biasness, Table 2 presents the estimated EGARCH parameters as well as diagnostic test for autocorrelation and heteroscedasticity for every index selected. Table 2 suggests that the all estimated coefficients are highly statistically significant. The β parameter implies high persistence of the log conditional variance process in all the Baltic stock markets, which means that volatility in the Baltic stock markets reverts or decays toward its long-run average very slowly. The α parameters indicate the presence of an ARCH effect. The asymmetric parameter (γ) is negative and significant for all stock indices, which points to a leverage effect. It means that negative shocks have more pronounced effect than positive shocks of the same magnitude in the equity markets. All EGARCH models have very sound statistical adequacy as pointed by the Ljung-Box diagnostic tests, suggesting the absence of serial correlation and heteroscedasticity. Based on the results in Table 2, it is possible to conclude that the conditional variances correctly present the time-varying volatilities in the Baltic stock markets as well as in German stock markets, and as such, can be further processed *via* wavelet methodology.

Table 2 EGARCH Estimates for the Baltic Indices

Estimated parameters	***OMXV***	***OMXR***	***OMXT***	***DAX***
Panel A: EGARCH estimates				
c	-0.123***	-0.187***	-0.170***	-0.082***
α	0.171***	0.278***	0.229***	0.116***
β	0.984***	0.957***	0.980***	0.979***
γ	-0.014***	-0.021***	-0.012***	-0.117***
Panel B: Diagnostic tests				
LB(Q)	0.217	0.107	0.125	0.285
LB(Q^2)	0.933	0.914	0.589	0.382

Notes: LB-Q and LB-Q^2 test denote p-values of Ljung-Box Q-statistics for level and squared residuals up to 20 lags.

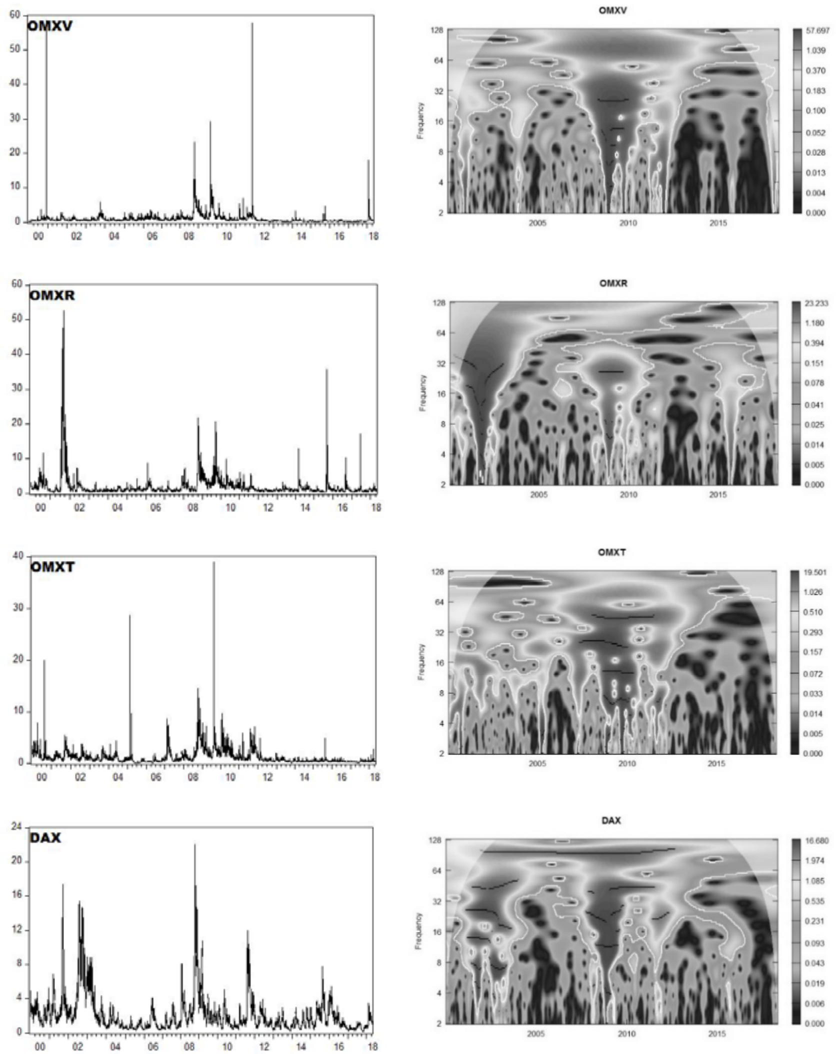
Table 3 Descriptive Statistics of Returns and Conditional Volatilities of the Selected Indices

Indices and their volatilities	***Mean***	***St. dev.***	***Skewness***	***Kurtosis***	***JB***
OMXV	10.332	1.011	-0.524	24.900	0.000
OMXR	12.348	1.394	-0.398	20.517	0.000
OMXT	11.592	1.064	0.119	12.759	0.000
DAX	3.276	1.493	-0.048	7.467	0.000
OMXV-EGARCH	1.032	1.915	9.601	128.307	0.000
OMXR-EGARCH	1.973	4.047	9.891	136.912	0.000
OMXT-EGARCH	1.190	1.428	3.999	28.893	0.000
DAX-EGARCH	2.105	2.230	3.123	15.909	0.000

Notes: Indices with suffix **“**EGARCH” indicate to conditional volatility of the indices, while indices without suffix stand for index returns. Mean of the index returns are annualized. JB stands for Jarque-Bera test.

