Silvo Dajcman[1], Mejra Festic[2], Alenka Kavkler[3]

COMOVEMENT BETWEEN CENTRAL AND EASTERN EUROPEAN AND DEVELOPED EUROPEAN STOCK MARKETS: SCALE BASED WAVELET ANALYSIS

Comovements between stock markets is of great importance for financial decisions of international investors. By applying a maximal overlap discrete wavelet transform correlation estimator, we investigate the level and dynamics of stock market return comovements between 3 Central and Eastern European stock markets (Slovenian, Hungarian and Czech) and 4 developed European stock markets (Austrian, French, German and UK). We find that stock market return comovements between CEE and developed European stock markets vary over time. The highest comovement between the stock market returns is normally achieved at the highest scales (5 and 6). At all scales, Hungarian and Czech stock markets are more connected to developed European stock markets than the Slovenian one.

Keywords: *Central and Eastern Europe; stock markets; European Union; global financial crisis; wavelets; comovement.*

JEL classification: F21, F36, G11, G15.

Сільво Дайчман, Мейра Фестіч, Аленка Кавклер

ВЗАЄМОЗАЛЕЖНИЙ РУХ НА РИНКАХ ЦСЄ ТА РОЗВИНЕНИХ КРАЇН ЄВРОПИ: ВЕЙВЛЕТ-АНАЛІЗ

У статті досліджується взаємозалежний рух на фондових ринках, який є надзвичайно важливим для міжнародних інвесторів при прийнятті ними фінансових рішень. Із застосуванням дискретного вейвлет-перетворення з максимальним перекриттям досліджено рівень та динаміку взаємних змін прибутків на фондових ринках 3 країн ЦСЄ (Словенія, Угорщина та Чехія) та 4 розвинених країн Європи (Австрія, Франція, Німеччина та Велика Британія). Продемонстровано, що взаємозалежні рухи між ринками ЦСЄ та розвинених країн Європи змінюються у часі. Найбільша залежність у пересуваннях прибутку на фондових ринках спостерігається у довготерміновій перспективі. Для всієї часової шкали дослідження ринки Угорщини та Чехії мають більш тісний зв'язок із фондовими ринками розвинених країн Європи, ніж ринок Словенії.

Ключові слова: *Центральна та Східна Європа; фондові ринки; Європейський Союз; світова фінансова криза; вейвлет; взаємозалежні рухи на ринках.*

Форм. 7. Табл. 4. Літ. 32.

Сильво Дайчман, Мейра Фестич, Аленка Кавклер

ВЗАИМОЗАВИСИМОЕ ДВИЖЕНИЕ НА РЫНКАХ ЦВЕ И РАЗВИТЫХ СТРАН ЕВРОПЫ: ВЕЙВЛЕТ-АНАЛИЗ

В статье исследуется взаимозависимое движение на фондовых рынках, чрезвычайно важное для международных инвесторов при принятии ими финансовых решений. С применением дискретного вейвлет-преобразования с максимальным перекрытием исследованы уровень и динамика взаимных изменений в прибылях на фондовых рынках 3

[1] Corresponding author, Department of Finance, Faculty of Economics and Business, University of Maribor, Slovenia.
[2] Bank of Slovenia, Ljubljana, Slovenia.
[3] Department of Quantitative Economic Analysis, Faculty of Economics and Business, University of Maribor, Slovenia.

стран ЦВЕ (Словения, Венгрия и Чехия) и 4 развитых стран Европы (Австрия, Франция, Германия и Великобритания). Показано, что взаимозависимые движения между рынками ЦВЕ и развитых стран Европы изменяются во времени. Наибольшая зависимость в передвижениях прибыли на фондовых рынках наблюдается для долгосрочных шкал. Для всей временной шкалы исследования рынки Венгрии и Чехии более привязаны к фондовыми рынками развитых стран Европы, чем рынок Словении.

Ключевые слова: *Центральная и Восточная Европа; фондовые рынки; Европейский Союз; мировой финансовый кризис; вейвлет; взаимозависимые движения на рынках.*

1. Introduction. Stock market integration, stock market comovements and return spillovers between developed and developing stock markets are of great importance for financial decisions of international investors. Increased comovements of stock market returns may diminish the advantage of internationally diversified investment portfolios (Ling and Dhesi, 2010).

