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ARE INTERDEPENDENCIES BETWEEN CENTRAL AND EASTERN EUROPEAN AND DEVELOPED EUROPEAN STOCK MARKETS RETURNS MULTISCALE? A WAVELET LEAD/LAG ANALYSIS

This paper investigates the interdependencies between CEE (Slovenian, Czech and Hungarian) and developed European (German, Austrian, French and UK) stock markets. Wavelet cross-correlation analysis is applied on daily return series to examine the lead/lag relationships between representative stock indices returns of the observed countries in time-frequency domain. The main findings of the paper may be summarized as follow: i) correlation between CEE and developed stock market return increases with time; ii) Hungarian and Czech stock markets are more correlated with developed European stock markets, Slovenian stock market is less; iii) Czech and Hungarian stock markets are not just more correlated with developed European stock markets, but their volatilities are also more time-synchronized with developed stock markets than those of Slovenian stock market.

Keywords: *stock market; Central and Eastern Europe; wavelet analysis; return spillovers.*

JEL classification: *F21, F36, G11, G15.*

Сільво Дайчман

ВЗАЄМОЗАЛЕЖНІСТЬ МІЖ ПРИБУТКАМИ ФОНДОВИХ РИНКІВ ЦСЄ І ЄС: ВЕЙВЛЕТ-АНАЛІЗ ВИПЕРЕДЖЕННЯ/ВІДСТАВАННЯ

У статті досліджено взаємозалежності між фондовими ринками ЦСЄ (Словенія, Чехія, Угорщина) і ЄС (Німеччина, Австрія, Франція і Велика Британія). До серії щоденних прибутків застосовано крос-кореляційний вейвлет-аналіз для вивчення залежності випередження/відставання між прибутками фондових ринків у вказаних країнах у частотній і часовій областях. Основні висновки: 1) кореляції між зростанням прибутків на ринках ЦСЄ і ЄС збільшуються з часом; 2) словенський ринок менш залежний від ринків ЄС, ніж угорський і чеський; 3) волатильність угорського і чеського ринків також більш синхронізована у часі з ринками ЄС, на відміну від словенського.

Ключові слова: *фондовий ринок; ЦСЄ; вейвлет-аналіз; переміщення прибутку.*

Сильво Дайчман

ВЗАИМОЗАВИСИМОСТЬ МЕЖДУ ПРИБЫЛЯМИ ФОНДОВЫХ РЫНКОВ ЦВЕ И ЕС: ВЕЙВЛЕТ-АНАЛИЗ ОПЕРЕЖЕНИЯ/ОТСТАВАНИЯ

В статье исследованы взаимозависимости между фондовыми рынками ЦВЕ (Словения, Чехия, Венгрия) и ЕС (Германия, Австрия, Франция и Великобритания). К серии ежедневных прибылей применен кросс-корреляционный вейвлет-анализ для изучения зависимости опережения/отставания между прибылями фондовых рынков в указанных странах в частотной и временной областях. Основные выводы: 1) корреляции между ростом прибылей на рынках ЦВЕ и ЕС увеличиваются во времени; 2) словенский рынок менее зависим от рынков ЕС, чем венгерский и чешский; 3) волатильность венгерского и чешского рынков также более синхронизирована по времени с рынками ЕС, в отличие от словенского.

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Ключевые слова: *фондовый рынок; ЦВЕ; вейвлет-анализ; перемещение прибыли.*

1. Introduction. Stock market comovements and stock market return spillovers between developed and developing stock markets are of great importance for financial decisions of international investors. The increased comovement of stock market returns may diminish the advantage of internationally diversified investment portfolios (Ling and Dhesi, 2010). Changes in comovement patterns call for an adjustment of portfolios (Savva and Aslanidis, 2010). Furthermore, if spillovers are found in a return series, then it is possible to exploit strategy profits, which is against market efficiency criteria (Harris and Pisedtasalasai, 2005).

In existing literature, the following methods are usually used to measure the level of stock market return (or price) comovement and spillovers: correlation coefficients (Longin and Solnik, 1995); vector autoregressive (VAR) models (Gilmore and McManus, 2002); cointegration analysis (Patev et al. 2006); GARCH models (Bae et al. 2003; Egert and Kocenda, 2010; Tse and Tsui, 2002) and regime switching models to model spillovers (Garcia and Tsafack, 2009). A more novel approach is wavelet analysis, which can be used to investigate both stock market comovements and spillovers.

Economic and financial phenomena may exhibit different characteristics over different time scales and wavelet analysis tools can enable us to investigate the time-frequency (or multiscale) features of these phenomena. Wavelets in finance are primarily used as a signal decomposition tool (Gencay et al., 2001a; Gencay et al., 2002; Vuorenmaa, 2006), or a tool to detect interdependence between time series (In and Kim, 2007; Kim and In, 2007).