Table 3 contains descriptive statistics of the index returns and their conditional volatilities of the selected indices. It is immediately noticeable that all the indices have very high kurtosis, which suggests the presence of extreme values and outliers. These results justify the usage of the wavelet methodology, because wavelet technique can tackle outliers, but also it can remove noises in original data (see Tabak and Feitosa, 2009). Jarque-Bera test suggests nonnormality of all time-series.

Figure 2 Conditional Volatility and The Wavelet Power Spectrum of the Selected Indices



Notes: Left-hand plots depicts conditional volatilities extracted from ARMA(n,m)-EGARCH(1,1) models, while right-hand plots depicts the wavelet power spectrum. The left vertical axis on the wavelet power spectrum represents scales (measured by days), while the right vertical axis refers to wavelet power (measured as volatility).

In order to further investigate raw data properties at various frequency scales, we compute continuous wavelet power spectrum of a single time-series and the plots are presented in Figure 2 along with the conditional volatilities which are calculated via EGARCH model.

The conditional volatility plots show a number of high volatility spikes, and it particularly applies for the period of global financial crisis. However, it can be seen also that OMXR experienced tremendous volatility in the middle of year 2001. Such short-lived increase in volatility was caused by the action of Latvian government, which sold substantial volume of shares of Latvijas Gaze for the price three times higher than market price. This event had a great impact on local stock market index (OMXR) as Figure 2 suggests, but also it affected neighbouring Lithuanian OMXV index, which jumped up and bounces back as a result of this action. DAX index experienced high volatility during GFC and ECDS, but also in the period 2002-2003, which is related to the invasion on Iraq.

As for the wavelet power spectrum plots, it is obvious that common pattern is characteristic for all the selected indices. Dark-shaded areas of the continuous power spectra indicate to strong volatility, while light-shaded surfaces represent weaker variability of a single time-series. Low volatility exists throughout whole sample period at lower scales as well as at higher scales (except for the GFC period), since lighter shades dominate. However, it can be seen that high volatility endures much longer during GFC, whereby dark-shaded areas spread up to 128 days, which particularly applies for OMXV, OMXT and DAX indices. However, despite its utility, the wavelet power spectrum does not present any local correlation and lead-lag relationship between the observed time-series. In that manner, next section contains the wavelet coherence, wavelet correlation and phase-difference results, computed for each pair of the selected indices.

Table 4 discloses averaged values of Pearson's correlation for returns and volatilities of empirical time-series. It is obvious that in the most cases the return correlations can be treated as small correlations. Volatility correlations are somewhat higher, whereby only OMXT-OMXV pair belongs to strong correlation category. These preliminary findings might indicate that some diversification potential exists, but further insight is needed because we work with the wavelet transformed series, which provide a wider picture in terms of different time-horizons.

Table 4 Pearson's Correlations Between Returns and Conditional Volatilities of The Selected Indices

	OMXR vs OMXV	*OMXR vs OMXT*	*OMXT vs OMXV*	*DAX vs OMXV*	*DAX vs OMXR*	*DAX vs OMXT*
Returns	0.237	0.214	0.444	0.180	0.079	0.246
Volatilities	0.299	0.350	0.643	0.276	0.243	0.416

Notes: Strong correlation exists if the coefficient value lies between ± 0.50 and ± 1. Medium correlation can be found between ± 0.30 and ± 0.49, while small correlation is present if the value lies below ± 0.29.

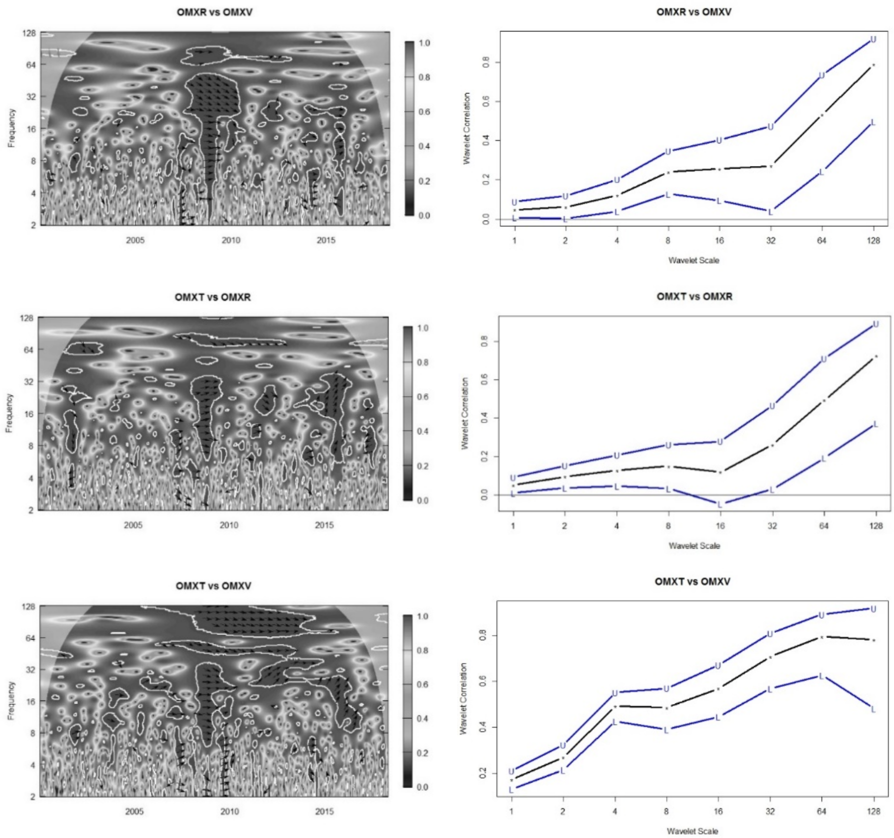
5. Volatility Co-Movements Among the Baltic Stock Markets

