II. THE INTERDEPENDENCE OF THE STOCK MARKETS OF SLOVENIA, THE CZECH REPUBLIC AND HUNGARY WITH SOME DEVELOPED EUROPEAN STOCK MARKETS – THE EFFECTS OF JOINING THE EUROPEAN UNION AND THE GLOBAL FINANCIAL CRISIS

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Abstract

This article examines how the interdependence of three Central and Eastern European (CEE) stock markets, represented by the stock indices LJSEX (Slovenia), PX (Czech Republic) and BUX (Hungary), and some developed European stock markets (Austria, represented by the ATX; France, represented by the CAC40; Germany, represented by the DAX; and Great Britain, represented by the FTSE100) has evolved in the period from April 1997 to May 2010. We have divided the total observation period into three sub-periods: the period before the three CEE countries joined the European Union, the period from European Union membership until the start of the global financial crisis, and the period after the global financial crisis began. A non-conditional correlation analysis and linear and nonlinear Granger causality tests were applied on the daily return series. The results showed that interdependence increased from the first to the third sub-period, and that the CEE stock markets have been less correlated than developed stock markets. Granger causality tests have revealed the existence of numerous statistically significant stock market return spillovers, which changed between the investigated sub-periods.

Keywords: stock markets, European Union, global financial crisis, stock market return comovement, correlation, Granger causality

JEL classification: F21, F36, G11, G15

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1. Introduction

The stock markets of Slovenia, the Czech Republic and Hungary share some common characteristics: they are markets with a recent post-communist era, relatively small market capitalization[3]; a relatively small number of listed companies[4], and are owned by a common holding company (together with the Vienna stock exchange, these three CEE stock exchanges form the CEE Stock Exchange Group). The global financial crisis similarly affected these stock markets: stock market capitalization of the listed companies was reduced, stock market liquidity fell, price volatility increased and the number of stock market investors was reduced. There are also some important differences between them: Czech and Hungarian stocks have attracted many foreign investors (Caporale and Spagnolo, 2010), the Slovenian market less so; the stock market turnover and liquidity of shares listed on the Ljubljana stock exchange is smaller than on its counterparts[5].

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

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 dependence in multivariate normal distributions (Embrechts et al., 1999). But correlations may be nonlinear and time-varying (Ling and Dhesi, 2010; Égert and Kočenda, 2010). Also, the 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 econometric methods. The VAR (Vector AutoRegression) method is often applied for this purpose (e.g. Malliaris and

[3] The stock market capitalization of all the shares listed on the Ljubljana stock exchange at the end of the year 2010 was, according to FESE (2010), 6.99 billion EUR. The stock market capitalization of all the shares listed on the Prague stock exchange, at the same time, reached 31.92 billion EUR and on the Budapest stock exchange 20.62 billion EUR. To compare this with some developed European stock markets: the stock market capitalization of all the shares listed on the Deutsche Börse at the end of 2010 was 1,066 billion EUR, on the Vienna stock exchange 93.94 billion EUR and on the NYSE Euronext 2,184 billion EUR. Only the three stock markets of the Central and Eastern European (CEE) region are chosen due to their similarity, historical and economical proximity to Austrian and the German markets, and because being considered to be the most advanced economies amongst the CEE countries.

[4] At the end of 2010, the Ljubljana stock exchange had 72 different companies listed, the Budapest stock market had 52, and the Prague stock market had 27. According to FESE (2010) NYSE Euronext had 1,135 stock companies listed, the Deutsche Börse 765, and the Vienna stock market 110.

[5] Ljubljana stock exchange equity turnover in 2010 was €0.7 billion, Prague stock exchange €30.5 billion and Budapest stock exchange €39.9 billion (CEEG, 2011).

Urrutia, 1992; Gilmore and McManus, 2002; Tudor, 2010), to investigate stock market return spillovers and Granger causality. Stock market return (or shock in return) spillovers analysis is based on the following reasoning: if the news in one stock market (reflected in its return) in time $t-1$ affects the returns of another stock market in time t, there are return spillovers and the returns of the first market have an explanatory power in explaining the returns of the other market.

In this article, we want to examine the level of comovements and return spillovers in CEE developing stock markets and developed European stock markets. Three CEE stock indices (the LJSEX, PX, and BUX) and four stock market indices from developed stock markets (the ATX, CAC40, DAX and FTSE) have been analyzed. Non-conditional correlation analysis and Granger causality tests (based on VAR models) were used on the daily return series for the period from April 1, 1997 to May 12, 2010. To check how comovements and spillovers have changed during the investigated period, three sub-periods were formed: the first period was the period before CEE countries joined European Union (April 1, 1997 to April 30, 2004); the second period covers the first three years in the European union and buoyant stock markets (May 1, 2004 to September 15, 2008); the third period starts with the global financial crisis and lasts until mid-May 2010 (September 16, 2008 to May 12, 2010).

2. Literature review

The ongoing integration of the CEE countries with the European Union economy, and the globalization of the world financial markets, should lead to the increasing interdependence of CEE stock markets with the more developed European stock markets[6]. The more recent empirical literature on the interdependence of CEE stock markets to developed stock markets, predominantly employ correlation analysis, Granger causality tests and cointegration analysis.

Serwa and Bohl (2005) investigated contagion in 17 European stock markets (among them three CEE countries: namely the Czech, Hungarian and Polish markets) associated with seven big financial shocks between 1997 and 2002. They applied heteroskedasticity-adjusted correlation coefficients to discriminate between contagion, interdependence and breaks in stock markets relationships. They found only modest evidence of significant instabilities in cross-market linkages after the crises. The authors concluded that CEE stock markets are not more vulnerable to contagion than Western European markets.