The most common method for measuring stock market comovements is linear correlation (Pearson's correlation coefficient). This is a symmetric, linear dependence metric (Ling and Dhesi, 2010), suitable for measuring the dependence in multivariate normal distributions (Embrechts et al., 1999). But correlations may be nonlinear or time-varying (Xiao and Dhesi, 2010; Egert and Kocenda, 2010). Also, dependence between two stock markets as the market rises may be different than the dependence as the market falls (Necula, 2010). A better understanding of stock market interdependencies may be achieved by applying wavelet analysis. This tool enables us to investigate the multiscale features of comovements between stock markets (Gencay et al., 2002 Gencay et al., 2001a; Gencay et al., 2003; Gencay et al., 2005; Vuorenmaa, 2006).

Empirical literature on the CEE and developed stock markets' interdependence predominantly apply simple (Pearson) correlation analysis (Serva and Bohl 2005, Tudor 2010, Harrison and Moore 2009), Granger causality tests (Patev et al. 2006, Horobet and Lupu, 2009), cointegration analysis (Syllignakis and Kouretas, 2006, Patev et al., 2006) and GARCH modeling (Scheicher 2001, Caporale and Spagnolo 2010). None of the studies examine time-scale comovements between CEE and developed stock market returns.

Using wavelet analysis, we aim to investigate whether return comovements between stock markets of 3 most developed CEE countries (Slovenia, Hungary and the Czech Republic) and some of the most developed European stock markets (Germany, the UK, France and Austria) differ across wavelet scales. Finding differences in the strength of comovement across different wavelet scales has important implications for financial investors as therewith diversification benefits of investing in international stock markets are affected.

The structure of this paper is as follows. The econometric methodology is described in the second chapter. The maximal overlap discrete wavelet transform (MODWT) is explained and some practical issues for MODWT analysis are addressed. In the third chapter, we will present our data, describe in detail our empirical study of unconditional correlations and wavelet correlations, and interpret the results. The primary implications of the empirical analysis are revisited in the conclusion.

2. Description of the method. Wavelets mean small waves, whereas by contrast, sinus and cosinus are big waves. Wavelet by definition is any function that integrates to zero and is square-integrable. The wavelet transform is a mechanism that allows us quantify how the averages of a time series over particular scales change from one interval of time to the next (Percival and Walden, 2000). These changes are quantified in wavelet coefficients, which form the bulk of any discrete wavelet transform.

Let[4] X be an N dimensional vector whose elements represent the real-valued time series. For any positive integer, J_0, the level J_0 MODWT of X is a transform consisting of the $J_0 + 1$ vectors $W_1,\ldots,W_{J_0}$ and V_{J_0}, all of which have the dimension N. The vector W_j contains the MODWT wavelet coefficients associated with changes on the scale $\tau_j = 2^{j-1}$ $(for\, j = 1,\ldots,J_0)$, while V_{J_0} contains MODWT scaling coefficients associated with averages on the scale $\lambda_{J_0} = 2^{J_0}$. Based upon the definition of MODWT coefficients, we can write (Percival and Walden, 2000, 200):

$$W_j = W_j X \text{ and } V_{J_0} = V_{J_0} X,$$

where W_j and V_{J_0} are $N \times N$ matrices. Vectors are denoted by bold fonts. By definition, the elements of W_j and V_{J_0} are outputs obtained by filtering X, namely:

$$\widetilde{W}_{j,t} = \sum_{l=0}^{L_j-1} \widetilde{h}_{j,l} X_{t-l \bmod N} \quad \text{and} \quad \widetilde{V}_{j,t} = \sum_{l=0}^{L_j-1} \widetilde{g}_{j,l} X_{t-l \bmod N}$$

for $t = 0,\ldots, N-1$, where $h_{j,l}$ and $g_{j,l}$ are jth MODWT wavelet and scaling filters.