This section discloses the time- and frequency-varying relationship between the conditional volatilities of the Baltic stock indices. The findings are presented via two complementary methodologies – wavelet coherence and wavelet correlations and Figure 3 contains these results. These methodologies are able to show the co-movement of risks at different frequencies, which allows researchers to gain an insight about synchronization of risks at higher frequencies (short-run) as well as lower frequencies (long-run). More specifically, wavelet correlation provides exact level of average correlation across particular wavelet scale, but without time-dimension, while wavelet coherence simultaneously observes two domains – time and frequency, whereby the strength of the coherence is not so accurate because it is depicted via black and white palette of shades. However, when they are observed together, a researcher can gain a holistic picture about the interdependence between two variables. As for the wavelet coherence plot, the horizontal axis denotes time component, while the left vertical axis represents frequency component, which goes up to seventh scale (128 days). The strength of the co-movement between analysed conditional volatilities is measured via black and white surfaces, were lighter shades indicates low coherence, while darker shades point to higher coherence. The black and white palette is presented at right Y-axis and it ranges from 0 to 1. The cone of influence designates the statistically significant area at 5% significance level estimated from a Monte Carlo simulation.

It can be seen in all the wavelet coherence plots that dark coherence areas are relatively scarce, which indicates that risk integration between the Baltic stock markets is not on a high level. It particularly applies for relatively short time-horizons, that is, up to 16 days, where low-coherence colours overwhelmingly prevail. Wavelet correlations further verify these results and provide more clear-cut conclusions. More specifically, we find relatively low volatility correlations for pairs OMXR-OMXV and OMXT-OMXR in short-term horizon (up to 32 days), while for the OMXT-OMXV combination, wavelet correlations are relatively high even at high frequency scales. Wavelet correlation plots show approximate strength of correlations, but in order to dispel any doubt about their levels, we additionally provide accurate wavelet correlations between the conditional volatilities in Table 3, along with the lower and upper boundaries. As can be seen, Table 3 shows that, up to 32 days, wavelet correlations for pairs OMXR-OMXV and OMXT-OMXR are 0.270 and 0.262, respectively, while for OMXT-OMXV it goes beyond 70%. These findings might indicate that both short-term and long-term risk-reducing investors should avoid Lithuanian OMXV and Estonian OMXT indices in a single portfolio. However, this conclusion is rather superficial, because the level of correlation is not the only important argument for portfolio construction. On the other hand, it seems that short-term risk-avoiding investors can couple Latvian and Lithuanian as well as Estonian and Latvian indices in a single portfolio, because their correlations are way below 30% in the short-term.

Our findings coincide very well with the paper of Marfatia (2017), who investigated volatility spillovers across 22 leading stock markets of the world, using the wavelet methodology. He found that the co-movement of risks between the US and European markets is strong mostly at longer time-horizons, while at lower wavelet scales low coherence is dominant. It should be said that OMXT vs OMXR plot visually has the lowest percentage of the strong coherence area, while OMXT vs OMXV plot has the highest percentage, which is in line with the wavelet correlation results and which contributes to the robustness of the results.

Figure 3 Wavelet Coherence and Wavelet Correlations of the Selected Baltic Pairs



Notes: Left-hand plots present wavelet coherence between the selected pairs of conditional volatilities, while right-hand plots depict wavelet correlations for the same pairs of conditional volatilities.

Table 5 Wavelet Correlations for the Baltic Conditional Volatilities With Upper and Lower Bounds

Wavelet scales	*OMXR vs OMXV*			*OMXT vs OMXR*			*OMXT vs OMXV*		
	Lower	*Wcorr*	*Upper*	*Lower*	*Wcorr*	*Upper*	*Lower*	*Wcorr*	*Upper*
Raw data – 1 day	0.007	0.048	0.089	0.011	0.052	0.093	0.131	0.171	0.210
D1 – 2 days	0.003	0.061	0.119	0.037	0.095	0.152	0.215	0.270	0.323
D2 – 4 days	0.040	0.122	0.202	0.047	0.129	0.208	0.426	0.491	0.551
D3 – 8 days	0.128	0.241	0.347	0.034	0.150	0.262	0.391	0.486	0.570
D4 – 16 days	0.095	0.256	0.404	-0.046	0.120	0.279	0.445	0.569	0.671
D5 – 32 days	0.040	0.270	0.474	0.030	0.262	0.466	0.567	0.708	0.809
D6 – 64 days	0.244	0.534	0.736	0.192	0.494	0.710	0.627	0.794	0.891
D7 – 128 days	0.498	0.790	0.921	0.373	0.724	0.894	0.482	0.782	0.918

Notes: Wcorr denotes wavelet correlations. “Lower” and “Upper” stand for lower and upper boundaries in regards to wavelet correlations.