Syllignakis and Kouretas (2006) examined the short- and long-term relationships between seven CEE countries (the Czech Republic, Poland, Hungary, Slovakia, Slovenia, Estonia and Romania) and two developed stock markets (Germany and the USA). Cointegration and the common trends analysis were applied on weekly return series of representative stock indices for the period from January 1995 to the end of December 2005. The results revealed that stock markets are partially integrated, since

[6] There are many empirical studies on the effects of European integration on the interdependence of the developed European stock markets, that confirm this assumption (see: Koch and Koch (1991), Kasa (1992), Longin and Solnik (1995) and Bessler and Yang (2003)).

they have more common trends than cointegrating relations that bind them together in the long run. There is also evidence that the five stock markets in CEE (the Czech Republic, Hungary, Poland, Slovenia and Slovakia) together with the German and the US stock markets have a significant common permanent component, which drives this system of stock exchanges in the long run. The authors argue that the benefits from diversifying into the Central Eastern European equity markets are reduced, since the level of integration among the markets in the CEE region and the developed markets (Germany, US) increased during the observed period.

Patev et al. (2006) investigated the CEE equity market co-movements before, during and after major emerging market crises (the 1997 Asian crisis, the 1998 Russian crisis and the 1999 Brazilian crisis). The study is based on the concept of co-integration. Three CEE stock markets (the Czech Republic, Hungary and Poland), as well as the Russian and U.S. stock markets, are included. The daily return series range from August 1996 to August 2001. The results of cointegration analysis (Johansen test) indicate that there is no long-run relationship between the US and the four Central European stock markets. By using the Granger causality test, the authors found a feedback effect and causality in one direction during and after the crisis period. Portfolio benefits decrease in the crisis period but they increase in the post-crisis period.

Harrison and Moore (2009) attempted to investigate the degree of comovement between stock exchanges in ten CEE countries (among them Slovenia, the Czech Republic and Hungary) and those in developed European markets (Great Britain and Germany). Three measures are employed on daily return series for the period 1990-2006: realized correlations, time-varying unit root tests, and recursive cointegration statistics. With the exception of the Czech Republic, Hungary and Poland, there is a relatively weak correlation between daily returns in CEE countries and those in Europe. However, the link between the exchanges has strengthened since 2002. The authors found evidence that stock exchanges experience similar shocks, and therefore have similar fluctuations in daily returns, but that equity prices do not consistently drift towards those in the major European exchanges.

Horobet and Lupu (2009) investigated the integration of five CEE stock markets (the Czech Republic, Hungary, Poland and Romania), the Russian stock market and four developed European Union stock markets (Austria, Germany, Great Britain and France) in the period from 2003-2007. The degree of market integration is interpreted from the standpoint of the rapidity in the markets' reactions to the information revealed in the past in other markets. By performing cointegration and Granger causality tests, the results indicated that the markets react quite quickly to the information included in the returns of the other markets, and that this flow of information takes place in both directions, from the developed markets to the emerging ones, and vice versa.

Allen et al. (2010) examined the implications for European investors of the European Union's expansion to encompass former Eastern bloc economies. Twelve CEE countries were considered (among them Slovenia, the Czech Republic and Hungary), data spans from January 1995 until September 2009 and is divided into two sub-periods: the pre- and post-EU period. A correlation analysis showed that in the pre-EU and post-EU period, the stock markets of the Czech Republic, Hungary and Poland seem to be more highly correlated with each other than other CEE stock markets.

Caporale and Spagnolo (2010) estimated a ˝VAR-GARCH-in-mean˝ model for weekly return data, for the period from January 1996 to March 2008, to examine volatility linkages between the stock markets of three CEE countries, namely the Czech Republic, Hungary and Poland, and the British and Russian stock markets. The empirical findings suggest that regional linkages have become stronger, and that therefore portfolio diversification within the region has become a less effective investment strategy. The author concludes that the results may be interpreted as reflecting deeper integration of the CEE countries with the "old" EU economies.

Égert and Kočenda (2007) analyze intraday connections between three stock markets in CEE (BUX, PX and WIG20 indices) and connections between Western European (DAX, CAC40, FTSE100) and CEE stock markets. Five-minute interval data is used for the period between June 2003 and February 2006. The authors found no robust cointegration relationship for any of the stock index pairs. The correlation coefficients between the three CEE stock indices are low (around 0.2), slightly higher between the individual CEE markets and the Western European stock markets (around 0.3), and strong between the DAX, CAC and FSTE stock market indices (in the 0.8-0.9 range). Significant Grange causal relationships were detected: stock returns in Frankfurt, London and Paris have a predictive power for stock returns in the three CEE countries. CEE stock market returns influence each other and stock returns in Frankfurt, London and Paris.

Tudor (2010) investigated the correlations and causal relationships among six CEE stock markets (the Czech Republic, Hungary, Bulgaria, Poland, Russia and Romania) and the U.S. stock market on daily return data from January 2006 to March 2009. The author observed that the financial crisis has increased the interconnections between the observed markets, especially among those markets that were less interconnected before the crisis (Bulgaria, Romania), while for the Czech and Hungarian stock market, the opposite conclusion in drawn. A Granger causality test was used to confirm the findings of increased interconnection after the financial crisis.

3. Unconditional correlation analysis

Unconditional correlation and Granger causality tests were performed on the differences in logarithmic daily closing prices in the following stock indices: LJSEX (Slovenia), PX (Czech Republic), BUX (Hungary), ATX (Austria), CAC40 (France), DAX (Germany) and FTSE100 (Great Britain). The first day of observation is April 1, 1997, 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 for the LJSEX, PX and BUX indices are from their respective stock exchanges, while the data source for the ATX, CAC40, DAX and FTSE100 indices is from Yahoo Finance.