The MODWT treats the series as if it were periodic, whereby the unobserved samples of the real-valued time series $X_{-1}, X_{-2}, \ldots X_{-N}$ are assigned the observed values at $X_{N-1}, X_{N-2}, \ldots X_0$. The MODWT coefficients are thus given by:

$$\widetilde{W}_{j,t} = \sum_{l=0}^{j-1} \widetilde{h}^{\circ}_{j,l} X_{t-l \bmod N} \quad \text{and} \quad \widetilde{V}_{j,t} = \sum_{l=0}^{N-1} \widetilde{g}^{\circ}_{j,l} X_{t-l \bmod N} \quad (\text{for } t = 0, \ldots, N-1)$$

This periodic extension of the time series is known as analyzing $\{X_t\}$ using "circular boundary conditions" (Percival and Walden, 2000; Cornish et al., 2006). There are $L_j - 1$ wavelet and scaling coefficients that are influenced by the extension ("the boundary coefficients"). Since L_j increases with j, the number of boundary coefficients increases with scale. The exclusion of boundary coefficients in the wavelet variance, wavelet correlation and covariance provides unbiased estimates (Cornish et al., 2006).

One of the important uses of the MODWT is to decompose the sample variance of a time series on a scale-by-scale basis. Since the MODWT is energy conserving (Percival and Mojfeld, 1997):

$$\|X\|^2 = \sum_{j=1}^{J_0} \left\|\widetilde{W}_j\right\|^2 + \left\|\widetilde{V}_{J_0}\right\|^2$$

a scale-dependent analysis of variance from the wavelet and scaling coefficients can be derived (Cornish et al., 2006):

[4] Concepts and notations as in Percival and Walden (2000) are used. Another thorough description of MODWT using matrix algebra can be found in Gencay et al. (2002).

$$\hat{\upsilon}_X^2 = \|X\|^2 - \overline{X}^2 = \frac{1}{N}\sum_{j=1}^{J_0}\left\|\widetilde{W}_j\right\|^2 + \frac{1}{N}\left\|\widetilde{V}_{J_0}\right\|^2 - \overline{X}^2$$

Wavelet variance is defined for stationary and nonstationary processes with stationary backward differences. Considering only the non-boundary wavelet coefficient, obtained by filtering the stationary series with MODWT, the wavelet variance $\upsilon^2_X(\tau_j)$ is defined as the expected value of $W^2_{j,t}$. In this case $\upsilon^2_X(\tau_j)$ represents the contribution to the (possibly infinite) variance of $\{X_t\}$ at the scale $j = 2^{j-1}$ and can be estimated by the unbiased estimator (Percival and Walden, 2000, 306):

$$\hat{\upsilon}_X^2(\tau_j) = \frac{1}{M_j}\sum_{t=L_{j-1}}^{N-1}\widetilde{W}_{j,t}^2$$

where $M_j = N - L_j + 1 > 0$ is the number of non-boundary coefficients at the jth level.

It is possible to prove that the asymptotic distribution of $\upsilon^2_X(\tau_j)$ is Gaussian, a result that allows the formulation of confidence intervals for the estimate (Percival, 1995; Serroukh et al., 2000).

Given two stationary processes $\{X_t\}$ and $\{Y_t\}$, an unbiased covariance estimator $\upsilon_{XY}(\tau_j)$ is given by (Percival, 1995):

$$\hat{\upsilon}_{XY}(\tau_j) = \frac{1}{M_j}\sum_{t=L_{j-1}}^{N-1}\widetilde{W}_{j,t}^{(X)}\widetilde{W}_{j,t}^{(Y)}$$

where $M_j = N - L_j + 1 > 0$ is the number of non-boundary coefficients at the jth level.

The MODWT correlation estimator for scale τ_j is obtained by making use of the wavelet cross-covariance and the square root of wavelet variances:

$$\hat{\rho}_{X,Y}(\tau_j) = \frac{\hat{\upsilon}_{X,Y}(\tau_j)}{\hat{\upsilon}_X(\tau_j)\hat{\upsilon}_Y(\tau_j)},$$

where $|\rho_{X,Y}(\tau_j)| \leq 1$. The wavelet correlation is analogous to its Fourier equivalent, the complex coherency (Gencay et al., 2002, 258).