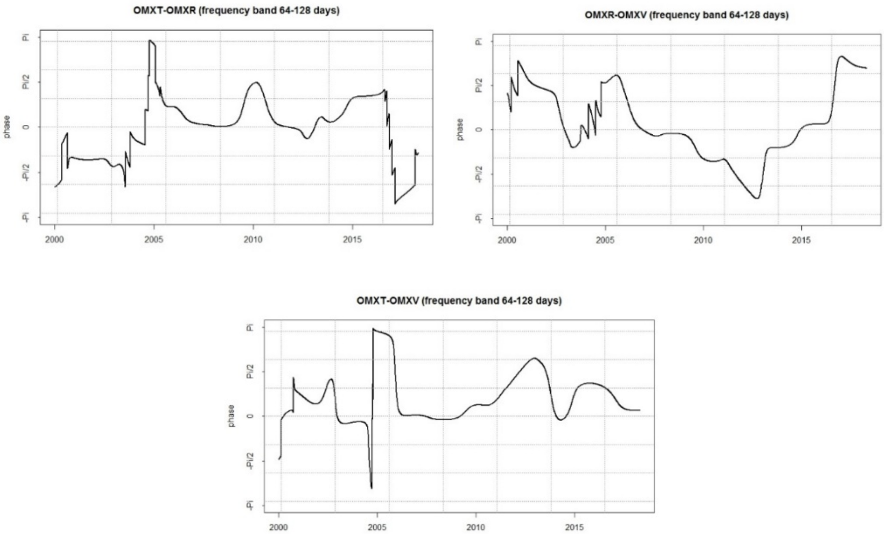
Since WTC plots can observe time-dimension, it is interesting to notice that in all WTC plots, a common pattern of increased coherence can be recognized in the period of the global financial crisis, whereby in the case of OMXR vs OMXV high coherence is present even at very low wavelet scales. This is not surprising, since many papers indicated the presence of a contagion effect during GFC. For instance, Alexakis et al. (2016) found that Latvian and Lithuanian stock markets were contagious during GFC, but they are immune to the adverse effects of the subsequent European sovereign debt crisis. The paper of Nikkinen et al. (2012), reported that the correlations between all the Baltic stock markets and developed European markets increased significantly during the global crisis, while Kuusk et al. (2011) found evidence to support the contagion hypothesis from the US stock market to the Baltic stock markets during the recent financial crisis. Madaleno and Pinho (2012) explained that co-movement in returns are stronger for geographically and economically closer markets. All these characteristics can be attributed to Baltic countries and that is the reason way strong and long-lasting coherence is found between the Baltic stock markets during GFC.

WTC plots contain phase arrows, which convey some information regarding the direction of coherence as well as the lead-lag relationship between conditional volatilities. Vast majority of phase arrows point to right, which indicates in-phase situation between the conditional volatilities, which is expected. These results are also in line with wavelet correlation plots, since all wavelet correlation are above zero.

5.1 Phase Difference Results

Information which phase arrows bear in WTC plots is relatively limited, since stable and uniform phase arrows' pattern can be seen only in high-power areas, whereas in low-power regions, phase arrows shift direction constantly, thereby preventing researchers to see clearly which variable lagging (leading) the other one. In order to circumvent phase arrows' shortcomings, we use complementary methodology – phase difference of Aguiar-Conraria and Soares (2011). This is a handy tool for providing information in terms of the direction of coherence and the leading (lagging) role of particular variable, throughout the observed sample and at specific frequency band. Dajčman (2013) addressed this issue, explaining that this type of information can be very useful for investors, because if they are aware empirically that one time-series leads the other one, then its realizations may be used to forecast the realizations of the lagging time-series. However, strong minimal phase difference does not exist under minimum dependency (see Aguiar-Conraria and Soares, 2011), so in order to avoid phase difference biasness, we calculate phase difference only at long-run, since stronger presence of high coherence is only found at long-term horizon, as WTC and wavelet correlation plots suggest. Figure 4 presents these findings.

Figure 4 Phase Difference for the Conditional Volatilities of the Baltic Stock Markets



Notes: If phase difference line is in range (π/2, 0) ∪ (0, -π/2) then the series move in phase. If phase difference line is in realm (π/2, 0) then the time-series y leads x. The time-series x leads y if phase difference line is in domain (-π/2, 0). An anti-phase situation, that is, negative correlation, happens if we have a phase difference in an area (-π/2, π) ∪ (-π, π/2). If phase difference line finds itself in (π/2, π) then x is leading. Otherwise, time-series y is leading if phase difference line belongs to the realm (-π, -π/2).

Long-term phase difference findings can help investors in making decision in which market to invest if they are not sure from which market volatility shocks originate and which market is volatility shock recipients. Looking at phase difference plots, it can be seen that phase difference line mostly moves in realm between $\pi/2$ and $-\pi/2$, which indicates an in-phase situation (positive correlation) for all pairs examined, which concurs in great deal with phase arrows in WTC plots as well as the wavelet correlations. Only in some occasions, phase difference breaches the $\pi/2$ or $-\pi/2$ boundaries and enters an anti-phase domain. In the OMXT-OMXR case, it happened in 2005 and 2017, while in the OMXR-OMXV plot, brief anti-phase situations are recorded in 2000, 2005, 2013 and 2017. As for the OMXT-OMXV case, volatility divergence is detected only in 2005. It can be noticed that phase difference line has relatively stable and long-lasting dynamics when it comes to the region where it moves, which can be used affectively for future decision making of long-term portfolio construction. For example, it can be seen that conditional volatility of Latvian OMXR index steadily leads Estonian volatility from 2005 onwards. As for the pair OMXT-OMXV, it is found that volatility of OMXV continuously has an upper hand relative to OMXT volatility since 2006. These results indicate that volatilities are transmitted from bigger stock markets towards the smaller market (see Table 1), which is usually the case. However, in the case of OMXR-OMXV, conditional volatilities are transmitted from smaller Latvian market towards the bigger Lithuanian market since 2007. This result deviate from the previous assertion and the usual pattern, and no obvious reason could explain why it is happening, so future studies may find interesting resolving this issue.