Wavelet correlation and cross-correlations may be used as a tool to analyze the lead/lag (spillover) relationship between two time series for different time scales. If one time series leads the other, then its realizations may be used to forecast the realizations of other time series. This tool is used in different scientific disciplines: biology (Hudson et al., 2010), physics (Turbelin et al., 2009), medicine (De Trad et al., 2001) and recently also in economics.

There are a few studies using wavelet cross-correlation to investigate spillover effects between financial variables for different time scales. Gallegati (2008) studied the relationship between stock market returns and economic activity. He applied a maximal overlap discrete wavelet transform (MODWT) analysis to study the lead/lag relationship between stock prices and industrial production for different time scales. His results show that stock markets tend to lead the level of economic activity, but only at the highest scales (lowest frequencies), and the leading period increases as the wavelet time scale increases.

Cardinali (2009), by using MODWT lead/lag analysis, found evidence that Eurodollar implied volatilities contain predictive information about realized volatilities.

Ranta (2010) applied MODWT cross-correlation tool to study the lead/lag relationship between stock indices DAX, FTSE 100, S&P 500 and Nikkei 225. Wavelet cross-correlation for the time scales of a day and a week showed a flow (spillover) of volatility from the S&P 500 to other indices. On a one month scale, there was flow of volatility from European indices, especially from DAX to S&P 500 and Nikkei 225.

The recent empirical literature on the interdependence of Central and Eastern European (hereafter CEE) stock markets and developed stock markets, predominantly employs correlation analysis (Harrison and Moore, 2009; Serva and Bohl, 2005), Granger causality tests (Horobet and Lupu, 2009; Patev et al., 2006) cointegration analysis (Syllignakis and Kouretas, 2006; Patev et al., 2006) and GARCH modeling (Scheicher, 2001; Caporale and Spagnolo, 2010). This is the first study to use wavelet cross-correlation to analyze return spillover dynamics between CEE and developed European stock markets returns.

2. Description of the maximal overlap discrete wavelet transform (MODWT)

Let[1] X be an N dimensional vector whose elements represent the real-valued time series $\{X_t : t=0,\dots,N-1\}$. For any positive integer, J_0, the level J_0 MODWT of X is a transform consisting of the J_0+1 vectors $\tilde{W}_1,\dots,\tilde{W}_{jo}$ and $\tilde{V}_{jo}$, all of which have the dimension N. The vector $\tilde{W}_j$ contains the MODWT wavelet coefficients associated with changes on the scale $\tau_j=2^{j-1}$ (for $j=1,\dots,J_0$), while $\tilde{V}_{jo}$ contains MODWT scaling coefficients associated with averages on the scale $\lambda_{jo}=2^{jo}$. Based upon the definition of MODWT coefficients, we can write (Percival and Walden, 2000):

$$\tilde{W}_j = \tilde{W}_j X \tag{1}$$

and

$$\tilde{V}_{J_0} = \tilde{V}_{J_0} X, \tag{2}$$

where $\tilde{W}_j$ and V_{j0} are NxN matrices. Vectors are denoted by bold fonts. By definition, the elements of $\tilde{W}_j$ and V_j are outputs obtained by filtering X, namely

$$\tilde{W}_{j,t} = \sum_{l=0}^{L_j-1} \tilde{h}_{j,l} X_{t-l \bmod N} \tag{3}$$

and

$$\tilde{V}_{j,t} = \sum_{l=0}^{L_j-1} \tilde{g}_{j,l} X_{t-l \bmod N} \tag{4}$$

for t=0,...,N-1, where $\tilde{h}_{j,l}$ and $\tilde{g}_{j,l}$ are j[th] 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 $X_{-1},X_{-2},\dots,X_{-N}$ are assigned the observed values at $X_{N-1}, X_{N-2},\dots,X_0$. The MODWT coefficients are thus given by:

$$\tilde{W}_{j,t} = \sum_{l=0}^{N-1} \tilde{h}^{\circ}_{j,l} X_{t-l \bmod N} \tag{5}$$

and

$$\tilde{V}_{j,t} = \sum_{l=0}^{N-1} \tilde{g}^{\circ}_{j,l} X_{t-l \bmod N} \tag{6}$$

for $t=1,\dots,N-1$; $\tilde{h}^{\circ}_{j,l}$ and $\tilde{g}^{\circ}_{j,l}$ are periodization of $\tilde{h}_{j,l}$ and $\tilde{g}_{j,l}$ to circular filters of length N. This periodic extension of the time series is known as analyzing time series $\{X_t\}$ using "circular boundary conditions" (Percival and Walden, 2000; Cornish et al., 2006). There are wavelet and scaling coefficients that are influenced by the extension ("the boundary coefficients"). The exclusion of boundary coefficients in the

[1] Concepts and notations as in Percival and Walden (2000) are used, where also a more comprehensive description of wavelets and MODWT is given.

wavelet variance, wavelet correlation and covariance provides unbiased estimates (Cornish et al., 2006).