3. Empirical results

3.1. Description of the data. Stock indices returns are calculated as differences of logarithmic daily closing prices of the stock indices $(ln(P_t) - ln(P_{t-1})$, where P is an index closing price). The following indices are considered: LJSEX (Slovenia), PX (Czech Republic), BUX (Hungary), ATX (Austria), CAC40 (France), DAX (Germany) and FTSE100 (Great Britain). The first day of the observations is April 1, 1997, the last day is May 12, 2010. Days of no trading on any of the observed stock markets are left out. Total number of observations is 3060 days. The data sources for LJSEX, PX and BUX indices are their respective stock exchanges; the data source for ATX, CAC40, DAX and FTSE100 indices is Yahoo Finance.

Table 1 presents some descriptive statistics of the data. Jarque-Bera test rejects the hypothesis of normally distributed observed time series, all indices are asymmetrically (left) distributed around the sample mean, kurtosis is greater than with normally distributed time series.

Table 1. **Descriptive statistics for stock index return time series**

	Min	Max	Mean	Std. deviation	Skewness	Kurtosis	Jarque-Bera statistics
LJSEX	-0.1285	0.0768	0.0003521	0.01062	-0.87	20.19	38,073.93***
PX	-0.199	0.2114	0.0002595	0.01667	-0.29	24.62	59,654.93***
BUX	-0.1803	0.2202	0.0004859	0.02021	-0.30	15.90	21,260.91***
ATX	-0.1637	0.1304	0.0002515	0.01558	-0.40	14.91	18,153.48***
CAC40	-0.0947	0.1059	0.0001206	0.01628	0.09	7.83	2,982.52***
DAX	-0.0850	0.1080	0.0002071	0.01756	-0.06	6.58	1,635.47***
FTSE100	-0.0927	0.1079	0.0000774	0.01361	0.09	9.30	5,069.61***

Note: The null hypothesis of the Jarque-Bera test is that the sample data come from a normal distribution with unknown mean and variance, against the alternative that it does not come from a normal distribution.*** indicate that the null hypothesis (of normal distribution) is rejected at the 1% significance, ** that the null hypothesis is rejected at the 5% significance and * that the null hypothesis is rejected at 10% significance.

To test the stationarity of stock index return time series, Augmented Dickey-Fuller (ADF) test, Phillips-Perron (PP) and Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test are applied. The results are presented in Table 2.

Table 2. **Results of time series tests of stationarity**

	KPPS test (a constant + trend)	KPSS test (a constant)	PP test (a constant + trend)	PP test (a constant)	ADF test (a constant + trend)	ADF test (a constant)
LJSEX	0.249*** (11)	0.591** (12)	-44.099*** (0)	-43.795*** (3)	-37.229*** (L=1)	-37.128*** (L=1)
PX	0.158* (10)	0.170 (10)	-55.022*** (10)	-55.029*** (10)	-16.676*** (L=8)	- 16.676*** (L=8)
BUX	0.065 (6)	0.065 (6)	-54.295*** (6)	-54.304*** (6)	-54.301*** (L=0)	- 54.310*** (L=0)
ATX	0.186** (12)	0.191 (13)	-53.586*** (15)	-53.594*** (15)	- 40.604** (L=1)	- 40.608*** (L=1)
CAC40	0.110 (15)	0.250 (15)	-57.840*** (14)	-57.787*** (14)	- 36.142*** (L=2)	- 36.108*** (L=2)
DAX	0.099 (1)	0.105 (1)	-57.805*** (3)	-57.812*** (3)	- 57.692*** (L=0))	- 57.698*** (L=0)
FTSE100	0.089 (9)	0.101 (9)	-58.284*** (7)	-58.287*** (7)	-29.112*** (L=3)	- 29.111*** (L=3)

Notes: KPSS and PP tests are performed for two models: for a model with a constant and for the model with a constant plus trend. Bartlet Kernel estimation method is used with Newey-West automatic bandwidth selection. Optimal bandwidth is indicated in parenthesis under the statistics. For ADF test, two models are applied: with a constant and with a constant plus trend; number of lags to be included (L) for ADF test is selected by SIC criteria (30 is the maximum lag). Exceeded critical values for rejection of null hypothesis are marked by *** (1% significance level), ** (5% significance level) and * (10% significance level).