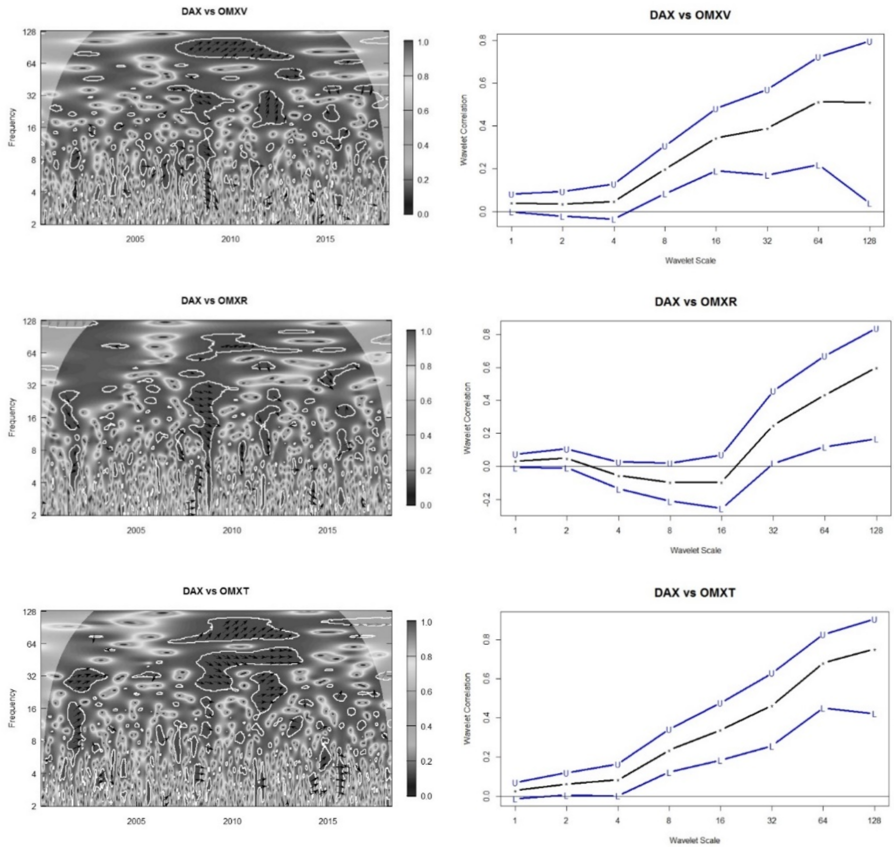
6. Volatility Co-Movements Between the Baltic Stock Markets and the German Market

This section presents the results of volatility co-movements between the Baltic stock indices and the German index, observing different time-horizons. In such way, it can be seen how closely less developed Baltic stock markets are integrated and well connected with the largest European stock market. This information might shed a new light on the potential of these growing stock markets in the context of diversification strategies.

The wavelet coherence plots show that light shades prevail throughout the whole sample and particularly in higher frequencies in all examined pairs. It is an indication that combining Baltic stock indices with the German index might yield good diversification results. Dark-shaded zones are only visible around the periods of GFC and ESDC and at higher wavelet scales, which is similar to the findings in Figure 4. Our results coincide very well with the assertion of Barunik and Vacha (2013) who indicated that the connection of the CEE markets to the leading market of the region is significantly lower in shorter time-horizons than longer time-horizons. Also, they reported significantly lower contagion between the CEE markets and the German DAX index after GFC. In addition, the recent study of Cărăuşu et al. (2018) researched how and when contagion occurred in 10 CEE financial markets in relation to the Western European and US financial markets during the period 2000–2016. As for the Baltic stock markets, they found that Lithuania and Latvia showed contagion in relation to the Western European and US markets, in the period 2005–2009, while the Estonian capital markets demonstrated no signs of contagion with both the Western European and US markets, during 2005–2009. These results coincide with our findings, because we find darker areas in lower wavelet scales for Lithuania and Latvia during GFC, while for Estonia, darker zones are visible in the longer time-horizons (32 days onwards). According to Dewandaru et al. (2016), when high correlation between financial markets is found in shorter time-horizons, than the contagion is probably the culprit. However, when high correlation is present in longer time-horizons, it is classified as interdependence.

As have been said previously, CWT plots give the dynamic outline of the strength of the connection between the two markets, but without exact values. Wavelet correlations overcomes this problem, providing exact numbers of average wavelet correlations. Right-hand plots in Figure 5 presents wavelet correlations, while Table 6 contains the exact values. Comparing Tables 5 and 6, it can be seen that the wavelet correlations between the Baltic stock indices are stronger than the correlations between the DAX index and the Baltic indices. This is expected, since the Baltic stock markets are all tightly connected by their geographical proximity as well as by their institutional setup. In addition, in the case of DAX-OMXR, some wavelet correlations are even below zero, which is good for hedging goals.

