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CO-MOVEMENTS OF LITHUANIAN AND CENTRAL EUROPEAN STOCK MARKETS ACROSS DIFFERENT TIME HORIZONS: A WAVELET APPROACH

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Abstract. *This paper investigates equity market risk and co-movements between the Lithuanian stock market and the Central European stock markets. We cover the equity market returns both in time and frequency domains. We focus our studies on the changes of the market risk and co-movements of the Lithuanian and the Central European markets returns during the period of 2000–2018. The wavelet analysis was applied to segregate the returns across different time horizons (frequencies). Our findings corroborate the findings from other authors, namely that crisis periods have a great impact on the interrelations of the Central European and Lithuanian markets. We discover that volatility is concentrated in the medium and long periods (medium and low frequencies) from 1 to 3,5 years for all the markets under consideration. The absolute maximum of volatility is achieved at the period of the frequencies corresponding to the period of 3 years. We found that the co-movements with Poland, the Czech Republic and Hungary are slightly lower after the announcement of the introduction of the euro in Lithuania by the European Commission. From the investment diversification point of view, the investment horizon plays a crucial role for the level of co-movements. Our conclusion is that for Lithuanian investors, diversification with Central European markets is not useful for long horizons, because of the high co-movements. The benefit of the diversification can be achieved for the investors with time horizons less than 1 year.*

Keywords*: market, wavelet, coherence, co-movements, wavelet power spectrum.*

1. Introduction

Estimation of the market risk plays a crucial role for investors. Diversification of investments is one of the main principles in reducing portfolio risk. The benefit of the diversification of a portfolio can be achieved if the value of the assets in the portfolio move not exactly in the same direction. Therefore, the stock market co-movement is of great importance to financial decision makers. The level of co-movement has a direct practical application in making decisions concerning asset allocation and risk management. The decreased co-movement of stock market returns may enhance the advantages of the international diversification of investments (Ling and Dhesi, 2010).

Fund managers have various objectives for their investments. The horizon of the investments replicates the goals of the investments. The studies of Forbes and Rigobon

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(2002) and Brooks and Del Negro (2005, 2006) have revealed that a co-movement of markets is not constant over time and changes depending on the length of the investments. Therefore, one can distinguish short-term and long-term risk which is related to the duration of the investments. The short term risk is associated with the fluctuations of the market returns in high frequencies, and the long-term risk reflects fluctuations in low frequencies. The different horizons of the investments requires analysts to have a tool to segregate risks for long and short term investments.

The financial series are usually heterogeneous, therefore, the analysis of the series by a classical econometric approach is faced with some methodological problems. The analysis across particular frequencies (different time horizons) make an econometric approach even more complicated. Dewandaru et al. (2015) stated that, a wavelet analysis is a proper tool for the investigation of the heterogeinity of the financial series. According to Chakrabarty et al. (2015), a wavelet based multi-scale analysis of financial time series has attracted much attention, from both academia and practitioners from all around the world.

The Lithuanian stock market and co-movements of the market with Central European markets was analyzed by a number of authors not paying particular attention to the length of the investment horizon. The models used for the analysis, mostly were based on econometric analysis. Nekhili et al. (2002) stressed that widely used parametric models, like the random walk with GARCH, random walk with stochastic volatility, jump diffusion processes etc., have been found insufficient in explicating the underlying dynamics of the financial market across all frequency levels. The purpose of this paper is to analyze the Lithuanian equity market with respect to Central European equity market risk across different time horizons. The wavelet transformation was employed to segregate the time series of the returns into time-frequency dimensions and estimate the risk and co-movements of the markets for various time horizons separately.

The rest of the paper is structured as follows. Section 2 presents a literature overview focusing on the advantages of the application of wavelets in finance. Section 3 succinctly describes the methodology of wavelets. Section 4 provides a description of the data used in the paper. Section 5 and Section 6 reveal the results of the paper. Section 7 presents the conclusion of the paper.

2. Literature Overview

A number of papers have been devoted to the study of the co-movement of the Lithuanian stock market with other stock markets. Deltuvaite (2016) analyzed the empirical aspects of the Baltic stock market integration in the period from 2000 to June 2014. Using a dynamic conditional correlation generalized autoregressive conditional heteroskedasticity model, Granger causality test and generalized impulse response analyzis, she found that all three Baltic stock markets were closely related. The author has found that the Latvian stock market was more isolated at the regional level as compared to the other two Baltic stock markets, whereas the Estonian and the Lithuanian stock markets were more interrelated. Nikkinen et al. (2012) revealed linkages between the stock markets of the Baltic countries and developed European markets, with a particular attention on the period of the financial crisis of 2008–2009. The results of the study indicated that the Baltic stock markets became closely related to the main European stock markets during and after the crisis. An asymmetric causal relationship between developed European stock markets (German, France and the U.K) and emerging Baltic markets (Estonia, Latvia and Lithuania) during the period of 2001–2014 was analyzed by Babalos et al. (2018). Their studies focused on the period before and after the countries' EU accession and pre- and post the global financial crisis. They found that Baltic markets have a significant predictive power for changes in the major stock returns, especially during periods of financial turmoil. Alexakis et al. (2016) investigated the contagion effect of the Baltics and developed European markets and explored asymmetric conditional correlation dynamics across stable and crisis periods. They find a diverse contagion pattern for the Baltic region across the Global Financial crisis and the Euro Zone Sovereign Debt crises. Time-varying co-movement and volatility transmission between the three Baltic stock markets and two international crude oil indices was analyzed by Bein (2017). A significant increase in correlations between developed (the USA and Germany) and emerging markets' (Central European countries and Estonia) stock returns was discovered by Syllignakis and Kouretas (2011). They analyzed the period from 1997 to 2009 using the DCC-GARCH model. Maneschiöld (2006) revealed the existence of long-run relationships among Baltic stock markets and major international stock markets using co-integration tests. The results showed that international investors can obtain diversification benefits given a long-term investment horizon because of the low degree of integration between the Baltic and international capital markets. It is worth mentioning that the conclusions have been made before the crises of 2008. Our analysis confirms the findings of the authors and expands the understanding of the markets, because we cover the crisis period and consider movements of the Lithuanian and the Central European markets across all frequencies.