Table 1 presents some descriptive statistics of the data. We can observe a higher spread between maximum and minimum daily returns in the PX and BUX indices as the other indices. The standard deviation of daily returns is smallest with the LJSEX index. The Jarque-Bera test rejects the hypothesis of a normally distributed observed time series, all indices are asymmetrically (left) distributed around the sample mean, kurtosis is greater than with a normally distributed time series.

Table 1

Descriptive statistics for the stock index return time series

	Min	Maks	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: Skewness: The skewness of the normal distribution (or any perfectly symmetric distribution) is zero. If the statistic is negative, then the data are spread out more to the left of the mean than to the right. If skewness is positive, the data are spread out more to the right. Kurtosis: The kurtosis of the normal distribution is 3. Fat-tailed distributions have kurtosis greater than 3; distributions that are less outlier-prone than normal distribution have kurtosis less than 3. Jarque-Bera test: the null hypothesis is that the sample data come from a normal distribution with an unknown mean and variance, against the alternative that it does not come from a normal distribution. Jarque-Bera statistics::*** indicate that the null hypothesis (of a normal distribution) is rejected at the 1% significance level (** that null hypothesis is rejected at 5% significance and * that the null hypothesis is rejected at 10% significance level).*

Table 2 presents unconditional correlation (Pearson's correlation coefficient) results for the total observation period.

Table 2

Unconditional correlation coefficients of stock index returns – total observation period (1.4. 1997 – 12.5. 2010)

	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.

The stock indices that are most correlated are the CAC40, FTSE100 and DAX. These markets seem to be the most integrated, which has been a common observation in existing empirical literature (e.g. Serwa and Bohl (2005), Harrison and Moore (2009)). The most interconnected are the CAC40 and FTSE100, with a correlation coefficient of 0.871. The LJSEX, PX and BUX show a smaller degree of comovement with the other CEE markets and with developed European stock markets. Among the observed stock indices, the Slovenian LJSEX is the least correlated. A PX index seems to comove the most with the ATX, BUX and FTSE100. The BUX is slightly less correlated with the observed stock indices than PX. The highest comovement is observed with the PX, DAX and ATX. The Austrian stock market is more internationally connected than CEE markets, but less than major European markets (CAC40, DAX, and FTSE100).

In the first sub-period, the interdependencies between all pairs of stock markets were smaller than in the succeeding sub-period (tables 3, 4 and 5). The Slovenian stock market was the least correlated with other markets in all three sub-periods. The comovement of the Czech stock market returns with developed European stock markets in the second sub-period increased more than the Hungarian one, so from the second sub-period on, the Czech stock market appears to be more integrated with European stock markets than the Hungarian stock market. European integration seems to have strengthened the interdependence of CEE as well as developed stock markets. These findings confirm the results of Koch and Koch (1991), Kasa (1992), Longin and Solnik (1995) and Bessler and Yang (2003) for developed markets, as well as the findings of Syllignakis and Kouretas (2006), Harrison and Moore (2009) and Allen et al. (2010) for the observed CEE markets.

Table 3

Unconditional correlation coefficients of stock index returns in the period before CEE countries joined the European Union (April 1, 1997 to April 30, 2004)

	LJSEX	PX	BUX	ATX	CAC40	DAX	FTSE100
LJSEX	1						
PX	0.129	1					
BUX	0.207	0.441	1				
ATX	0.172	0.291	0.377	1			
CAC40	0.073	0.395	0.380	0.446	1		
DAX	0.144	0.362	0.468	0.416	0.722	1	
FTSE100	0.088	0.398	0.405	0.436	0.815	0.656	1

Table 4

Unconditional correlation coefficients of stock index returns for the period after CEE countries entered the European Union until the start of the global financial crisis (May 1, 2004 – September 15, 2008)

	LJSEX	PX	BUX	ATX	CAC40	DAX	FTSE100
LJSEX	1						
PX	0.208	1					
BUX	0.098	0.584	1				
ATX	0.160	0.676	0.547	1			
CAC40	0.129	0.565	0.492	0.749	1		
DAX	0.132	0.558	0.470	0.692	0.898	1	
FTSE100	0.122	0.582	0.496	0.766	0.910	0.817	1

Patev et al. (2006) found that in periods of financial crisis, the interdependence between stock markets strengthens. We can confirm this finding for the latest financial global financial crisis. Since the start of the global financial crisis (the collapse of Lehman Brothers on September 16, 2008, is taken as a milestone) the interdependence between stock markets has strengthened. For all pairs of index returns, higher correlation coefficients can be observed (Table 5) than in the two preceding periods. By strengthening the interdependence, the benefits of portfolio diversification in these markets have been reduced.