Figure 5 Wavelet Coherence and Phase Difference for Conditional Volatilities Between the Baltic Stock Markets and the German Stock Market



Notes: Left-hand plots present wavelet coherence between the selected pairs of conditional volatilities, while right-hand plots depict wavelet correlations for the same pairs of the conditional volatilities.

Table 6 Wavelet Correlations Between the Baltic and German Conditional Volatilities

Wavelet scales	***DAX vs OMXV***			***DAX vs OMXR***			***DAX vs OMXT***		
	Lower	Wcorr	Upper	Lower	Wcorr	Upper	Lower	Wcorr	Upper
Raw data – 1 day	-0.001	0.040	0.081	-0.007	0.034	0.075	-0.012	0.029	0.070
D1 – 2 days	-0.022	0.036	0.094	-0.008	0.050	0.108	0.005	0.063	0.120
D2 – 4 days	-0.035	0.047	0.129	-0.136	-0.054	0.028	0.002	0.084	0.164
D3 – 8 days	0.084	0.199	0.308	-0.210	-0.096	0.020	0.123	0.235	0.342
D4 – 16 days	0.190	0.344	0.482	-0.254	-0.094	0.071	0.184	0.338	0.476
D5 – 32 days	0.171	0.389	0.571	0.019	0.251	0.458	0.258	0.463	0.629
D6 – 64 days	0.218	0.514	0.724	0.119	0.435	0.671	0.451	0.682	0.827
D7 – 128 days	0.041	0.511	0.796	0.167	0.600	0.839	0.422	0.750	0.905

Notes: Wcorr denotes wavelet correlations. “Lower” and “Upper” stand for lower and upper boundaries in regards to wavelet correlations.

In the most cases, our results indicate that stronger wavelet correlations are present at longer time-horizons, that is, in the midterm and long-term. However, as have been said previously, this indicator is only a hint which instruments could be combined in a portfolio, because the level of correlation is not the only parameter that need to be considered in diversification efforts. Therefore, in order to cast away any doubt which indices are the most appropriate for diversification, we design two asset portfolios in next section and calculate the hedge effectiveness indices (HEI). This will help us to determine is it more optimal to combine the Baltic indices between themselves or with the DAX index, and at which particular wavelets scale.

7. Calculating Risk-Minimizing Portfolios with the Selected Indices

In order to create optimal risk-minimizing portfolios, combining the selected indices, we refer to Kroner and Ng (1998), who designed simple but rather effective concept of portfolio construction. Their equation can build a two-asset portfolio that minimizes risk without lowering expected returns. Inputs required to calculate optimal weights of a secondary (auxiliary) asset in a portfolio are variances of two instruments and their mutual covariance. Kroner and Ng (1998) equation looks as follows:

$$W_t^{X,Y} = \frac{\sigma_t^{2\,(X)} - \sigma^{2\,(X,Y)}}{\sigma_t^{2\,(X)} - 2\sigma^{2\,(X,Y)} + \sigma_t^{2\,(Y)}}, \tag{10}$$

$$W_t^{X,Y} = \begin{cases} 0, & if \quad W_t^{X,Y} < 0 \\ W_t^{X,Y}, & if \quad 0 < W_t^{X,Y} < 1, \\ 1, & if \quad W_t^{X,Y} > 1 \end{cases} \tag{11}$$

where $W_t^{X,Y}$ represents the dynamic weight of secondary asset in a 1$ portfolio of a two-asset holding. The labels $\sigma_t^{2\,(X)}$ and $\sigma_t^{2\,(Y)}$ refer to conditional variances of primary and secondary asset in a portfolio, respectively. It should be said that all conditional variances in equation (10) are time-varying wavelet decomposed signals. Symbol $\sigma^{2\,(X,Y)}$ denotes wavelet covariance between primary and secondary asset, and this value is static, that is, it takes the same value throughout the whole sample. Table 7 presents the wavelet covariances for the selected pairs of assets. The weight of primary asset in a portfolio is calculated as: $1 - W_t^{X,Y}$.

The order of indices in Table 7 is deliberately set, and the same order is also followed in a portfolio construction process. In other words, a riskier index is always set to be the primary asset in a portfolio, while the less risky index is the secondary one. According to Mirović et al. (2017), this is the right way to produce accurate portfolio weights via Kroner and Ng (1998) equation.

Table 7 Wavelet Covariances for the Selected Pairs of Indices

	OMXR vs OMXV	*OMXT vs OMXR*	*OMXT vs OMXV*	*DAX vs OMXV*	*DAX vs OMXR*	*DAX vs OMXT*
D1 – 2 days	0.005	0.010	0.020	0.007	0.009	0.007
D2 – 4 days	0.012	0.033	0.082	0.009	-0.014	0.010
D3 – 8 days	0.057	0.049	0.126	0.049	-0.035	0.039
D4 – 16 days	0.156	0.081	0.216	0.101	-0.076	0.074
D5 – 32 days	0.301	0.260	0.325	0.167	0.423	0.154
D6 – 64 days	0.416	0.416	0.374	0.267	0.660	0.304
D7 – 128 days	0.583	0.261	0.279	0.189	0.315	0.315

Notes: This Table contains calculated wavelet covariances for the selected pairs of indices.