Risk assessment is the key issue for fund managers and it constantly attracts much attention from academics. A number of econometric models were used to estimate the risk of the stock market return: random walk with GARCH type models (see Egert and Kocenada 2010) variation of Vector Autoregressive (VAR) models (see for example Gilmorea and McManus 2002), coi-ntergration analysis to find long-run relationships between stock markets returns (Patev et al (2006) and others. For the fund manager, the level of co-movement has a direct practical application in making decisions concerning asset allocation and risk management. The decreased co-movement of stock market returns may enhance the advantages of international diversification of investments (see for example Ling and Dhesi, (2010)). The correlation coefficient of times series of the returns is one of the concepts most commonly used for measuring the co-movement of financial markets. The studies of Forbes and Rigobon (2002) and Brooks and Del Negro (2005, 2006) have revealed that co-movement of markets is not constant over time and changes depending on the length of the investments. Therefore, there is a need to estimate co-movements for different time periods. For this purpose, a rolling window correlation coefficient or non-overlapping sample periods were applied by King and Wadhawani (1990) and Lin et al. (1994). Candelon et al. (2008) noticed that in addition to the time variation of risk and co-movements, a distinction between the short-term and the long-term goals should be taken into account. Banulescu-Radu et al. (2016) stressed that volatility and co-movements of the markets are not constant across the frequencies. As defined by Dewandaru et al. (2015), we treat the frequency below 1 year as a higher frequency and the frequency above 1 year as a lower frequency. We treat long-term and short-term investors as it is defined by Calderon et al. (2008) and Rua and Nunes (2012). Short-term investors are more interested in risk assessment at higher frequencies, i.e., short-term fluctuations, whereas long-term investors focus on risk at lower frequencies, i.e., long term fluctuations. According to Chakrabarty et al. (2015),

> Short term fluctuations are induced by short term traders (like day traders, intra-day traders and hedge funds) who rely on idiosyncratic (firm specific) news more than systematic (market specific) news. Hence their trading activities are un-correlated with the common market dynamics. Long term traders (like central Government and pension funds), on the other hand, relies more on systematic (market and economy specific) news and hence their trading activities are more correlated with the market movements.

In this paper, we analyze the risk of the Lithuanian and Central European stock markets and co-movements between the Lithuanian stock markets and the Central European stock markets in both time and frequency domains. We use a wavelet analysis to explore the risk and co-movements of equity markets. The wavelet transformation has been found to be particularly useful for analyzing signals which can best be described as periodic, noisy and so on. (see Addison 2017). For a long time, a wavelet transformtion analysis has been applied in image processing, physics, geology and meteorology. The application of wavelet transformations in economics and finance were started by the studies of currency markets by Ramsey and Zhang (1996; 1997) and Ramsey and Lampart (1998). These pioneering studies were followed by a number of researchers: Kim and In (2003; 2005) and Babalos et al. (2016) have found some relationship between financial indicators and real economic activity by applying a wavelet transformation. Gallegati (2008) and Yogo (2008) analyzed business cycles, Gallegati et al. (2014) applied wavelets for interest rate spreads and output, Rua (2012) studied money growth and inflation issues of the Euro, and others. A number of authors applied wavelet transformation to reveal the co-movements of equity markets. Co-movements between the stock market returns of the major developed economies was investigated by Rua and Nunes (2009) by means of a wavelet analysis. Dajcman (2012) used maximal overlap discrete wavelet transformations to study the dynamics of the co-movement of the stock market returns of Central Europe and Developed Europe. Baruník and Vacha (2013) analyzed contagion dynamics of correlations between the Central and Eastern European (CEE) stock markets and the German DAX at various investment horizons at a very high frequency.

The novelty of this paper lies in its use, for the first time, of a wavelet analysis for investigating the relationship between the Lithuanian and Central European markets in a time-frequency domain. We found the time and the frequencies at which co-movements are high or low.

3. Wavelet Analysis

We apply a wavelet transformation analysis for the time series of stock market returns. A wavelet transformation analysis uses "small waves" functions known as wavelets. A family of wavelets $\psi_{\tau,s}(t)$, called daughters wavelets, is defined using the basic wavelet functions $\psi(t)$, called a mother wavelet, in the following way:

$$\psi_{\tau,s}(t) = \frac{1}{\sqrt{s}}\,\psi\left(\frac{t-\tau}{s}\right)$$

There, the coefficient $1/\sqrt{s}$ is a normalization factor, the variable s (dilation parameter) is the scale and τ (translation parameter) is the time. The scale s is proportional to the inverse of the frequency.