Table 5

Unconditional correlation coefficients of stock index returns from the onset of the global financial crisis (September 16, 2008 to May 12, 2010)

	LJSEX	PX	BUX	ATX	CAC40	DAX	FTSE100
LJSEX	1						
PX	0.559	1					
BUX	0.423	0.716	1				
ATX	0.517	0.788	0.681	1			
CAC40	0.460	0.685	0.685	0.837	1		
DAX	0.417	0.658	0.686	0.806	0.945	1	
FTSE100	0.452	0.671	0.662	0.807	0.957	0.914	1

4. Granger causality test of spillovers between stock market returns

3.1. Description of the method

Many studies use the Granger causality test (Granger, 1969; Granger and Morgenstern, 1970) to analyze one or two-sided causal relationships between stock market returns (e.g. Malliaris and Urrutia (1992), Gilmore and McManus (2002) as well as Tudor (2010)). We use the Granger causality test to test if the lagged value of one variable significantly explains the present value of another. More specifically, let us assume that $\{X_t, Y_t, t \geq 1\}$ are two scalar-valued strictly stationary time series[7]. $\{X_t\}$ Granger causes $\{Y_t\}$ if past and current values of X contain additional information on future values of Y that is not contained only in the past and current Y_t values. Let $F_{X,t}$ and $F_{Y,t}$ denote the information sets consisting of past observations of X_t and Y_t up to and including time t and $\sim$ denote the equivalence in distribution. Then $\{X_t\}$ Granger causes $\{Y_t\}$ if for $k \geq 1$

$$(Y_{t+1},...,Y_{t+k}) \big| (F_{X,t}, F_{Y,t}) \sim (Y_{t+1},...,Y_{t+k}) \big| F_{X,t}\,. \qquad (1)$$

When $k = 1$, testing for Granger (non)-causality amounts to comparing the one step ahead conditional distribution of $\{Y_t\}$ with and without past and current observed

[7] *For the explanation of Granger causality test we follow Bekiros and Diks (2008).*

values of $\{X_t\}$. A conventional approach of testing for granger causality among stationary time series is to assume a parametric, linear, time series model for the conditional mean $E(Y_{t+1}|(S_{X,t},F_{Y,t}))$. Then causality can be tested by comparing the residuals of a fitted autoregressive model of $\{Y_t\}$ with those obtained by regressing $\{Y_t\}$ on past values of both $\{X_t\}$ and $\{Y_t\}$ (Granger, 1969; Granger and Morgenstern, 1970). Relationship among the variables, however, can also be non-linear and the rejection of linear causality does not imply there is no non-linear causality - this is because VAR focuses only on linear relations (Baek and Broeck 1992).

Diks and Panchenko (2006) proposed a non-linear nonparametric Granger causality test. Let us assume delay vectors $\boldsymbol{X}_t^{l_X}=(X_{t-l_X+1},...,X_t)$ and $\boldsymbol{Y}_t^{l_Y}=(Y_{t-l_Y+1},...,Y_t)$, $(l_X,l_Y\geq 1)$. in practice the null hypothesis that past observations of $\boldsymbol{X}_t^{l_X}$ contain no additional information (beyond that in $\boldsymbol{Y}_t^{l_Y}$) about Y_{t+1} is tested, i.e.

$$H_0:Y_{t+1}|(\boldsymbol{X}_t^{l_X};\boldsymbol{Y}_t^{l_Y})\sim Y_{t+1}|\boldsymbol{Y}_t^{l_Y} . \tag{2}$$

For a strictly bivariate time series equation (2) comes down to a statement about the invariant distribution of the ((l_X+l_Y+1) -dimensional vector $\boldsymbol{W}_t=(\boldsymbol{X}_t^{l_X},\boldsymbol{Y}_t^{l_Y},Z_t)$, where $Z_t=Y_{t+1}$. Now, considering the null hypothesis is a statement about the invariant distribution of $(\boldsymbol{X}_t^{l_X},\boldsymbol{Y}_t^{l_Y},Z_t)$ and dropping the time index and setting $l_X=l_Y=1$, under the null the conditional distribution of Z given $(X,Y)=(x,y)$ is the same as that of Z given $Y=y$. Further, equation (2) can be restated in terms of ratios of joint distributions. More specifically, the joint probability density function

$$\frac{f_{X,Y,Z}(x,y,z)}{f_Y(y)}=\frac{f_{X,Y}(x,y)}{f_Y(y)}\cdot\frac{f_{Y,Z}(y,z)}{f_Y(y)} . \tag{3}$$

This explicitly states that X and Y are independent conditionally on $Y=y$ for each fixed value of y . Diks and Panchenko (2006) show that this reformulated H_0 implies:

$$q\equiv E\left\lfloor f_{X,Y,Z}(X,Y,Z)f_Y(Y)-f_{X,Y}(X,Y)f_{Y,Z}(Y,Z)\right\rfloor=0 . \tag{4}$$

Let $\widehat{f}_W(W_i)$ denote a local density estimator of a d_W -variate random vector $\boldsymbol{W}$ at W_i defined by $\widehat{f}_W(W_i)=(2\varepsilon_n)^{-d_W}(n-1)^{-1}\sum_{j,j\neq i}I_{ij}^W$ where $I_{ij}^W=I(\|W_i-W_j\|<\varepsilon_n)$ with $I(\cdot)$ the indicator function and ε_n the bandwidth, depending on the sample size n. Given this estimator, the test statistic is the sample version of equation (4):

$$T_n(\varepsilon_n)=\frac{n-1}{n(n-2)}\cdot\sum_i(\hat{f}_{X,Z,Y}(X_i,Z_i,Y_i)\hat{f}_Y(Y_i)-\hat{f}_{X,Y}(X_i,Z_i)\hat{f}_{Y,Z}(Y_i,Z_i)).\quad(5)$$

For $l_X=l_Y=1$, if $\varepsilon_n=Cn^{-\beta}(C>0,\frac{1}{4}<\beta<\frac{1}{3})$ then Diks and Panchenko (2006) prove under strong mixing that the test statistic in equation (5) satisfies:

$$\sqrt{n}\frac{(T_n(\varepsilon_n)-q)}{S_n}\xrightarrow{D}N(0,1),\quad(6)$$

where $\xrightarrow{D}$ denoted convergence in distribution and S_n is an estimator of the asymptotic variance of $T(\cdot)$ (Diks and Panchenko, 2006).