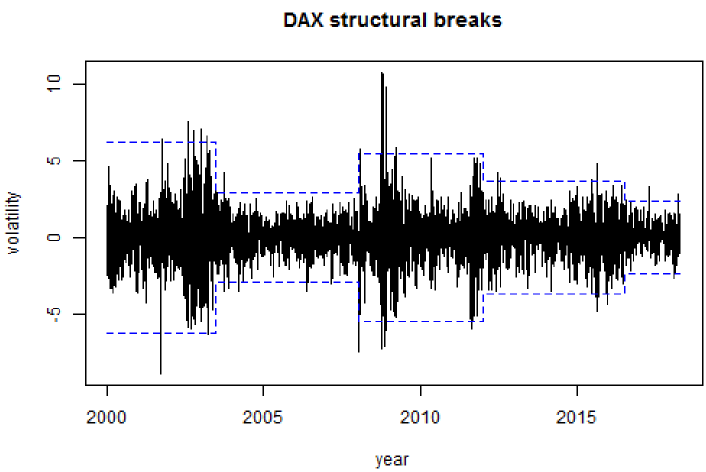
The hedging effectiveness performances are gauged via variance reduction method, according to equation (12). This approach incorporates both upside and downside risk, assigning an equal weight to positive and negative returns. According to equation (12), as much as HEI_{Var} is closer to 1, the grater risk reduction is. HEI_{Var} is calculated as follows:

$$HEI_{Var} = \frac{Var_{unhedged} - Var_{hedged}}{Var_{unhedged}}, \tag{12}$$

where $Var_{unhedged}$ stands for the variance of the unhedged portfolio, which is primary, i.e. riskier index, while Var_{hedged} denotes the variance of the portfolio, composed of primary and secondary (auxiliary) indices.

We observe GFC and ESDC as one comprehensive period, hence the second subsample depicts this more turbulent period, while the first and third subsamples are more tranquil ones. In order to avoid arbitrariness in the process of subsamples determination, we utilize modified iterative cumulative sum of squares (modified ICSS) algorithm of Sans´o *et al*. (2004). In this manner, we can determine exact break dates around GFC and ESDC, and divide the full sample into three subsamples – before, during and after these crises. For this type of calculation, we consider DAX index, because the German stock market is more efficient than the Baltic stock markets, which means that the German stock market processes global information more quickly comparing to the Baltic stock markets. Therefore, the calculated break dates are more accurate. We stipulate via modified ICSS that structural break occurred before GFC on January 14, 2008, while the end of the ESDC is set on January 3, 2012. Following these break dates, we divide the full sample into three subsamples. Figure 6 presents calculated break dates for the DAX index.

Figure 6 Calculated Structural Breaks for the DAX Index



Notes: Structural breaks are determined via modified ICSS algorithm of Sans´o *et al*. (2004).

Table 8 presents HEI_{Var} values for full sample as well as three subsamples, regarding different time-horizons. By dividing full sample into three subsamples, we can measure is there any differences when distinctively different subperiods are taken into account. Observing Panel A, which depicts the full sample, it can be seen that risk-reducing results can be achieved either when the Baltic indices are combined between themselves or when they enter a portfolio with DAX. The risk-reducing benefits are particularly significant in the longer time-horizons, i.e. from scale 4 onwards. The reason why so high HEI_{Var} values are present in all Panels at higher scales lies in a fact that variances of single indices increase constantly and significantly across the wavelet scales, while variances of the portfolios constantly and strongly decrease across the scales.

Table 8 HEI_{Var} Values for the Selected Pairs of the Stock Indices

	OMXR vs OMXV	*OMXR vs OMXT*	*OMXT vs OMXV*	*DAX vs OMXV*	*DAX vs OMXR*	*DAX vs OMXT*
Panel A: Full sample						
D1 – 2 days	-1.773	-2.462	-11.964	-4.266	-36.779	-5.345
D2 – 4 days	0.377	0.217	-4.016	-2.604	-6.103	-3.411
D3 – 8 days	0.874	0.827	-0.272	-0.344	-0.487	-0.594
D4 – 16 days	0.948	0.929	0.624	0.720	0.659	0.684
D5 – 32 days	0.983	0.980	0.823	0.907	0.912	0.878
D6 – 64 days	0.993	0.992	0.888	0.962	0.975	0.950
D7 – 128 days	0.996	0.996	0.948	0.985	0.990	0.984
Panel B: First subsample (1/3/00 – 1/14/08)						
D1 – 2 days	-0.191	-0.633	-10.933	-2.797	-35.419	-3.871
D2 – 4 days	0.774	0.683	-4.742	-1.495	-5.775	-2.339
D3 – 8 days	0.948	0.922	-0.945	-0.050	-0.984	-0.274
D4 – 16 days	0.974	0.961	0.362	0.744	0.597	0.685
D5 – 32 days	0.992	0.990	0.765	0.937	0.929	0.906
D6 – 64 days	0.997	0.997	0.865	0.962	0.961	0.946
D7 – 128 days	0.998	0.998	0.875	0.986	0.987	0.978
Panel C: Second subsample (1/15/07 – 1/3/12)						
D1 – 2 days	-7.133	-8.128	-10.691	-5.220	-27.380	-6.123
D2 – 4 days	-1.965	-2.420	-3.173	-3.513	-5.033	-3.952
D3 – 8 days	0.325	0.145	0.063	-0.609	-0.012	-0.793
D4 – 16 days	0.873	0.837	0.750	0.779	0.777	0.734
D5 – 32 days	0.945	0.944	0.841	0.876	0.917	0.851
D6 – 64 days	0.963	0.963	0.893	0.960	0.990	0.954
D7 – 128 days	0.987	0.990	0.964	0.986	0.994	0.985
Panel D: Third subsample (1/4/12 – 4/28/18)						
D1 – 2 days	-2.721	-4.623	-42.475	-8.420	-128.910	-10.207
D2 – 4 days	-0.637	-1.401	-12.663	-4.426	-15.349	-7.052
D3 – 8 days	0.535	0.315	-2.582	-0.809	-2.235	-1.465
D4 – 16 days	0.862	0.807	0.071	0.297	0.095	0.425
D5 – 32 days	0.946	0.919	0.858	0.875	0.726	0.835
D6 – 64 days	0.967	0.952	0.905	0.964	0.920	0.949
D7 – 128 days	0.979	0.966	0.946	0.982	0.985	0.982

Notes: HEI_{Var} values are calculated according to equation (12) for the selected pairs of indices, taking into account the full sample and the three subsamples.