The null hypothesis of KPSS test (i.e., the time series is stationary) for a model with a constant plus trend can be rejected at the 5% significance level for the return series of LJSEX and ATX. Since trend is not significantly different from zero, we give advantage to KPSS model results with no trend. For that model we cannot refute the null hypothesis of stationary process for any stock index return series (expect for LJSEX) at the 1% significance level. The null hypothesis of PP and ADF tests is refuted for all stock indices. On the basis of the stationarity tests we conclude that all index return time series are stationary.

3.2. Unconditional correlation analysis results. The most common method of measuring stock market comovements is linear correlation (Pearson's correlation coefficient). Table 3 presents the unconditional correlation (Pearson's correlation coefficient) results.

Table 3. **Unconditional correlation coefficients for the stock index returns**

	LJSEX	PX	BUX	ATX	CAC40	DAX	FTSE100
LJSEX	1						
PX	0.306	1					
BUX	0.244	0.551	1				
ATX	0.308	0.597	0.504	1			
CAC40	0.202	0.516	0.481	0.627	1		
DAX	0.210	0.469	0.519	0.560	0.799	1	
FTSE100	0.211	0.527	0.494	0.635	0.871	0.740	1

Note: All correlation coefficients are significantly different from zero at 1% significance level.

The most interdependent stock indices are CAC40, FTSE100 and DAX. The stock markets of France, the UK and Germany seem to be the most integrated, which is a common observation in literature (e.g., Serva and Bohl, 2005; Harrison and Moore, 2009). The highest comovement is observed between CAC40 and FTSE100 returns, with a correlation coefficient of 0.871. LJSEX, PX and BUX show a smaller degree of comovement with other CEE markets and with developed European stock markets. Among the observed stock indices, Slovenian LJSEX is the least correlated. The PX index seems to comove the most with ATX, BUX and FTSE100. BUX is slightly less correlated with other observed stock indices than PX. The highest comovement of BUX is observed with PX, DAX and ATX.

In the empirical literature on stock market comovements, more factors have been determined to influence the level of international comovements of a specific stock market. Forbes and Chinn (2004) found evidence that direct trade flows, proxying for import demand, have positive effect on cross-country correlations across stock markets, while competition in the third markets tends to have negative effect. Quinn and Voth (2008) provide evidence that more open countries face higher stock market correlations with those abroad, relative to closed economies. Didier et al. (2011) showed evidence, upon investigating the factors of international stock market comovements during the recent global financial crisis, that stock market liquidity can also significantly explain stock market comovements. We believe that the latter factor might be the most relevant in explaining differences between the correlations of LJSEX and BUX (and PX) stock markets with developed European stock markets[5].

3.3. Wavelet correlation analysis results. The MODWT transformation of the indices return series is performed by using a Daubechies least asymmetric filter with a wavelet filter length 8 (LA8). This is a common wavelet filter in other empirical studies on financial market interdependencies (Gencay et al., 2001b; Ranta, 2010).

[5] The most important differences between Slovenia's and the other two CEE stock markets are: i) Czech and Hungarian stock markets have attracted many foreign investors (Caporale and Spagnolo, 2010), while Slovenian market has struggled to do so. Further, the liquidity of shares listed on Ljubljana stock exchange is significantly smaller than at Prague and Budapest stock exchanges. According to CEEG (2011), Ljubljana stock exchange equity turnover in 2010 was 0.7 bln., that of Prague stock exchange was 30.5 bln. and that of Budapest was 39.9 bln.

The wavelet coefficients W_1 to W_6 correspond to changes in averages over physical scales of $\tau_j = 2^{j-1}$ days, while scaling coefficient V_6 corresponds to the averages of the index return series over the scale of $\lambda_j = 2^j$ (Percival and Walden, 2000). To achieve optimal balance between sample size and the length of the filter, the maximum number of levels that we use in the decomposition is 6 ($J_0 = 6$). Scale 1 measures the dynamics of returns over 2-4 days, scale 2 over 4-8 days, scale 3 over 8-16 days, scale 4 over 16-32 days, scale 5 over 32-64 days and scale 6 over 64-128 days.