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

$$\hat{v}_X^2(\tau_j) = \frac{1}{M_j} \sum_{t=L_j-1}^{N-1} \widetilde{W}_{j,t}^2, \tag{7}$$

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

Given two stationary processes $\{X_t\}$ and $\{Y_t\}$, an unbiased covariance estimator $\hat{v}_{X,Y}(\tau_j)$ is given by (Percival, 1995):

$$\hat{v}_{X,Y}(\tau_j) = \frac{1}{M_j} \sum_{t=L_j-1}^{N-1} \widetilde{W}_{j,t}^{(X)} \widetilde{W}_{j,t}^{(Y)}, \tag{8}$$

where $M_j \equiv N - L_j + 1 > 0$ 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:

$$\hat{\rho}_{X,Y(\tau_j)} = \frac{\hat{v}_{XY}(\tau_j)}{\hat{v}_X(\tau_j)\hat{v}_Y(\tau_j)}, \tag{9}$$

where $\left|\hat{\rho}_{X,Y}(\tau_j)\right| \leq 1$.

Calculation of confidence intervals of wavelet correlation estimates is based on Percival (1995) and Percival and Walden (2000). The random interval

$$\left[tanh\left\{ h[\rho_{XY}(\tau_j)] - \frac{\Phi^{-1}(1-p)}{\sqrt{N_j - 3}} \right\}, tanh\left\{ h[\rho_{XY}(\tau_j)] + \frac{\Phi^{-1}(1-p)}{\sqrt{N_j - 3}} \right\} \right] \tag{10}$$

captures the true wavelet correlation and provides an approximate 100(1-2p)% confidence interval. Function $h(p) = tanh^{-1}\hat{\rho}$ defines the Fisher's z-transformation. N_j is the number of wavelet coefficients obtained by jth-level of DWT and not by the MODWT transformation. This is because the Fisher's z-transformation assumes uncorrelated observations and the DWT is known to approximately decorrelate a wide range of power-law processes (Ranta, 2010).

The MODWT cross-correlation for scale τ_j at lag π is defined as:

$$\hat{\rho}_{\pi,XY}(\tau_j) = \frac{\hat{\upsilon}_{\pi,XY}(\tau_j)}{\hat{\upsilon}_X(\tau_j)\hat{\upsilon}_X(\tau_j)} \tag{11}$$

Cross-correlation is a method for estimating the degree to which two time series are correlated. We can shift one time series (either lag (π is then negative) or lead (π is then positive)) and then calculate the correlation between the two time series.

Cross-correlations help to identify which time series return innovations are leading the other time series return innovations (the latter time series is thus said to be lagging). The size and significance of cross-correlations tell if the leading time series has predictive power for the lagging time series. Just as the usual time-domain cross-correlation is used to determine lead/lag relationships between two time series, the wavelet cross-correlation will provide a lead/lag relationship on a scale-by-scale basis.

Wavelet cross-correlation takes values $-1 \le \hat{\rho}_{\pi,XY}(\tau_j) \le 1$, for all τ and j. This can be shown using Cauchy-Schwartz inequality[2].

2. Empirical results

3.1 Description of data

Stock indices returns are calculated as the differences of logarithmic daily closing values of indices ($\ln(P_t) - \ln(P_{t-1})$), where P is an index value). The following CEE stock market indices are considered: BUX (Hungary), PX (the Czech Republic) and LJSEX (Slovenia). Developed stock markets are represented by CAC40 (French stock market), DAX (German stock market), FTSE100 (the UK stock market) and ATX (Austrian stock market)[3]. The first day of observation is April 1, 1997, and the last day is May 12, 2010. Days of no trading on any of the observed stock markets were left out. The total number of observations amounts to 3,060 days. The data sources of 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. **Descriptive statistics for stock index return time series**

	Min	Max	Mean	Std. deviation	Skewness	Kurtosis	Jacque-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: Jarque-Bera test: the null hypothesis 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. Jarque-Bera statistics: *** indicates that the null hypothesis (of normal distribution) is rejected at the 1% significance, ** indicates that the null hypothesis is rejected at the 5% significance and * indicates that the null hypothesis is rejected at 10% significance.