The continuous wavelet transformation (CWT) of a time series x(t) with respect to $\psi(t)$ is defined trough the following formula:

$$W_x(\tau,s) = \int_{-\infty}^{\infty} x(t)\psi^*_{\tau,s}(t)dt$$

There, the function $\psi^*_{\tau,s}$ denotes the complex conjugate of the function $\psi_{\tau,s}(t)$. For a discreet time series x(t), for t=1,2,…,N CWT is calculated as follows:

$$W_x(\tau,s) = \sum_{t=1}^{N} x(t)\psi^*_{\tau,s}(t)$$

The CWT transforms the initial time series x(t) into another representation, separating time τ and scale (frequency) s.

The wavelet power spectrum (WPS) for each s and τ is defined as follows:

$$\mathrm{WPS}(\tau,s) = |W_x(\tau,s)|^2$$

It measures the time series variance at each time and at each scale s with respect to the mother wavelet ψ. A plot of the WPS is called a scalogram. The average of WPS across time for each scale s-is known as the global wavelet power spectrum GPWS (see Tiwari at el. 2017) or energy distribution at a specific scale (see Addison 2017).

$$E(s) = \frac{1}{N}\sum_{\tau=1}^{N} |W_x(\tau, s)|^2$$

E(s) measures average variance at the frequency corresponding scale s. Peaks in *E(s)* highlight the dominant scales within the time series x(t).

A cross-wavelet spectrum of two time series x(t) and y(t) with wavelet transforms $W_x(\tau, s)$ and $W_y(\tau, s)$ is defined as $W_{xy}(\tau, s) = W_x(\tau, s)W_y^*(\tau, s)$. It captures the covariance between two-time series in the time-frequency space.

We define the wavelet transformation coherence (WTC) or simply the coherency of two-time series x(t) and y(t) in the way it is described by Torrence and Compo (1998) with the following formula:

$$R^2(\tau, s) = \frac{|S(s^{-1}W_{xy}(\tau,s))|^2}{S(s^{-1}|W_x(\tau,s)|^2)S(s^{-1}|W_y(\tau,s)|^2)}$$

There, S(•) is a smoothed (see Torrence and Compo 1998) operator, and s^{-1} is the inverse to the wavelet scale. WTC allows us to estimate the presence of the simple cause-effect relationship between the phenomena recorded in the time series. The coherency is the analogy of the correlation coefficient around each moment in time and each frequency. One can define the average coherency across time at each scale for discreet series of time τ as follows:

$$AC(s) = \frac{1}{N}\sum_{\tau=1}^{N} R^2(\tau, s)$$

We use the complex Morlet wavelet as a mother wavelet, which is defined as follows:

$$\psi(t) = \pi^{-\frac{1}{4}}e^{i\omega_0 t}e^{-\frac{t^2}{2}}$$

In this way, the Morlet function (see, for example, Addison 2017) consists of the multiplier $e^{i\omega_0 t} = \cos(\omega_0 t) + isin(\omega_0 t)$ which is a periodic function with a period of $\frac{2\pi}{\omega_0}$, the normalization factor $\pi^{-\frac{1}{4}}$ and the Gausian envelope $e^{-\frac{t^2}{2}}$ which tends to zero as $t \to \pm\infty$. We fix $\omega_0 = 6$, because it provides for a good balance of time and frequency (see Grinsted et al. 2004).

4. Data

We use OMX Vilnius (Lithuania), WIG20 (Poland), PX (Czech Republic), BUX (Hungary), SAX (Slovak) as indices representing the Lithuanian and Central European stock markets. We do not investigate the Slovenian market because of the lowest capitalization as compared with other Central European markets. The data of OMX Vilnius were imported from the OMX Nasdaq website, WIG20 from Investing.com, PX from the Prague stock exchange website, BUX from the Budapest stock exchange website and SAX from the Bratislava stock exchange website. The data sample ranges from January 2000 to January 2018. In total, our time series consists of 217 monthly data points.

In order to make the value of each index in January 2000 to be equal to 1, we multiplied the values of each index by the normalized factor. The indices under consideration are presented in FIG. 1.

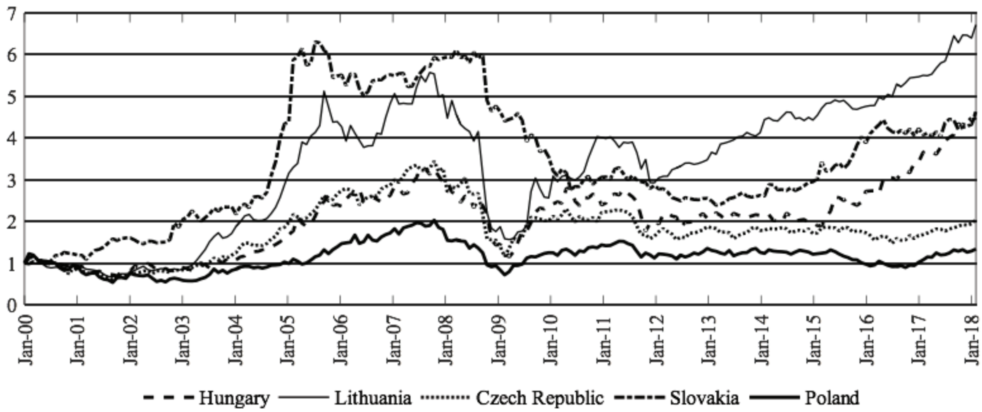

FIG. 1. **Values of the normalized indices of Lithuania, Hungary, Poland, the Czech Republic, and Slovakia.**
Source: gathered by the authors.