Unbiased estimates for wavelet correlations are achieved by considering only non-boundary coefficients. There are 2,619 MODWT wavelet coefficients not affected by the boundary condition. A major drawback of using a higher maximum number of levels in the MODWT decomposition is losing sample size. As we also want to include the period after the start of the global financial crisis (from September 16, 2008 onwards) we decided not to take a J_0 value greater than 6.

The results of the wavelet multiscale correlation analysis for the Slovenian, Hungarian and Czech stock markets are presented in Table 4. The most important findings are: i) the correlation for each stock indices pair varies over time scales. The highest correlation of index returns is normally achieved at the highest scales (scale 5 or 6, with a few exceptions for the PX index); ii) at all scales, Hungarian and Czech stock markets are more connected to developed European stock markets than Slovenian stock market; iii) by comparing Pearson and wavelet correlation estimates, we would argue that making international stock market investments based on Pearson's correlations may be misleading.

Table 4. **Wavelet correlation between CEE and developed stock markets returns at scales 1-6**

Correlation of LJSEX returns with returns of						
Scale	BUX	PX	ATX	DAX	CAC40	FTSE100
1	0.1971	0.3057	0.2392	0.1534	0.1521	0.1622
2	0.2190	0.3050	0.3347	0.2248	0.2610	0.2514
3	0.2295	0.3618	0.4116	0.2951	0.2908	0.2811
4	0.2928	0.2885	0.3930	0.2629	0.2466	0.2627
5	0.4892	0.3439	0.4441	0.3621	0.3134	0.3017
6	0.4375	0.3745	0.2244	0.2650	0.2835	0.2153
Correlation of BUX returns with returns of						
Scale	LJSEX	PX	ATX	DAX	CAC40	FTSE100
1	0.1971	0.5491	0.4609	0.4870	0.4683	0.4811
2	0.2190	0.5258	0.5255	0.4994	0.5052	0.5260
3	0.2295	0.5727	0.4809	0.5056	0.4847	0.5053
4	0.2928	0.6681	0.5706	0.5608	0.5115	0.5614
5	0.4892	0.6255	0.5907	0.5264	0.4544	0.4577
6	0.4375	0.7727	0.6163	0.6567	0.6878	0.6125
Correlation of PX returns with returns of						
Scale	LJSEX	BUX	ATX	DAX	CAC40	FTSE100
1	0.3057	0.5491	0.5898	0.4500	0.5187	0.5274
2	0.3050	0.5258	0.6316	0.4741	0.5354	0.5667
3	0.3618	0.5727	0.5867	0.5093	0.5043	0.5022
4	0.2885	0.6681	0.5933	0.5494	0.5388	0.5144
5	0.3439	0.6255	0.4327	0.4475	0.4439	0.4356
6	0.3745	0.7727	0.4805	0.6046	0.6429	0.5256

The comovement of LJSEX returns with other stock indices increases up to scale 5 (except for PX, where the highest correlation is achieved at scale 6) but then drops at scale 6. At scale 1, the highest comovement of LJSEX with PX is observed. At scale 2, the correlation with ATX is the highest, and this also is true for scales 3 and 4. At scale 5 and 6, the comovement with BUX is the largest while the correlation with ATX is the second largest. The correlation of LJSEX with major European stock markets (German, French and UK) does not exceed 0.37 at any scale. Generally, Slovenian stock market seems to be the most correlated with Austrian and Hungarian markets. Hungarian stock market is the most correlated with Czech stock market and the least with Slovenian market, at all scales. For Czech stock market, at lower scales (scale 1, 2 and 3) the greatest return comovement is observed with Austrian stock market, while at higher scales (scales 4, 5 and 6) with Hungarian stock market. The correlation of PX returns with DAX and CAC40 returns is the highest at scale 6, while for PX and FTSE100, the maximum correlation of returns is achieved at scale 2. Our findings support and complement the findings of Harrison and Moore (2009), Horobet and Lupu (2009) and Allen et al. (2010) with scale-based evidence.

