INTERDEPENDENCE BETWEEN THE SLOVENIAN AND EUROPEAN STOCK MARKETS – A DCC-GARCH ANALYSIS

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ABSTRACT

This paper examines the comovement and spillover dynamics between the Slovenian and some European (the UK, German, French, Austrian, Hungarian and the Czech) stock market returns. A dynamic conditional correlation GARCH (DCC-GARCH) analysis is applied to returns series of representative national stock indices for the period from April 1997 to May 2010 to answer the following questions: i) Is correlation (comovement) between the Slovenian and European stock markets time-varying; ii) Are there return and volatility spillovers between European and Slovenian stock markets; iii) What effect did financial crises in the period from April 1997 to May 2010 have on the comovement between the investigated stock markets? Results of the DCC-GARCH analysis show that comovement between Slovenian and European stock markets is time-varying and that there were significant return spillovers between the stock markets. Financial crises in the observed period increased comovement between Slovenian and European stock markets.

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I. INTRODUCTION

International stock market linkages are of great importance for the financial decisions of international investors. Since the seminal works of Markowitz (1958) and the empirical evidence of Grubel (1968), it has been widely accepted that international diversification reduces the total risk of a portfolio. This is due to non-perfect positive comovement between the returns of portfolio assets. Increased comovement between asset returns can therefore diminish the advantage of internationally diversified investment portfolios (Ling and Dhesi, 2010).

Modeling the comovement of stock market returns is a challenging task. The conventional measure of market interdependence, known as the Pearson correlation coefficient, is a symmetric, linear dependence metric (Ling and Dhesi, 2010), suitable for measuring dependence in multivariate normal distributions (Embrechts et al., 1999). However, correlations may be nonlinear and time-varying (Xiao 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). It only represents an average of deviations from the mean without making any distinction between large and small returns, or between negative and positive returns (Poon et al., 2004). A better understanding of stock market interdependencies may be achieved by applying econometric methods: Vector Autoregressive (VAR) models (Malliaris and Urrutia, 1992; Gilmore and McManus, 2002), cointegration analysis (Gerrits and Yuce, 1999; Patev et al., 2006), GARCH models (Tse and Tsui, 2002; Bae et al., 2003; Égert and Kočenda, 2010; Cho and Parhizgari, 2008) and regime switching models (Garcia and Tsafack, 2009; Schwender, 2010). Among them, the GARCH (Generalized Autoregressive Conditional Heteroskedasticity) models gained a lot of popularity.

The GARCH models are used to analyze the volatility of individual assets (Bollerslev et al.; 1994; Palm, 1996; Shephard, 1996), while international investors are more interested in comovement and spillovers between the assets (or markets). A time-varying comovement between assets (or markets) can be effectively analyzed by multivariate GARCH (MGARCH – Multivariate Generalized Autoregressive Conditional Heteroskedasticity) models (Tse and Tsui, 2002; Bae et al., 2003; Égert and Kočenda, 2010; Cho and Parhizgari, 2008; Xiao and Dhesi, 2010; Égert and Kočenda, 2010).

There are several MGARCH models[3], of which the DCC-GARCH (Dynamic Conditional Correlation GARCH) models have greatly increased in popularity. They offer both the flexibility of univariate GARCH models and the simplicity of parametric correlation in the model (Swaray and Hamad, 2009). They are an extension of CCC-GARCH (Constant Conditional Correlation GARCH) models (Silvennoinen et al., 2005). More DCC-GARCH models have been developed: the version by Engle (2002), the version by Engle and Sheppard (2001), the model by Tse and Tsu (2002), a model by Christodoulakis and Satchell (2002), a model by Lee et al. (2006).

The paper aims to answer these question i) Is correlation (comovement) between the Slovenian and European stock markets time-varying; ii) Are there return and volatility spillovers between European and Slovenian stock markets; iii) What effect did financial crises

[3] An overview of the MGARCH models can be found in Bauwens et al. (2006), Silvennoinen and Teräsvirta (2009) or Linton (2009).

in the period from April 1997 to May 2010 have on the comovement between the Slovenian and European stock markets? These questions will be answered by applying a DCC-GARCH model of Engle and Sheppard (2001).