Returns of stock indices are calculated as follows

$$r_t = ln\left(\frac{V_t}{V_{t-1}}\right)$$

There r_t is the return of the index at the time t, and V_t is the value of the index at time *t* Descriptive statistics of the monthly returns are presented in Table 1. During the period of 217 months, the average of monthly returns of the Lithuania exceeded 0,88% and was the highest among Central European countries. The lowest monthly return was in Poland, which equals 0.13%.

TABLE 1. **Descriptive statistics of the monthly returns of stock indices.**

	Min	**Max**	**Mean**	**Variance**	**Volatility**
Lithuania	0.3509	0.3608	0.0088	0.0045	0.6708
Hungary	0.3300	0.1719	0.0069	0.0044	0.0663
The Czech Republic	0.3165	0.1711	0.0033	0.0040	0.0632
Slovakia	0.2047	0.2908	0.0071	0.0028	0.0528
Poland	0.2668	0.2039	0.0013	0.0045	0.0672

Source: gathered by the author.

5. Analysis of the Wavelet Power Spectrum of Returns

Table 1 shows that volatility (standard deviation) of the markets of Lithuania, Hungary, Poland and the Czech Republic is in the range from 0.0632 to 0.0672. The lowest, which is equal to 0.0528, is observed for the market of Slovakia. Our next focus was to investigate the variance at different time moments and at different frequencies (time periods). We converted the frequency into time units (years), ranging from the highest frequency, which corresponds to the period of 0.25 years, to the lowest frequency corresponding to the period of 4 years. The minimal scale of 0.25 corresponds to 0.25 years or 3 months, and the maximum scale corresponds to 4 years or 48 months. FIG. 2 presents a contour plot of wavelet power spectrum for each market. The x-axis refers to time and the y-axis refers to the period or frequency. We use black colour for the low value of WPS and white for the high value of WPS.

Some findings can be made from the analyzis of WPS of the markets of Lithuania and Central European countries. As we see from FIG. 2, the magnitude of WPS and, consequently, the volatility of the monthly returns is not uniform in frequency and time. In the time dimension, the highest volatility is observed in the markets of Lithuania, Poland, the Czech Republic and Hungary from 2007 to 2012 (bright colours). The above is related to the global financial crisis, which began in the US in December 2007. After the collapse of Lehman Brothers in September 2008 the crisis spreads across the world and became a global one. The world financial crisis in the Europe was followed by the European sovereign debt crisis, which was partially resolved by establishing the European Stability Mechanism and restructuring the Greece sovereign debt in the March of 2012. As we see from FIG. 2, the mentioned circumstances had an impact on the markets of consideration, except for the market of Slovakia.

The wavelet power spectrum is different for Slovakia. The highest values of WPS are observed in the years from 2003 to 2007. The economic growth of Slovakia was stable and the highest among the markets of consideration. The tax reform created favorable investment conditions. The strict fiscal policy, which sought to satisfy the Maastricht conditions for the introduction of the Euro, restricted the budget deficit, which was a positive signal for foreign investors. During the global financial crisis, the volatility of the Slovakia market was lower if compared with other markets under consideration. The introduction of the Euro in 2009 diminished the impact of the crisis; Slovakia faced the crisis being well prepared for it. Our finding that the global crisis had slight impact on the market of Slovakia is in line with conclusion of Carausu et al. (2018) – that the correlation between the Slovakian market and the US market is weak.

In the frequency dimension, volatility is concentrated in the medium and long periods for all the markets except Slovakia. The impact of the crisis is reflected in the scales from 0.75 to 3.5 years for all the markets under consideration, except for Slovakia. We must note that the highest volatility is observed at the scale of around 3 years. It is worth to no-