Table 1 presents some descriptive statistics of the data. We can observe higher spread between maximum and minimum of daily returns in PX and BUX indices as

[2] Proof can be found in Percival (1995).

[3] The ATX is considered because the strong historical and economic ties of the 3 CEE countries with Austria and because the stock exchanges of these 3 countries are owned by a common holding company, which, together with Vienna stock exchange form the CEE Stock Exchange Group.

with the other indices. Standard deviation of daily returns is the smallest for LJSEX. Jarque-Bera test rejects the hypothesis of normal distribution for all the stock indices.

The results[4] of the tests of stationarity of stock index return time series (augmented Dickey-Fuller (ADF) test, Phillips-Perron (PP) and Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test were applied) led to conclusion that the time series are stationary.

2.2 Results of the lead/lag analysis

MODWT transformations of the indices' return series were performed by using a Daubechies least asymmetric filter with a wavelet filter length of 8 (LA8) as in Gencay et al. (2001b) and Gallegati (2005). The maximum level of MODWT is 6 (J_o=6) to achieve an optimal balance between sample size and the length of the filter. Scale τ_1 measures the dynamics of returns over 2 to 4 days; scale τ_2 over 4 to 8 days; scale τ_3 over 8 to 16 days; scale τ_4 over 16 to 32 days; scale τ_5 over 32 to 64 days; and scale τ_6 over 64 to 128 days.

To obtain unbiased estimates of wavelet correlations, only non-boundary coefficients must be considered. There are 2,619 MODWT wavelet coefficients not affected by the boundary condition. A major drawback of taking higher maximum number of levels in the MODWT decomposition is losing sample size. As we also wanted to include the period after the start of global financial crisis (the date of September 16, 2008, when Lehman Brothers collapsed, which precipitated a global financial market panic, is commonly taken as the start of the global financial crisis) we decided not to take a j_o greater than 6.

We explore cross-correlations between pairs of stock market returns by calculating and then plotting cross-correlation functions for 50 time leads/lags (π=-50,-49,...,0,...,49,50)[5]. We thus calculate cross-correlations between two stock return time series by first lagging the second time series by 50 time units. Then, we sequentially repeat the calculation of cross-correlation for other time shifts (from lags of 49 time units to leads of 50 time units). When two stock indices time series are time-aligned, (wavelet) cross-correlation is equal to the standard (scale) correlation coefficient. If no correlation coefficient at leads or lags ($\pi \neq 0$) of one time series is statistically significantly different from zero, then no time series is leading (or lagging) the other time series. If there are significant cross-correlations for non-zero lags/leads, then one time series is leading the other. So, zero-lag cross-correlations measure comovements (the contemporaneous relationship) between the stock indices returns, while non-zero lag cross-correlations measure the lead-lag (spillover) relationship between two time series.

Only the raw (i.e. untransformed) scale τ_1, scale τ_2 and scale τ_6 return series cross-correlations were analyzed. More findings emerge from the analysis. Firstly, observing cross-correlations at zero-lag, we notice that the correlation increases with the time scale, suggesting that the return comovement between CEE and developed stock markets is scale dependent (Table 2). Rational international investors in the

[4] Results are not presented here, but can be obtained from the author.

[5] Similarly, Ranta (2010) chose 50 lags to study cross-correlation dynamics between the developed stock market of the US, Germany and Japan.

investigated CEE stock markets should therefore investigate correlations corresponding to their investment horizon in these stock markets. Ranta (2010) and Zhou (2011) arrived at a similar conclusion when investigating other stock markets. This finding of our study is contributing to empirical literature on CEE stock market comovement with developed stock markets. However, existing literature (e.g., Allen, Powell and Golab 2010; Horobet and Lupu, 2009) investigates only the raw return series and not scale return dynamics. Our study results are indicative that the findings from the existing empirical literature can also be extended to time scales.

Table 2. **Cross-correlation between time-aligned time series of developed and CEE stock markets returns**

	ATX and			CAC40 and			DAX and			FTSE100 and		
	BUX	PX	LJSEX	BUX	PX	LJSEX	BUX	PX	LJSEX	BUX	PX	LJSEX
Raw returns	0.50	0.60	0.31	0.48	0.52	0.20	0.52	0.47	0.21	0.49	0.53	0.21
Scale τ_1	0.46	0.59	0.24	0.47	0.52	0.15	0.49	0.45	015	0.48	0.53	0.16
Scale τ_4	0.57	0.59	0.39	0.51	0.54	0.25	0.56	0.55	0.26	0.56	0.51	0.26
Scale τ_6	0.62	0.48	0.22	0.69	0.64	0.28	0.66	0.60	0.27	0.61	0.53	0.22

Source: Own calculations.