The finding that the comovement between stock market increases as the investment horizon (time scale) is prolonged, has a theoretical explanation. At shorter scales, linkages between the markets are to a great extent influenced by sporadic events, market sentiments, and psychological factors that can cause short-term changes in market behaviour (Malkiel, 2003; Zhou, 2011). Over the long run (higher scales), as argued by Boudoukh et al. (2008) and Zhou (2011), market returns become more predictable as macrovariables exert more predictable influences on market linkage over longer scales and cause the correlation to increase. Recent empirical findings from stock markets seem to confirm this (e.g., Ranta, 2010; Zhou, 2011).

Foreign investors at CEE stock markets should investigate wavelet scale correlations that correspond with their investment horizons. Furthermore, as benefits of international portfolio diversification increase with the reduced comovement (correlation) between the portfolio assets, the findings of our study have important implications for international portfolio investments at CEE stock markets: the increasing correlation reduces international diversification benefits for longer investment horizons. The diversification effects for long-term foreign investors that simultaneously invest in CEE stock indices are reduced with the increased investment horizons.

By comparing the Pearson's and wavelet correlation estimates, we argue that making international stock investments in CEE stock markets based on Pearson's correlations, may be misleading. For instance, Pearson's correlation show that LJSEX is the least correlated with CAC40, so if one were to seek international investment diversification in just two stock market indices, (one of them being LJSEX), benefits of an investment combination in these two indices would presumably be the greatest of all. On the other hand, if we consider the investment horizon of 64-128 days, which corresponds to scale 6, the correlation between LJSEX and CAC40 is the second largest – it therefore follows that for longer investment horizons, one has to consider wavelet correlations at scales that correspond to the investment horizon. As put forth by Gencay et al. (2002) the Pearson correlation is estimated using the aggregate time series, which from the time scale perspective can be considered an amalgam of subseries defined over different time scales. Since the Pearson correlation can be interpreted as the correlation averaged over all time scales (Zhou, 2011), international investors should use the wavelet correlations pertaining to their investment horizons.

4. Conclusion. In this paper, stock market comovements between CEE stock markets and some major developed European stock markets (represented by Austrian, French, German and UK markets) are analyzed for the period 1997-2010. By applying MODWT wavelet correlation and rolling wavelet correlation technique, the most important findings of the paper are as follows: i) stock market return comovements between CEE and developed European stock markets vary over time scales; ii) the highest comovement between the stock market return is normally achieved at the highest scales (scale 5 or 6); iii) at all scales Hungarian and Czech stock markets are more connected to developed European stock markets than Slovenian stock market; iv) wavelet correlation is not just scale dependent, but also time dependent, as the rolling correlations exhibit high volatility. The key finding, which is of great importance for international investors investigating stock markets, is that foreign investors at CEE stock markets should investigate wavelet scale correlations between them corresponding to their investment horizons.

References:

1. *Allen, E.D., Powell, R. J. and Golab, A.* (2010). Volatility and correlations for stock markets in the emerging economies of Central and Eastern Europe: implications for European investors. Available at http://papers.ssrn.com/sol3/papers.cfm?abstract_id=1611472 (accessed 3 March 2011).

2. *Boudoukh, J., Richardson. M. and Whitelaw, R. F.* (2008). The myth of long-horizon predictability, Review of Financial Studies, 21, 1577-1605.

3. *Caporale, M. G. and Spagnolo, N.* (2010). Stock market integration between three CEECs. Brunel University Working Paper, No. 10-9.

4. CEEG – CEE Stock Exchange Group (2011). Factsheet, January 2011. Available at http://www.ceeseg.com/static/cms/sites/ceeseg/en/media/pdf/factsheet/cee-stock-exchange-group-fs-1-2011.pdf (accessed 10 April 2001).

5. *Cornish, R.C., Bretherton, C. S. and Percival, D. B.* (2006). Maximal Overlap Discreete Wavelet Statistical Analysis with Application to Atmospheric Turbulence, Boundary-Layer Meteorology, 119, 339-374.

6. *Daubechies, I.* (1992). Ten Lectures on Wavelets, Philadelphia, SIAM.

7. *Didier, T., Love, I. and Martinez Peria, M. S.* (2011). What explains comovement in stock market returns during the 2007-2008 crisis? Available at http://onlinelibrary.wiley.com/doi/10.1002/ijfe.442/abstract (accessed 20 April, 2011).