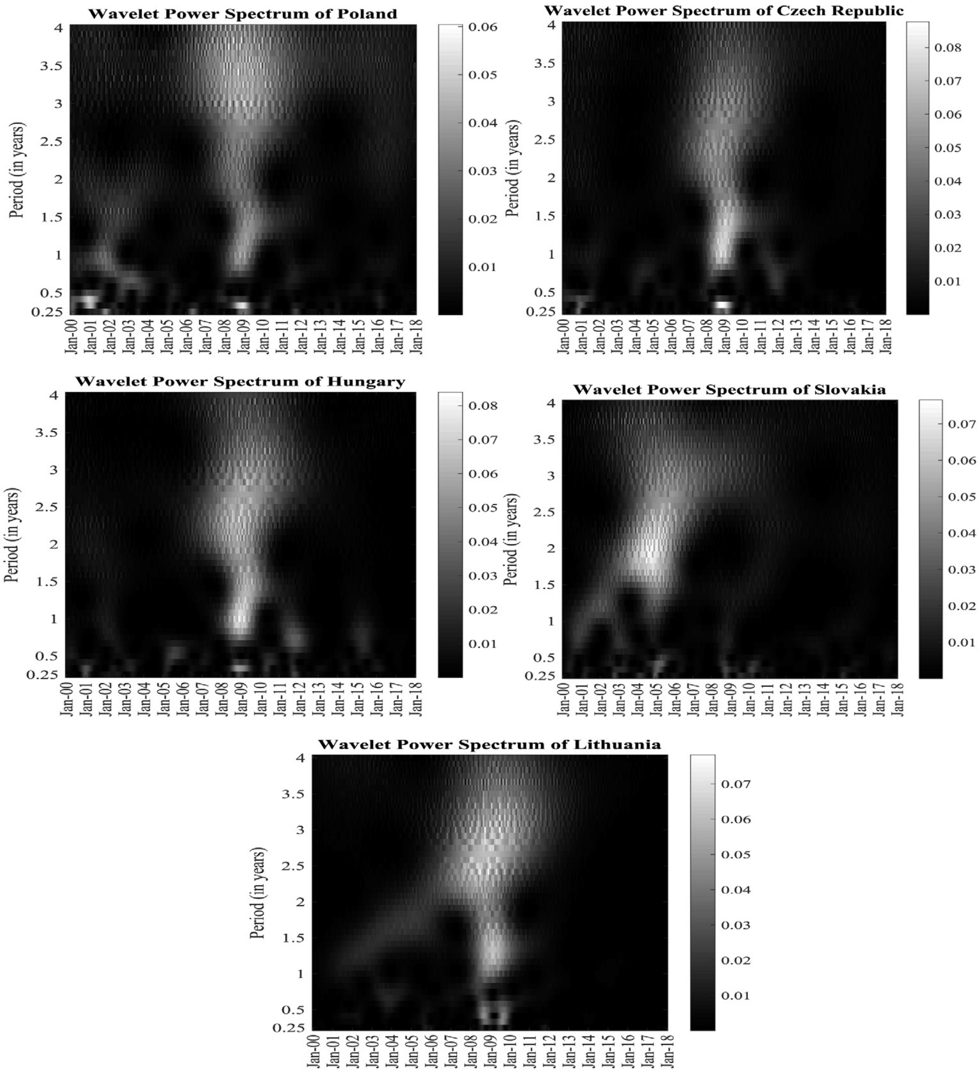

FIG. 2. **WPS for Lithuania, Hungary, Poland, the Czech Republic, Hungary, Poland and Slovakia.**
Source: gathered by the authors.

tice, that Rua and Nunes (2012) found that regarding the volatility of the emerging markets the returns were concentrated at high frequencies during the period of 1988–2008. The differences can be explained by world financial crisis of 2008-2009, which created a long-lasting impact on the returns of stock markets. This period is not covered by the analyzis of Rua and Nunes (2012).

A more aggregate measure of volatility is the average of WPS across the time in each scale, which is denoted by E(s). FIG. 3 presents E(s) for all the markets under consideration. The maximum of E(s) for the markets of Lithuania, the Czech Republic and Hungary is achieved for the period around 2.5 years, and for the market of Poland, for the period of 3.5 years. It can be explained by the fact that Poland effectively used its exchange rate policy to diminish the short-term effect of the world crisis. The curve E(s) for the Slovakian market is almost flat from 2 to 3 years, where the maximal value is achieved. It shows us that Slovakia did not suffer from the crisis as hard as other countries.

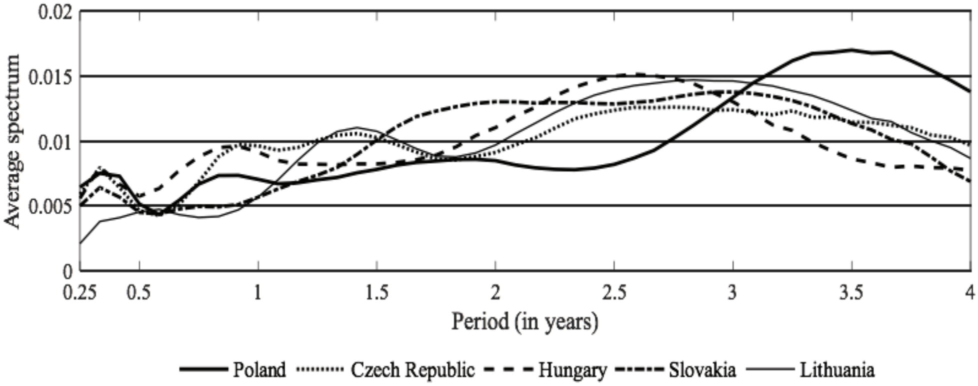

FIG. 3. **The average of wavelet power spectrum E(s) of Lithuania, Hungary, Poland, the Czech Republic, and Slovakia.**
Source: gathered by the authors.

6. Analysis of the Wavelet Coherence of Returns

The relationship between two variables can be measured by the correlation. Pearson's correlation coefficients between returns of the markets are presented in Table 2.

TABLE 2. **Pearson's correlation coefficients between stock market returns.**

	Poland	**The Czech Republic**	**Hungary**	**Slovakia**	**Lithuania**
Poland	1.00000	0.71050***	0.04904	0.19253***	0.35288
The Czech Republic	0.71050***	1.00000	0.11802*	0.22213	0.49185
Hungary	0.04904	0.11802*	1.00000	0.07695	0.31188
Slovakia	0.19253***	0.22213***	0.07695	1.00000	0.19773***
Lithuania	0.35288***	0.49185***	0.31188	0.19773***	1.00000

* 10% significance level **, 5% significance level, *** 1% significance level

Source: gathered by the authors.