Another finding of the paper is that Hungarian and Czech stock markets are more correlated with developed European stock markets, Slovenian stock market is less. We notice that this finding is valid at all the scales. According to portfolio theory of Markowitz (1958), international diversification into LJSEX index would bring greater benefits than diversification into BUX or PX indices.

Next, we observe high volatility in cross-correlations for the raw return series and scale τ_1 return series cross-correlations (Figures 1 to 4). As the scale increases (scale τ_4 and τ_6), the variability in cross-correlation decreases. This is expected, as investors with longer time horizons don't react to sporadic events, market sentiment, and psychological factors that can cause short-term changes in the market behavior (Spyrou et al., 2007).

As the scale increases, more cross-correlation coefficients become significantly different from zero also at non-zero lags, indicating bidirectional spillovers. Existing empirical literature (Patev et al., 2006; Egert and Kocenda, 2007; Harrison and Moore, 2009) provides evidence of bidirectional return spillovers between developed and CEE stock markets for the daily (raw) return series. Wavelet cross-correlation analysis shows that bi directional spillovers are time-frequency phenomena. Analyzing lead/lag relationships between the stock market returns in more detail, the following observations are made:

- For the raw (daily) return dynamics, cross-correlations for all the stock indices pairs are the highest at zero lag (Figures 1 to 4). We can observe that only few cross-correlations at non-zero lags are significant, indicating that most of the innovations in stock returns (caused by shocks, due to some sporadic events, change in market sentiment or new information at the market) are transmitted between developed and CEE stock markets the same day and, more occasionally, within a few days after the shock. CEE stock markets at 1 day return horizon (raw return series) seem to be well time-synchronized with developed European stock markets.

- At scale τ_1, corresponding to return dynamics of 2-4 days, for BUX and PX the highest cross-correlation with developed stock markets is observed at a zero lag, indicating a high level of time synchronicity between these two markets and the developed stock markets. The LJSEX return dynamics at this scale is not as well time-synchronized with developed stock markets. For instance, between LJSEX and DAX, the highest cross-correlation coefficient is observed at lag 1, which means that LJSEX 2-4 day return dynamics leads DAX 2-4 day return dynamic.
- At scale τ_4 (16-32 day investment horizon return dynamics), for BUX and PX, again the highest cross-correlations with the developed stock market returns are observed at zero lag. Positive and negative cross-correlations are indicative of bi-directional spillovers - from developed to CEE stock markets, and in the opposite direction. For LJSEX and developed stock markets, the highest cross-correlation is noticed for a one-day lead of developed stock markets, meaning the return innovations in stock market returns are mostly transmitted from developed stock markets to Slovenian stock market with a one-day lag.
- At scale τ_6, a symmetric cross-correlation function appears between BUX and PX pairs with developed stock markets indices. For BUX, the highest cross-correlation with ATX and CAC40 is achieved at zero lag, for a one-day lead of the DAX and two-day lead of the FTSE100. For PX, the highest cross-correlations are achieved at zero lag with ATX, at the 3-day lead of DAX, one-day lead of CAC40 and 2-day lead of FTSE100. Significant positive as well as negative cross-correlations for the leads and lags of the developed stock indices are observed, indicating that innovations are not transmitted only from developed markets to PX, but also that bidirectional spillovers exist. For LJSEX and the developed stock market indices, cross-correlation figures are more asymmetric, indicative of larger lead/lag relationships between developed markets and Slovenian stock market.