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

9. *Embrechts, P., McNeil, A. J. and Straumann, D.* (1999). Correlation and Dependence in Risk Management: Properties and Pitfalls, in Risk Management: Value at Risk and Beyond (Ed.) M. A. H. Dempster, Cambridge University Press, Cambridge, pp. 176-223.

10. *Forbes, K. and Chinn, M.* (2004)/ A Decomposition of Global Linkages in Financial Markets Over Time, Review of Economics and Statistics, 86, 705-722.

11. *Gencay, R., Selcuk, F. and Whitcher, B.* (2001a). Scaling properties of foreign exchange volatility, Physica A: Statistical Mechanics and its Applications, 289, 249-266.

12. *Gencay, R., Selcuk, F. and Whitcher, B.* (2001b). Differentiating intraday seasonalities through wavelet multi-scaling, Physica A, 289, 543-556.

13. *Gencay, R., Selcuk, F., Whitcher, B.* (2002). An Introduction to Wavelet and Other Filtering Methods in Finance and Economics, San Diego, Academic Press.

14. *Gencay R, Selcuk F. and Whitcher, B.* (2003). Systematic risk and timescales, Quantitative Finance, 3, 108-116.

15. *Gencay R, Selcuk F. and Whitcher, B.* (2005). Multiscale systematic risk, Journal of International Money and Finance, 24, 55-70.

16. *Harrison, B. and Moore, W.* (2009). Stock market comovement in the European Union and transition countries, Financial Studies, 13, 124-151.

17. *Horobet, A. and Lupu, R.* (2009). Are Capital Markets Integrated? A Test of Information Transmission within the European Union, Romanian Journal of Economic Forecasting, 10, 64-80.

18. *Ling, X. and 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.

19. *Malkiel, B. G.* (2003). A random walk down Wall Street, New York, Norton.

20. *Necula, C.* (2010). Modeling the dependency structure of stock index returns using a copula function, Romanian Journal of Economic Forecasting, 13, 93-106.

21. *Patev, P., Kanaryan, N., Lyroudi, K.* (2006). Stock market crises and portfolio diversification in Central and Eastern Europe, Managerial Finance, 32, 415-432.

22. *Percival, D. B.* (1995). On the Estimation of the Wavelet Variance, Biometrika, 82, 619-631.

23. *Percival, D. B. and Mojfeld, H. O.* (1997). Analysis of subtidal coastal sea level fluctuations using wavelets, Journal of the American Statistical Association, 92, 868-880.

24. *Percival, D. B. and Walden, A. T.* (2000). Wavelet Methods for Time Series Analysis, New York, Cambridge University Press.

25. *Quinn, D. and Voth, H. J.* (2008). A Century of Global Equity Market Correlations, American Economic Review, 98, 535-540.

26. *Ranta, M.* (2010). Wavelet multiresolution analysis of financial time series, Acta Wasaensia Papers, No. 223.

27. *Scheicher, M.* (2001). The comovements of stock markets in Hungary, Poland and the Czech Republic, International Journal of Finance & Economics, 6, 27-39.

28. *Serroukh, A., Walden, A. T. and Percival, D. B.* (2000). Statistical Properties and Uses of the Wavelet Variance Estimator for the Scale Analysis of Time Series, Journal of the American Statistical Association, 95, 184-196.

29. *Syllignakis, M. and Kouretas, G.* (2006). Long And Short-Run Linkages In Cee Stock Markets: Implications For Portfolio Diversification And Stock Market Integration. William Davidson Institute Working Papers Series, No. 832.

30. *Vuorenmaa, T. A.* (2006). A wavelet analysis of scaling laws and long-memory in stock market volatility. Bank of Finland Research Discussion Paper 27.

31. *Xiao, L. and 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.

32. Zhou, J. (2011). Multiscale analysis of international linkages of REIT returns and volatilities, Journal of Real Estate Financial Economics. Available at http://www.springerlink.com/content/33v342432q29j835 (accessed 20 March).

Стаття надійшла до редакції 15.08.2011.