In order to estimate co-movements of the two-time series in the time-frequency dimension we apply wavelet transformation and find the coherence $R^2(\tau, s)$ for each τ and s. The coherence plays a role of the correlation coefficient, which varies depending on time τ and frequency as measured by s. The coherence between the Lithuanian market and the markets of Central European countries is presented in FIG. 4.

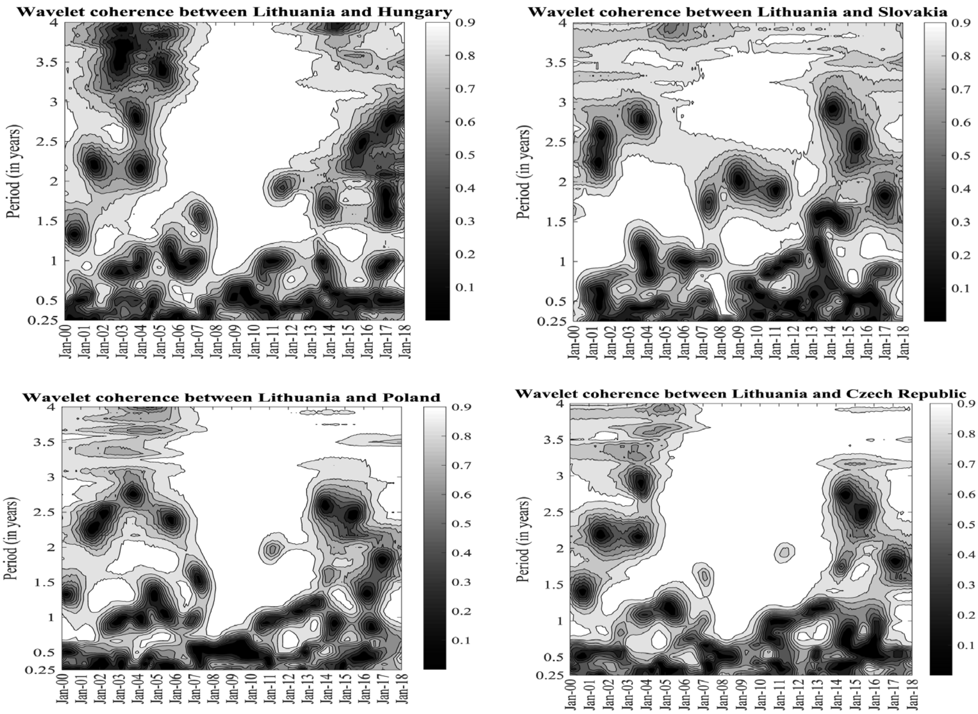

FIG. 4. **The coherence between the markets of Lithuania and Central European countries.**

Source: gathered by the authors.

When looking at the time scales in FIG. 4, we can find that the coherence between the Lithuanian market and the markets of the Central European countries had increased (white colour is dominant) from 2007 to 2013 for all the periods exceeding 1 year. During this period, the coherence decreased between the markets after the year of 2013. This was the time when the sovereign debt problem was resolved partially, and the tension had decreased in all the markets. The weakest coherence during the crisis was observed with the Lithuanian and Slovakian markets in frequencies around 1.5 and 2.5 years. The coherence is high only in frequencies between 2.5 and 3.5 years. It is worth noticing that the co-movements of the Lithuanian and Hungarian markets are high in low frequencies only in times of crisis.

It is noteworthy that, starting from 2001 to May 2004 (all countries under consideration countries accessed the EU), the coherence of the Lithuanian market and the markets of the Czech Republic and Hungary increased in the frequencies corresponding to around 1.5 years. The coherence of the Lithuanian and Polish markets increased in the frequencies around 2 years.

In the middle of 2014, an announcement was issued by the European Commission concerning the introduction of the euro in Lithuania. We see some decrease in coherence between the Lithuanian and Polish, Hungarian and Czech markets. These countries do not have any intention to introduce the Euro. The coherence of the Lithuanian market and the market of Slovakia is weak during the crisis and after the crisis in periods around 2 years.

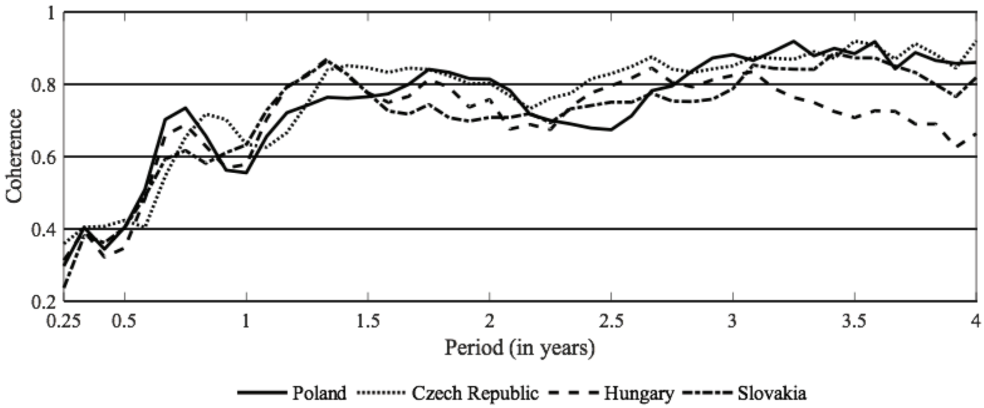

FIG. 5. **The average coherence AC(s) between markets of Lithuania and Central European countries.**

Source: gathered by the authors.