The time series stationarity must be checked before Granger causality tests can be performed[8]. We use the Augmented Dickey-Fuller (ADF) test, the Phillips-Perron (PP) and the Kwiatkowski-Phillips-Schmidt-Shin (KPSS) tests.

We first present the results of the stationarity tests (Table 6).

Table 6

Results of time series stationarity tests (for the total observation period, April 1, 1997 to May 12, 2010)

	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 a model with a constant plus trend. The Bartlett Kernel estimation method is used with the Newey-West automatic bandwidth selection. Optimal bandwidth is indicated in parenthesis under statistics. For the ADF test, two models are applied: Auto Regressive (AR) and the trend

[8] *The following steps were applied when examining the linear Granger causal connections between economic variables (Pop Silaghi, 2009): First, the presence of unit roots in the time series is checked. If the time series are stationary, we proceed with estimating a VAR model. The VAR results are used to examine Granger causal connections.*

*stationary model; number of lags to be included (L) for the ADF test was selected by SIC criteria (30 was a maximum lag). Exceeded critical values for the rejection of the null hypothesis are marked by *** (1% significance level), ** (5% significance level) and * (10% significance level).*

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

4.2 Granger causality test results

An important element in linear Granger causality test is specifying a VAR model and to determine the optimal lag of the explanatory variables. More criteria can be used. In the empirical literature, the most frequently used ones are: SIC (Schwarz Information Criterion), HQC (Hannan-Quinn Criterion), AIC (Akaike Information Criterion), LR test (Likelihood Ratio test), FPE (Final prediction error) and BIC (Bayesian information criteria). Liew (2004), in a simulation study, compared these criteria and his findings showed that the performance of the selection criteria depends on the size of the sample to which they are applied. For the small sample sizes (30 to 60 observations) the best results are achieved with the AIC and FPE criteria, whereas for larger sample sizes (120 and more observations) the best results are obtained by the HQC and SIC criteria. In a similar simulation study, Ashgar and Abdi (2007) found evidence that generally supported the findings of Liew (2004): HQC performs best for sample sizes of 120 observations, whereas for larger sample sizes (of more than 240 observations) the SIC criterion outperforms all other criteria. With this foundation, we used SIC criteria to select the optimal lag length of the VAR model, applied in Granger causality tests.

The first step in specifying the optimal lag length of the VAR model is an arbitrary decision of the largest considered lag length. We consider a lag length of 20 (4 trading weeks or approximately one trading month) as sufficient to capture stock index return spillovers (the same maximum lag length was used by Tudor (2010)).The optimal lag length selected by SIC criteria is indicated in the following tables in the parenthesis under the Granger causality test results.

Table 7 presents the linear and nonlinear Granger causality test results for the total observation period (April 4, 1997 to May 12, 2010). The one-day lagged returns of the ATX index are statistically significant and explain the returns of the LJSEX index on the following day; the reverse is not the case in the linear Granger causality test. However, the nonlinear Diks and Panchenko test (2006)[9] show bi-directional causality. In the case of the LJSEX and other stock indices, a feedback mechanism is observed both for linear as well as nonlinear test: LJSEX returns could be used to predict the

[9] *The authors are grateful to dr. Valentyn Panchenko for graciously providing the C code to implement the nonlinear causality test.*

returns of other stock markets, and the return of other indices could predict LJSEX returns.

Table 7

Granger causality tests for the total observed period (1.4. 1997 – 12.5. 2010)

	PX	BUX	ATX	CAC40	DAX	FTSE100
LJSEX	$LJSEX \xrightarrow{1\%(10\%)} PX$ $LJSEX \xleftarrow{1\%(1\%)} PX$ (lag=1)	$LJSEX \xrightarrow{5\%(10\%)} BUX$ $LJSEX \xleftarrow{1\%(1\%)} BUX$ (lag=1)	$LJSEX \xrightarrow{No(1\%)} ATX$ $LJSEX \xleftarrow{1\%(1\%)} ATX$ (lag=1)	$LJSEX \xrightarrow{1\%(1\%)} CAC$ $LJSEX \xleftarrow{1\%(1\%)} CAC$ (lag=1)	$LJSEX \xrightarrow{1\%(5\%)} DAX$ $LJSEX \xleftarrow{1\%(1\%)} DAX$ (lag=1)	$LJSEX \xrightarrow{1\%(1\%)} FTSE$ $LJSEX \xleftarrow{1\%(1\%)} FTSE$ (lag=1)
PX		$PX \xrightarrow{No(1\%)} BUX$ $PX \xleftarrow{1\%(1\%)} BUX$ (lag=1)	$PX \xrightarrow{No(10\%)} ATX$ $PX \xleftarrow{1\%(1\%)} ATX$ (lag=1)	$PX \xrightarrow{1\%(1\%)} CAC$ $PX \xleftarrow{1\%(1\%)} CAC$ (lag=1)	$PX \xrightarrow{10\%(1\%)} DAX$ $PX \xleftarrow{1\%(5\%)} DAX$ (lag=1)	$PX \xrightarrow{1\%(1\%)} FTSE$ $PX \xleftarrow{1\%(1\%)} FTSE$ (lag=1)
BUX			$BUX \xrightarrow{1\%(1\%)} ATX$ $BUX \xleftarrow{1\%(1\%)} ATX$ (lag=1)	$BUX \xrightarrow{No(5\%)} CAC$ $BUX \xleftarrow{1\%(1\%)} CAC$ (lag=1)	$BUX \xrightarrow{No(5\%)} DAX$ $BUX \xleftarrow{5\%(5\%)} DAX$ (lag=1)	$BUX \xrightarrow{No(1\%)} FTSE$ $BUX \xleftarrow{1\%(1\%)} FTSE$ (lag=3)
ATX				$ATX \xrightarrow{1\%(1\%)} CAC$ $ATX \xleftarrow{1\%(No)} CAC$ (lag=1)	$ATX \xrightarrow{No(1\%)} DAX$ $ATX \xleftarrow{1\%(No)} DAX$ (lag=1)	$ATX \xrightarrow{1\%(1\%)} FTSE$ $ATX \xleftarrow{1\%(5\%)} FTSE$ (lag=1)
CAC40					$CAC \xrightarrow{1\%(1\%)} DAX$ $CAC \xleftarrow{1\%(1\%)} DAX$ (lag=3)	$CAC \xrightarrow{No(1\%)} FTSE$ $CAC \xleftarrow{No(1\%)} FTSE$ (lag=1)
DAX						$DAX \xrightarrow{1\%(1\%)} FTSE$ $DAX \xleftarrow{1\%(1\%)} FTSE$ (lag=3)