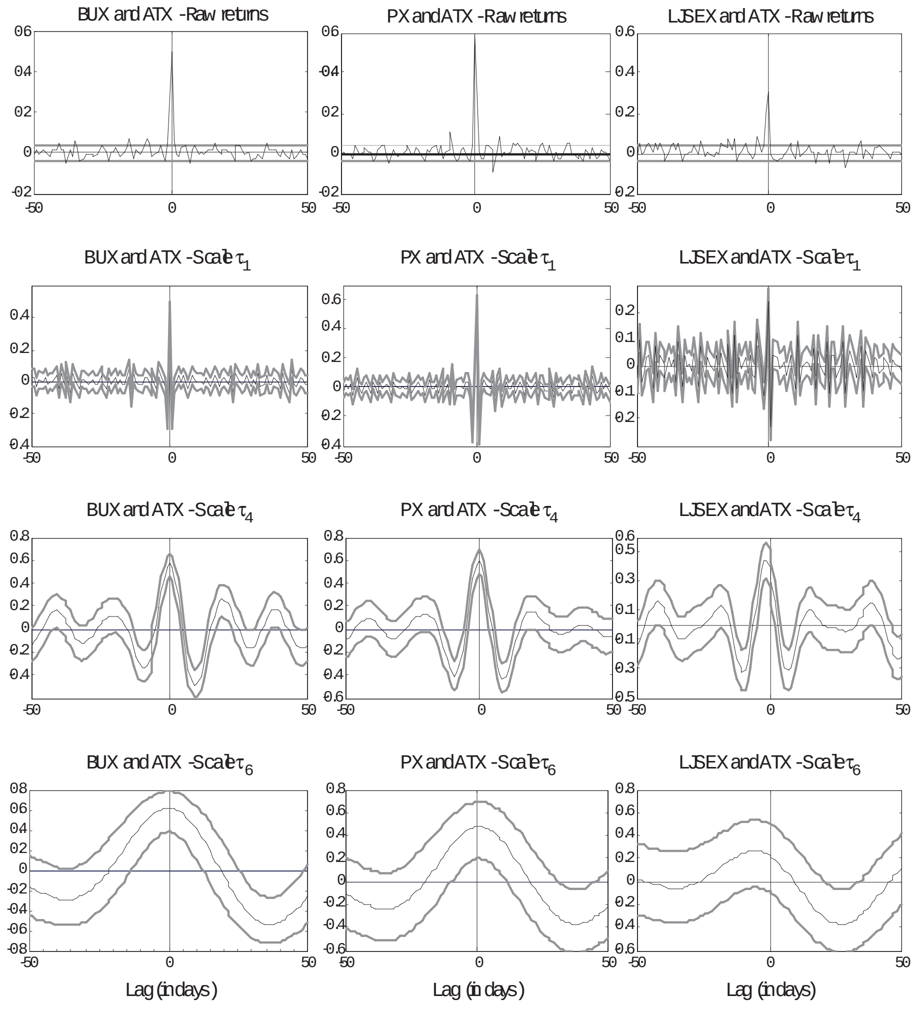

Figure 1. **Cross-correlations of the CEE stock market returns with the returns of ATX**

Notes: The cross-correlation is calculated by shifting the time series of returns of the second index in the pair (in Figure 1 this is the returns series of ATX). The 95% confidence intervals are drawn with a dotted line. For the raw return series the 95% confidence interval that the cross-correlation between the two time series is zero is drawn and is calculated using Matlab's built-in cross-correlation function. For the wavelet cross-correlation the 95% confidence intervals around the cross-correlation estimate are drawn based on equation (10).

Source: Own calculations.