The average of $R^2(\tau, s)$ which is measured by AC(s), is presented in FIG. 5. We see that the average coherence is higher than 0.7 in longer periods (low frequencies), i.e., from 1.25 to 4 years, and lower in shorter periods. The Hungarian market is an exception, where coherence with the Lithuanian market is decreasing for the frequencies longer than 3 years. The above shows that the co-movements of the Lithuanian market with the Central European markets are very high for long periods. The average coherence between the Central European markets and the Lithuanian market is small for the periods shorter than 0.5 years. Hence, co-movements are high for long periods and low for short periods.

The economies of the Lithuanian and Central European countries are closely linked to the EU economies. Therefore, the stocks markets of these countries depend on the fundamentals of the EU and that the co-movements are high at the low frequencies (long periods). Co-movements were increased in the result of the accession to the EU and in the time of the global financial crisis. The weak co-movements in the higher frequencies related to the low liquidity of the Lithuanian market and issues specific to certain countries.

Conclusions

If compared to previous studies, the novelty of this paper can be its investigation of Lithuanian and Central European markets across different frequencies. We use a wavelet analysis which has a very important advantage: it allows one to assess the time and frequency varying co-movements within a unified framework. The decomposition of the time series of returns into time and frequency dimensions creates opportunities for comparing different markets not only in time, but also in frequency. Our findings corroborate the findings from other authors, namely that crisis periods have a great impact on the interrelations of the Central European and Lithuanian markets and Lithuanian market is firmly integrated with European stock markets during crisis periods. Our investigation had a closer look at the inside of the co-movements. We have discovered that the co-movements of the markets are high in the period from 2007 to 2013, for investments longer than 1 year.

We discovered that volatility is concentrated in the medium and long periods (medium and low frequencies) from 1 to 3.5 years for all the markets under consideration. The absolute maximum of volatility is achieved at the periods of 2.5–3 years and persisted from the year 2007 to 2012 for Lithuania, the Czech Republic and Hungary and, at the period of 3.5 years, for Poland. For Slovakia, the absolute maximum of volatility is achieved from the year 2001 to 2008 for the periods ranging from 2 to 3 years.

We found some impact of the accession to the EU and the introduction of the euro on co-movements between the Lithuanian equity markets and the Central European markets. Starting from 2001 (in May 2004, all countries under consideration accessed the EU, and active negotiations had begun in 2001), the co-movement increased in the frequencies corresponding to the period around 1.5 years. The impact of the introduction of the euro is moderate. The co-movements with Poland, the Czech Republic and Hungary are slightly lower after the announcement of the introduction of the euro by the European Commission for Lithuania.

The economies of the Lithuania and Central Europe countries are closely linked to the EU economies. Therefore, the stocks markets of these countries depend on the fundamentals of the other EU and that the co-movements are high at the low frequencies (long periods).

From the investment diversification point of view, the effect depends on the investment horizon. We established that the co-movement of the Lithuanian market with the Hungarian and Czech markets was very high in low frequencies. The co-movements of Lithuanian and Hungarian markets are high in low frequencies just only in times of crisis. The co-movements of Lithuanian market with the Slovakian market is high in very low frequencies (more than 2.5 years). Hence, our conclusion is that for the investor in Central European markets with the time horizon of over 1 years, the diversification with the Lithuanian market is not very efficient. For the Lithuanian investors, diversification with Central European markets is not useful, especially in time of crisis. The benefit of the diversification can be achieved for the investors with time horizons less than 1 year.

REFERENCES

Addison, P.S. (2017). The Illustrated Wavelet Transform Handbook: Itroductionary Theory and Applications in Science, Engineering, Medicine and Finance. CRC Press.

Alexakis, D. P., Kenourgios, D., Dimitriou, D. (2016). On emerging stock market contagion: the Baltic region. *Research in International Business and Finance*, 36, 312–321.

Babalos, V., Balcilar, M., Loate, T.B. (2018). Did Baltic stock markets offer diversification benefits, *Empirica* , 36,29-47.https://doi.org/10.1007/s10663-016-9344-4

Banulescu-Radu, D., Hurlin, C., Candelon, B., Laurent, S. (2016). Do we need high frequency data to forecast variance? *Annals of Economics and Statistics, GENES* 123, 135-174.

Baruník, J., Vacha, L. (2013). Contagion among Central and Eastern European stock markets during the financial crisis. *Czech Journal of Economics and Finance*, 63(5), 443-453.

Bein, A.M. (2017). Time-varying Co-Movement And Volatility Transmission Between The Oil Price And Stock Markets In The Baltics And Four European Countries. *Inzinerine Ekonomika-Engineering Economics* 28(5), 482–493.

Brooks, R. and Del Negro, M. (2005). Country versus region effects in international stock returns. *Journal of Portfolio Management*, Summer 2005, 67-72.

Brooks, R. and Del Negro, M. (2006). Firm-level evidence on international stock market comovement. *Review of Finance,* (10), 69-98.

Candelon, B., Piplack, J. and Straetmans, S. (2008). On measuring synchronization of bulls and bears: The case of East Asia. *Journal of Banking and Finance,* (32), 1022-1035.