Note: The direction of the arrow indicates the direction of the Granger causality and the number on the arrow is the significance level of the Granger causality (based on the F-test). The word No indicates that no Granger causality is identified (the stock index returns from where the arrow starts have no explanatory power for the returns of the stock index pointed to by the arrow). The first number above the arrow denotes significance of rejecting the null hypothesis of the linear Granger causality test, while the second number (in parenthesis) the significance of rejecting the null of the Diks and Panchenko (2006) test. In parenthesis, under the Granger causality tests, the optimal lag length for linear test, as by SIC criteria, is indicated. The bandwidth for Diks and Panchenko (2006) test is defined based on their study, so setting C=7.5 and $\beta = 2/7$, the bandwidth is $\varepsilon_{3060} = 0.76$.

Strong bidirectional (feedback) Granger causality (linear and nonlinear) can be observed also between PX and other observed stock indices returns.

Taking the results of linear Granger causality test, BUX returns could be explained by lagged returns of other indices (except the PX), and the past returns of the BUX could help predict returns for the LJSEX, PX and ATX. From this it follows that the CAC40, DAX and FTSE100 Granger caused the BUX. The index BUX Granger caused the index PX. Between the Hungarian and stock markets of Slovenia (and Austria) a bidirectional Granger cause (i.e. feedback mechanism) existed. The nonlinear granger causality test points out that there is a strong nonlinear Granger causal relationship between the Hungarian and other European stock returns.

Linear and nonlinear Granger causality is detected also between the more developed European stock markets. An interesting finding is that we can not find a linear Granger causality relationship between the CAC40 and FTSE100 indices; however the nonlinear test shows a strong Granger causal feedback mechanism.

The results obtained are in line with (albeit for a longer observed time period and covering more markets) conclusions drawn from the research of Égert and Kočenda (2007), Patev et al. (2006) or Horobert and Lupu (2009): not only stock returns in the developed stock markets of Austria, France, Germany and Great Britain Granger cause stock returns in the three CEE markets, but also CEE's stock market returns influence stock returns in developed markets.

Next, stock market interconnections in each sub-period are analyzed.

In the pre-EU period (April 1, 1997 to April 31, 2004), to start with Slovenia and linear Granger causality test, the lagged returns of all other indices could be used to explain LJSEX returns. No strongly significant proof (with a significance level of at least 5%) is found for the explanatory power of lagged LJSEX returns. The nonlinear Granger causality test shows that the evidence of nonlinear Granger causal relationship between the Slovenian and other European stock market returns is weak.

In the pre-EU period, the PX returns (linearly) Granger caused the BUX and ATX (nonlinearly) Granger caused PX returns, while between the PX and other indices no significant causal relations were observed.

The ATX, CAC40 and FTSE100 Granger caused BUX returns.

The ATX index Granger caused the DAX and the FTSE100 caused ATX. Between the returns of the ATX and CAC40 only a weak (at 10% significance) causal relationship could be identified. From the linear Granger causality test follows that the CAC40 Granger caused the DAX, while the nonlinear test shows that there was a feedback mechanism. The nonlinear test also shows a Granger causal feedback mechanism between CAC40 and FTSE100 returns. Similarly, between the DAX and FTSE100 a feedback Granger causal relationship existed.

Table 8

Granger causality tests for the period before CEE countries entered the European Union (1.4. 1997 – 31.4. 2004)

	PX	BUX	ATX	CAC40	DAX	FTSE100
LJSEX	$LJSEX \xrightarrow{No(No)} PX$ $LJSEX \xleftarrow{1\%(No)} PX$ (lag=1)	$LJSEX \xrightarrow{No(5\%)} BUX$ $LJSEX \xleftarrow{1\%(5\%)} BUX$ (lag=1)	$LJSEX \xrightarrow{No(No)} ATX$ $LJSEX \xleftarrow{1\%(5\%)} ATX$ (lag=1)	$LJSEX \xrightarrow{No(No)} CAC$ $LJSEX \xleftarrow{1\%(1\%)} CAC$ (lag=1)	$LJSEX \xrightarrow{10\%(No)} DAX$ $LJSEX \xleftarrow{1\%(No)} DAX$ (lag=1)	$LJSEX \xrightarrow{No(No)} FTSE$ $LJSEX \xleftarrow{1\%(10\%)} FTSE$ (lag=1)
PX		$PX \xrightarrow{1\%(1\%)} BUX$ $PX \xleftarrow{No(No)} BUX$ (lag=1)	$PX \xrightarrow{No(No)} ATX$ $PX \xleftarrow{No(5\%)} ATX$ (lag=1)	$PX \xrightarrow{No(No)} CAC$ $PX \xleftarrow{No(No)} CAC$ (lag=1)	$PX \xrightarrow{No(No)} DAX$ $PX \xleftarrow{No(No)} DAX$ (lag=1)	$PX \xrightarrow{No(10\%)} FTSE$ $PX \xleftarrow{No(No)} FTSE$ (lag=1)
BUX			$BUX \xrightarrow{No(No)} ATX$ $BUX \xleftarrow{1\%(1\%)} ATX$ (lag=1)	$BUX \xrightarrow{No(No)} CAC$ $BUX \xleftarrow{1\%(5\%)} CAC$ (lag=1)	$BUX \xrightarrow{No(No)} DAX$ $BUX \xleftarrow{No(No)} DAX$ (lag=1)	$BUX \xrightarrow{No(10\%)} FTSE$ $BUX \xleftarrow{1\%(1\%)} FTSE$ (lag=3)