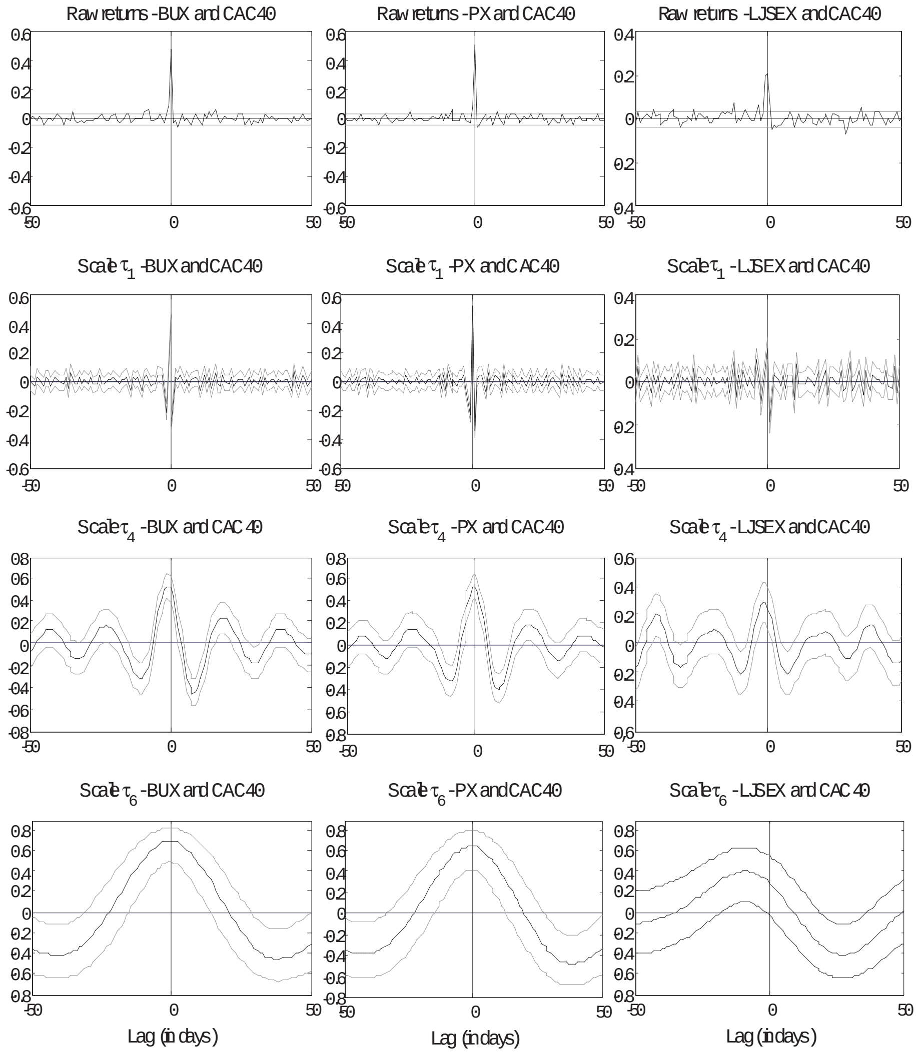

Figure 2. **Cross-correlations of the CEE stock markets with the returns of CAC40**

Notes: See notes for Figure 1.

Source: Own calculations.

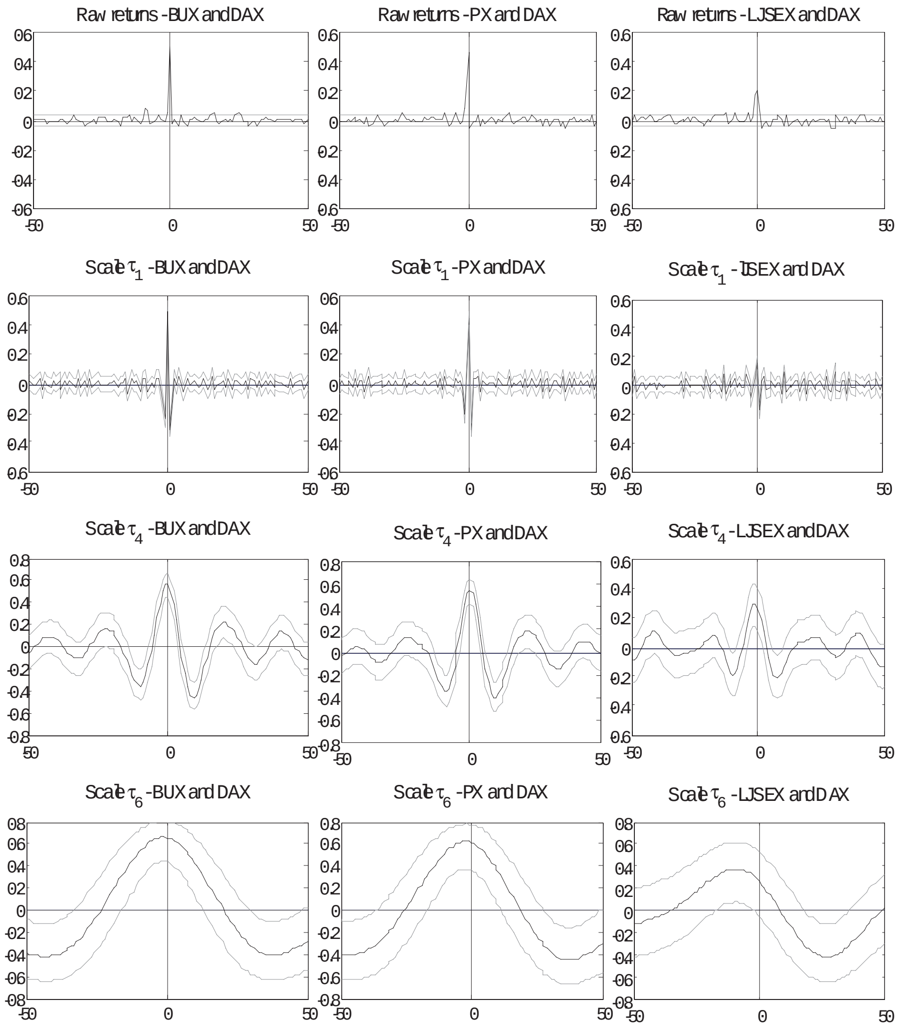

Figure 3. **Cross-correlations of the CEE stock market returns with the returns of DAX**

Notes: See notes for Figure 1.
Source: Own calculations.