As for portfolios with only Baltic indices, they all have bad performance in scale 1, which denotes very short time-horizon of 2 days. However, even at scale 2 (4 days), it is better to combine OMXR with OMXV and OMXT, than to invest solely in the OMXR index. Combining OMXT and OMXV pays off in terms of lower risk only when investors target somewhat longer time-horizons, i.e. 16 days onwards. For investors who trade at the midterm and particularly the long-term, the risk reduction is very high, whichever Baltic indices they combine in a portfolio. When investors combine Baltic indices with German index, the risk-reduction benefits are evident from the scale 4 (16 days) onwards, and it applies for all the Baltic indices. In these cases, the risk is also significantly reduced in the longer time-horizons.

Regarding the three subsamples, we can see that the best hedging performances have portfolio which couples OMXR and OMXV indices in the pre-crisis period, even at very short time-horizons (2 days), while OMXR and OMXT follows. In the crisis period, hedging benefits came to the fore at somewhat longer time-horizons, i.e. from 8 days onwards. Investors who combine DAX with the Baltic indices achieve the risk-reducing benefits from 16 days onwards. In the longer time-horizons, all Baltic indices are good diversification instruments in combination with DAX. In third subsample, the pairs OMXR-OMXV and OMXR-OMXT yield good hedging results in the shorter time-horizon (8 days). For all other Baltic pairs as well as for pairs with the DAX index, it is achieved from the scale 4 onwards.

Not many papers investigated how inclusion of CEE indices in a portfolio affect the risk reduction benefits, and to the best of our knowledge this paper is the first one that does an extensive analysis on the Baltic stock indices. However, some recent papers reported that in spite of relatively high integration between the CEE stock markets and the developed stock markets, the combination of these two relatively different set of instruments in a single portfolio is not unfounded. For instance, Syriopoulos and Roumpis (2009) studied the linkages, comovements and interdependences between six major South European equity markets in the Balkan region and the leading mature equity markets (US and Germany). They contended that dynamic portfolio diversification to the Balkan equity markets can offer potential rewarding investment opportunities and improve investors' risk-return profiles. In addition, Guidi and Ugur (2014) investigated is there any diversification benefits if five CEE stock markets are coupled with their developed counterpart – the German stock index. Their portfolio analysis revealed that diversification benefits were available, despite of increased correlation between these markets.

8. Conclusion

Increased stock market risk integration across borders plays a crucial role in international portfolio diversification and broader economic policy decisioning. Therefore, this paper investigates volatility transmission and portfolio construction between the three Baltic stock indices – OMXV, OMXR and OMXT as well as between the Baltic indices and the DAX index. For the research purposes, the parametric EGARCH model and the three non-parametric approaches – wavelet coherence, wavelet correlation and phase difference are combined. This empirical investigation brings a novel understanding of volatility transmission between the selected stock markets, highlighting the importance of time and frequency-varying properties of the stock volatilities co-movement.

The wavelet coherence findings indicated that risk integration between the Baltic stock markets as well as between these markets and the German market is not so strong. This is because the majority of wavelet coherence surfaces are under lighter shades in all WTC plots, which implies low correlation between the market volatilities. This is particularly true for the high-frequency wavelet scales, that is, short time-horizons. Due to the fact that an assessment of a coherence in WTC plots is not so accurate and can be misleading, we combined WTC plots with the wavelet correlations, which provide clearer estimation of average wavelet correlations. Our findings showed that all wavelet correlations rise with the rise of wavelet scales, but they are not so high, except for the midterm and the long-term horizons. Generally, these results could be indicative in terms of which indices should be combined in a portfolio, but they cannot bring definite conclusions.

Therefore, in order to unequivocally determine which indices should be put in a single portfolio, and at which time-horizons, we constructed wavelet-based two asset portfolios, referring to the Kroner and Ng (1998) equation. The results showed that hedging opportunities can be achieved when the Baltic indices are combined between themselves, but also when they are coupled with the DAX index, and this particularly applies for the longer time-horizons. The OMXR vs OMXV pair turns out to be the most suitable combination, since these indices have good hedging performances even at very short time-horizons and across all subsamples. As for very short horizon (2 days), HEI_{Var} values suggested that it is more optimal to invest in a single index. In addition, phase difference pointed out that the conditional volatility of OMXR index leads OMXV and OMXT volatilities, while OMXV precedes OMXT.

This study contains relevant implications for various risk-reducing stakeholders, who pursue their objectives in the Baltic region at different time-horizons. Based on the overall findings, it could be concluded that diversification-seeking investors who act at longer time-horizons (32 days onwards), might achieve great risk-reducing benefits if they design their portfolios combining only the Baltic indices or if they couple these indices with the German DAX index.

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