Carauşu, D. N., Filip, B. F., Cigu, E., Toderaşcu, C., Contagion of Capital Markets in CEE Countries: Evidence from Wavelet Analysis, *Emerging Markets Finance and Trade*, 54 (3) (2018), 618-641.

Chakrabarty, A., De, A. Gunasekaran, A.,Dubey. R.,(2015) Investment horizon heterogeneity and wavelet: Overview and further research directions, *Physica A. Statistical Mechanics and its Applications,* 429 (2015) 45–61

Dajcman, S. (2012). The dynamics of return comovement and spillovers between the Czech and European stock markets in the period 1997–2010. *Czech Journal of Economics and Finance*, 61(4), 368–390.

Deltuvaitė, V. (2016). Investigation of Stock Markets Integration in the Baltic Countries. *Economics and Business,* (28), 38-44.

Dewandaru, G., Masih, R.,. Masih, A., M.,M (2015) Why is no financial crisis a dress rehearsal for the next? Exploring contagious heterogeneities across major Asian stock markets, *Physica A. Statistical Mechanics and its Applications,* 419 241-259

Egert, B. and Kocenda, E. (2010). Time_varying synchronization of European stock markets. *Empirical Economics, (*40), 393-407.

Forbes, K. and Rigobon, R. (2002). No contagion, only interdependence: Measuring stock market comovements. *Journal of Finance,* (57), 2223-2261.

Gilmore, G. C. and McManus, G. M. (2002). International portfolio diversification: US and Central European equity markets. *Emerging Markets Review,* (3), 69-83.

Gallegati, M. (2008). Wavelet analysis of stock returns and aggregate economic activity. *Computational Statistics & Data Analysis,* 52(6), 3061-3074.

Gallegati, M., Ramsey, J. and Semmler, W. (2014). Interest rate spreads and output: A time scale decomposition analysis using wavelets. *Computational Statistics & Data Analysis,* 76(C), 283-290.

Grinsted, A., Moore, J., Jevrejeva, S. (2004). Application of the cross wavelet transform and wavelet coherence to geophysical time series. *Nonlinear processes in geophysics,* 11.5/6: 561-566.

King, M. and Wadhwani, S. (1990). Transmission of volatility between stock markets. *Review of Financial Studies,* (3), 5-33.

Kim, S. and In, F. (2003). The relationship between financial variables and real economic activity: evidence from spectral and wavelet analyses. *Studies in Nonlinear Dynamics & Econometrics,* (7), no. 4, 1-18.

Kim, S. and In, F. (2005). The relationship between stock returns and inflation: new evidence from wavelet analysis. *Journal of Empirical Finance,* (12), 435-444.

Kuusk, A., Paas, T., Viikmaa, K. (2011). Financial contagion of the 2008 crisis: Is there any evidence of financial contagion from the US to the Baltic states. *Eastern Journal of European Studies, 2*(2), 61–76.

Lin, W.-L., Engle, R. and Ito, T. (1994). Do bulls and bears move across borders? International transmission of stock returns and volatility. *Review of Financial Studies*, vol. 7, no. 3, 507-538.

Ling, X., Dhesi, G. (2010). Volatility spillover and time varying conditional correlation between the European and US stock markets. *Global Economy and Finance Journal,* (3), 148-164.

Nekhili, R., Aslihan A-S. & Gençay, R. (2002). Exploring exchange rate returns at different time horizons. *Physica A,* 313, 671-682.

Nikkinen, J., Piljak, V., Äijö, J. (2012). Baltic stock markets and the financial crisis of 2008–2009. *Research in International Business and Finance,* (26), 398-409.

Maneschiöld, P. O. (2006). Integration between the Baltic and international stock markets. *Emerging Markets Finance and Trade, 42*(6), 25–45.

Syllignakis, M. N. and Kouretas, G. P. (2011). Dynamic correlation analysis of financial contagion: Evidence from the Central and Eastern European markets. *International Review of Economics and Finance, (20*), 717–732.

Ramsey, J. and Lampart, C. (1998). The decomposition of economics relationships by time scale using wavelets: expenditure and income. *Studies in Nonlinear Dynamics and Econometrics,* (3), 23-42.

Ramsey, J. and Zhang, Z. (1996). The application of wave form dictionaries to stock market index data. In: Kratsov, Y. and Kadtke, J., Springer (eds) Predictability of complex dynamical systems

Ramsey, J. and Zhang, Z. (1997). The analysis of foreign exchange data using waveform dictionaries. *Journal of Empirical Finance,* (4), 341-372.

Rua, A., Nunes, L.C. (2009). International comovement of stock market returns: A wavelet analysis. *Journal of Empirical Finance,* (16), 632-639.

Rua, A. (2012). Money growth and inflation in the euro area: a time-frequency view. *Oxford Bulletin of Economics and Statistics,* (74), 875-885.

Rua, A., Nunes, L. C. (2012). A wavelet-based assessment of market risk: The emerging markets case. *Quarterly Review of Economics and Finance*, 52, 84-92.

Tiwari, A.,K.,Cunado, J.,Gupta, R.,Wohar, M.,(2017).Are stock returns and inflation hedge for the UK? Evidence from a wavelet analysis using over three centuries of data., University of Pretoria Working papers, 2017-35.

Torrence, C. and Compo, G. (1998). A practical guide to wavelet analysis. *Bulletin of the American Meteorological Society, (*79), 61-78.

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