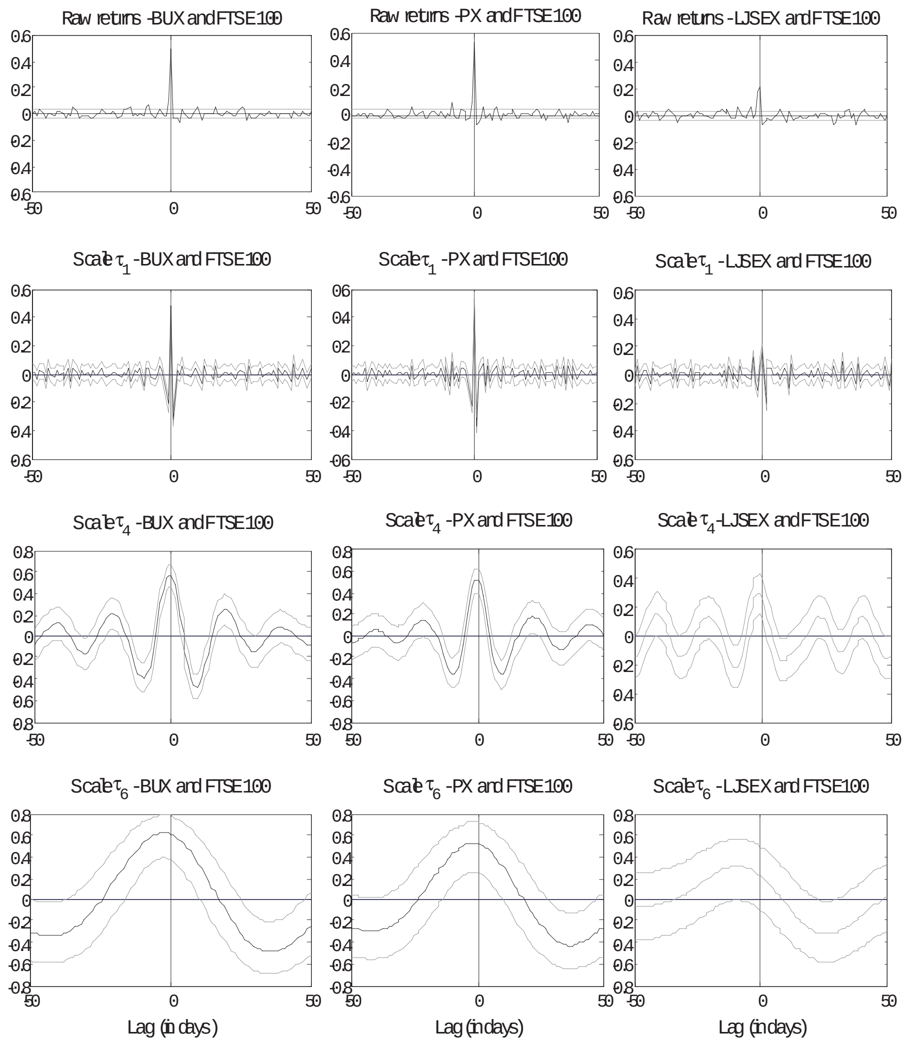

Figure 4. **Cross-correlations of the CEE stock market returns with the returns of FTSE100**

Notes: See notes for Figure 1.

Source: Own calculations.

Czech and Hungarian stock markets are not just more correlated with developed European stock markets, but also more time-synchronized than Slovenian stock market. Similar findings were also reported by the studies of Harrison and Moore (2009), Horobet and Lupu (2009) and Allen et al. (2010) and can be attributed to the fact that

Czech and Hungarian stock markets have attracted many foreign investors (Caporale and Spagnolo, 2010), while Slovenian stock market has struggled to do so. Further, the liquidity of the shares listed at Ljubljana stock exchange is significantly smaller than at Prague and Budapest stock exchanges which, according to the study of Didier, Love and Martinez Peria (2011), can also explain why LJSEX index is less connected with foreign stock markets[6]. However, the authors investigate only daily return series and not time scales dynamics. But, as argued by Zhou (2011), a financial market consists of a variety of agents with different time horizons, and therefore it is postulated that market linkage could differ across time scales. Our findings confirm this — comovements and spillovers of returns between stock markets are scale phenomena.

4. Conclusion. This paper investigates multiscale lead/lag return dynamics between CEE stock markets (Slovenian, Czech and Hungarian) and developed European (German, Austrian, French and United Kingdom) stock markets by applying maximal overlap discrete wavelet transform cross-correlations tool.

The key findings of this paper are the following: i) correlation between CEE and developed stock market return increases with time scale, suggesting that the return comovement between stock markets is scale dependent; ii) Hungarian and Czech stock markets are more correlated with developed European stock markets, Slovenian stock market is less; iii) there are significant bidirectional return spillovers: from developed to CEE stock markets and in the opposite direction; iv) Czech and Hungarian stock markets are not just more correlated with developed European stock markets, but their volatilities are also more time synchronized with developed stock markets than the ones of Slovenian stock market.

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