	PX	BUX	ATX	CAC40	DAX	FTSE100
ATX				$ATX \xrightarrow{10\%(10\%)} CAC$ $ATX \xleftarrow{10\%(10\%)} CAC$ (lag=1)	$ATX \xrightarrow{1\%(10\%)} DAX$ $ATX \xleftarrow{No(5\%)} DAX$ (lag=1)	$ATX \xrightarrow{No(10\%)} FTSE$ $ATX \xleftarrow{5\%(5\%)} FTSE$ (lag=1)
CAC40					$CAC \xrightarrow{1\%(1\%)} DAX$ $CAC \xleftarrow{No(1\%)} DAX$ (lag=3)	$CAC \xrightarrow{No(5\%)} FTSE$ $CAC \xleftarrow{No(5\%)} FTSE$ (lag=1)
DAX						$DAX \xrightarrow{5\%(1\%)} FTSE$ $DAX \xleftarrow{1\%(1\%)} FTSE$ (lag=3)

Note: See the notes for Table 7. The bandwidth is $\varepsilon_{1654} = 0.90$.

Since the observed CEE countries joined the European Union and until the start of the global financial crisis, all index returns have had forecasting power for LJSEX returns (the same as in the pre-EU period). Linear Granger causality test shows that LJSEX only had a weak explanatory power for PX and DAX returns, while nonlinear version of the tests reveals a feedback mechanism between LJSEX and the stock index returns of the developed European stock markets (Table 9).

The BUX index in this sub-period Granger caused the LJSEX and ATX indices. There was also a significant nonlinear causal relationships between the BUX and ATX, while between the BUX and other indices no causal relationships were observed.

The PX index was linearly and nonlinearly Granger caused by the CAC40 and FTSE 100 and nonlinearly also by ATX and DAX indices.

Between the developed stock market returns strong nonlinear Granger causal relationships were detected.

Table 9

Granger causality tests for the period after CEE countries entered the European Union until the start of global financial crisis (May 1, 2004 to September 15, 2008)

	PX	BUX	ATX	CAC40	DAX	FTSE100
LJSEX	$LJSEX \xrightarrow{10\%(10\%)} PX$ $LJSEX \xleftarrow{1\%(1\%)} PX$ (lag=2)	$LJSEX \xrightarrow{No(No)} BUX$ $LJSEX \xleftarrow{5\%(No)} BUX$ (lag=2)	$LJSEX \xrightarrow{No(1\%)} ATX$ $LJSEX \xleftarrow{1\%(1\%)} ATX$ (lag=3)	$LJSEX \xrightarrow{No(1\%)} CAC$ $LJSEX \xleftarrow{1\%(1\%)} CAC$ (lag=3)	$LJSEX \xrightarrow{10\%(1\%)} DAX$ $LJSEX \xleftarrow{1\%(1\%)} DAX$ (lag=2)	$LJSEX \xrightarrow{No(1\%)} FTSE$ $LJSEX \xleftarrow{1\%(1\%)} FTSE$ (lag=3)
PX		$PX \xrightarrow{No(No)} BUX$ $PX \xleftarrow{No(No)} BUX$ (lag=1)	$PX \xrightarrow{No(1\%)} ATX$ $PX \xleftarrow{No(5\%)} ATX$ (lag=1)	$PX \xrightarrow{No(1\%)} CAC$ $PX \xleftarrow{5\%(1\%)} CAC$ (lag=1)	$PX \xrightarrow{No(5\%)} DAX$ $PX \xleftarrow{10\%(5\%)} DAX$ (lag=1)	$PX \xrightarrow{No(5\%)} FTSE$ $PX \xleftarrow{5\%(1\%)} FTSE$ (lag=1)
BUX			$BUX \xrightarrow{5\%(5\%)} ATX$ $BUX \xleftarrow{No(5\%)} ATX$ (lag=1)	$BUX \xrightarrow{No(No)} CAC$ $BUX \xleftarrow{No(No)} CAC$ (lag=1)	$BUX \xrightarrow{No(No)} DAX$ $BUX \xleftarrow{No(No)} DAX$ (lag=1)	$BUX \xrightarrow{No(No)} FTSE$ $BUX \xleftarrow{No(No)} FTSE$ (lag=3)
ATX				$ATX \xrightarrow{10\%(1\%)} CAC$ $ATX \xleftarrow{No(1\%)} CAC$ (lag=1)	$ATX \xrightarrow{No(1\%)} DAX$ $ATX \xleftarrow{No(10\%)} DAX$ (lag=1)	$ATX \xrightarrow{10\%(1\%)} FTSE$ $ATX \xleftarrow{10\%(1\%)} FTSE$ (lag=1)

	PX	BUX	ATX	CAC40	DAX	FTSE100
CAC40					$CAC \xrightarrow{No(1\%)} DAX$ $CAC \xleftarrow{No(No)} DAX$ (lag=2)	$CAC \xrightarrow{No(10\%)} FTSE$ $CAC \xleftarrow{No(1\%)} FTSE$ (lag=1)
DAX						$DAX \xrightarrow{No(No)} FTSE$ $DAX \xleftarrow{No(1\%)} FTSE$ (lag=1)

Note: See the notes for Table 7. The bandwidth is $\varepsilon_{1020} = 1.03$.

The global financial crisis increased the number as well as the strength (as indicated by level of significance of the F-test) of Granger causal interconnections between CEE stock markets, developed markets and CEE countries with developed markets. Both Granger causality tests indicate that the LJSEX index developed feedback Granger causal connections with all of the indices. Also the PX and BUX indices became more interdependent with other investigated stock indices, as measured by the number of feedback Granger causal connections.

Similarly, the number and strength of the causal relationships between the developed stock markets also increased.

Table 10

Granger causality tests for the period after the start of world financial crisis (September 16, 2008 to May 12, 2010)

	PX	BUX	ATX	CAC40	DAX	FTSE100
LJSEX	$LJSEX \xrightarrow{1\%(5\%)} PX$ $LJSEX \xleftarrow{1\%(1\%)} PX$ (lag=1)	$LJSEX \xrightarrow{5\%(1\%)} BUX$ $LJSEX \xleftarrow{1\%(1\%)} BUX$ (lag=1)	$LJSEX \xrightarrow{No(1\%)} ATX$ $LJSEX \xleftarrow{1\%(1\%)} ATX$ (lag=1)	$LJSEX \xrightarrow{1\%(5\%)} CAC$ $LJSEX \xleftarrow{1\%(1\%)} CAC$ (lag=1)	$LJSEX \xrightarrow{1\%(5\%)} DAX$ $LJSEX \xleftarrow{1\%(1\%)} DAX$ (lag=1)	$LJSEX \xrightarrow{1\%(5\%)} FTSE$ $LJSEX \xleftarrow{1\%(1\%)} FTSE$ (lag=1)
PX		$PX \xrightarrow{5\%(1\%)} BUX$ $PX \xleftarrow{1\%(1\%)} BUX$ (lag=1)	$PX \xrightarrow{No(5\%)} ATX$ $PX \xleftarrow{1\%(1\%)} ATX$ (lag=1)	$PX \xrightarrow{5\%(5\%)} CAC$ $PX \xleftarrow{1\%(5\%)} CAC$ (lag=1)	$PX \xrightarrow{1\%(5\%)} DAX$ $PX \xleftarrow{1\%(10\%)} DAX$ (lag=1)	$PX \xrightarrow{1\%(10\%)} FTSE$ $PX \xleftarrow{1\%(1\%)} FTSE$ (lag=1)
BUX			$BUX \xrightarrow{1\%(1\%)} ATX$ $BUX \xleftarrow{No(1\%)} ATX$ (lag=1)	$BUX \xrightarrow{No(5\%)} CAC$ $BUX \xleftarrow{No(No)} CAC$ (lag=1)	$BUX \xrightarrow{No(5\%)} DAX$ $BUX \xleftarrow{5\%(No)} DAX$ (lag=1)	$BUX \xrightarrow{No(5\%)} FTSE$ $BUX \xleftarrow{10\%(5\%)} FTSE$ (lag=3)
ATX				$ATX \xrightarrow{No(1\%)} CAC$ $ATX \xleftarrow{10\%(No)} CAC$ (lag=1)	$ATX \xrightarrow{10\%(1\%)} DAX$ $ATX \xleftarrow{1\%(No)} DAX$ (lag=1)	$ATX \xrightarrow{5\%(5\%)} FTSE$ $ATX \xleftarrow{5\%(5\%)} FTSE$ (lag=1)
CAC40					$CAC \xrightarrow{1\%(1\%)} DAX$ $CAC \xleftarrow{1\%(No)} DAX$ (lag=3)	$CAC \xrightarrow{5\%(5\%)} FTSE$ $CAC \xleftarrow{5\%(1\%)} FTSE$ (lag=1)
DAX						$DAX \xrightarrow{No(No)} FTSE$ $DAX \xleftarrow{No(5\%)} FTSE$ (lag=3)

Note: See the notes for Table 7. The bandwidth is $\varepsilon_{386} = 1.37$.

Conclusion

In this article, we examined the level of CEE markets and developed European stock markets return comovement and return spillovers. Three CEE stock indices (the LJSEX, PX, and BUX) and four stock market indices from developed stock markets (the ATX, CAC40, DAX and FTSE) were analyzed. Non-conditional correlation analysis and Granger causality tests (based on Vector AutoRegression models) were used on the daily return series for the period from April 1, 1997 to May 12, 2010, which was divided into three sub-periods: the period before the CEE countries joined the European Union, the period that covers the first three years of CEE countries in the European Union and buoyant stock markets, and the period that began with the global financial crisis.

The main findings are as follows: i) The stock indices that are most correlated are the CAC40, FTSE100 and DAX. The stock markets of France, Great Britain and Germany seem to be the most integrated, which is a common observation in existing literature; ii) The CEE stock markets showed a smaller degree of comovement with other CEE and developed European stock markets; iii) Among the observed stock indices, the Slovenian stock market was the least correlated with other stock markets; iv) Not only stock returns in the developed stock markets of Austria, France, Germany and Great Britain Granger cause stock returns in the three CEE markets - the CEE stock market returns also influence the stock returns in developed markets; v) European integration and the global financial crisis seem to have strengthened the interdependence of CEE and developed stock markets (as measured by correlation coefficients and the strength and number of Granger causal connections).

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