II. THE DCC-GARCH MODEL

The DCC-GARCH model of Engle and Sheppard (2001) assumes that returns from k assets are conditionally multivariate normal with zero expected value of return (r_t)[2] and covariance matrix H_t . Returns of the asset (stocks, stock indices), given the information set available at time $t-1$ (ξ_{t-1}), have the following distribution[4]:

$$r_t \middle| \xi_{t-1} \sim \boldsymbol{N(0,H_t)} \tag{1}$$

and

$$H_t \equiv D_t R_t D_t \tag{2}$$

where D_t is a $k \times k$ diagonal matrix of time varying standard deviations from univariate GARCH models with $\sqrt{h_{it}}$ on the i-th diagonal, and R_t is the time varying correlation matrix.
The loglikelihood of this estimator is written as:

$$L = -\frac{1}{2}\sum_{t=1}^{T}(k\log(2\pi) + 2\log(|D_t|) + \log(|R_t|) + \varepsilon' R_t^{-1}\varepsilon_t), \tag{3}$$

where $\varepsilon_t \sim \boldsymbol{N(0,R_t)}$ are the residuals standardized by their conditional standard deviation. Elements of the matrix D_t are given by a univariate GARCH model (Engle and Sheppard 2001)

$$h_{it} = \omega_i + \sum_{p=1}^{P_i}\alpha_{ip} r_{it-p}^2 + \sum_{q=1}^{Q_i}\beta_{iq} h_{it-q} \tag{4}$$

for $i = 1,2,...,k$ (variables, in our case stock indices), with the usual GARCH restrictions (for

non-negativity and stationarity $\sum_{p=1}^{P_i}\alpha_{ip} + \sum_{q=1}^{Q_i}\beta_{iq} < 1$).

Dynamic correlation structure is defined by the following equations

$$Q_t = (1 - \sum_{m=1}^{M}\alpha_m - \sum_{n=1}^{N}\beta_n)\overline{Q} + \sum_{m=1}^{M}\alpha_m(\varepsilon_{t-m}\boldsymbol{\varepsilon'_{t-m}}) + \sum_{n=1}^{N}\beta_n Q_{t-n} \tag{5}$$

[4] The description of the DCC-GARCH models is from Engle and Sheppard (2001). The same notations as by the authors are used.

$$R_t = Q_t^{*-1} Q_t Q_t^{*-1} \tag{6}$$

where M is the length of the innovation term in the DCC estimator, and N is the length of the lagged correlation matrices in the DCC estimator ($\alpha_m \geq 0$, $\beta_n \geq 0$, $\sum_{m=1}^{M} \alpha_m + \sum_{n=1}^{N} \beta_n < 1$).

$\overline{Q}$ is the unconditional covariance of the standardized residuals resulting from the first stage estimation and Q_t^* is a diagonal matrix composed of the square root of the diagonal elements of Q_t:

$$Q_t^* = \begin{bmatrix} \sqrt{q_{11}} & 0 & 0 & \cdots & 0 \\ 0 & \sqrt{q_{22}} & 0 & \cdots & 0 \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ 0 & 0 & 0 & \cdots & \sqrt{q_{kk}} \end{bmatrix} \tag{7}$$

The elements of the matrix R_t are:

$$\rho_{ijt} \equiv \frac{q_{ijt}}{\sqrt{q_{ii} q_{jj}}} \tag{8}$$

The DCC-GARCH model is estimated in two stages. In the first stage univariate GARCH models are estimated for each residual series, and in the second stage, residuals, transformed by their standard deviation estimated during the first stage, are used to estimate the parameters of the dynamic correlation. More specific, the parameters of the DCC-GARCH model, θ, are written in two groups: $(\phi_1, \phi_2, ..., \phi_k, \psi) = (\phi, \psi)$, where the elements of ϕ_i correspond to the parameters of the univariate GARCH model for the i-th asset series, $\phi_i = \omega_i, \alpha_{1i}, ..., \alpha_{P_i i}, \beta_{1i}, ..., \beta_{Q_1 i}$.

In empirical applications, normally a bivariate DCC(1,1)-GARCH(1,1) model is estimated, with two financial assets, $r_{1,t}$ and $r_{2,t}$ (Engle, 2002; Lebo and Box-Steffensmeier, 2008; Égert and Kočenda, 2010).

To estimate a DCC(1,1)-GARCH(1,1) model of stock indices return comovements, we first estimate a VAR (Vector Autoregressive) model:

$$r_{1,t} = \mu_1 + \sum_{i=1}^{p} a_{1,i} r_{1,t-i} + \sum_{i=1}^{p} b_1 r_{2,t-i} + \varepsilon_{1,t} \tag{9}$$

$$r_{2,t} = \mu_2 + \sum_{i=1}^{p} a_{2,i} r_{2,t-i} + \sum_{i=1}^{p} b_{2,i} r_{1,t-i} + \varepsilon_{2,t} \tag{10}$$

and then, using residuals of the VAR model, estimate a DCC(1,1)-GARCH(1,1) model:

$$\begin{aligned} h_{it} &= \omega_i + \alpha_{i1} r_{it-1}^2 + \beta_{i1} h_{it-1} \\ Q_t &= (1-\alpha_1-\beta_1)\overline{Q} + \alpha_1(\varepsilon_{t-1}\varepsilon_{t-1}') + \beta_1 Q_{t-1} \end{aligned} \tag{11}$$

III. EMPIRICAL RESULTS

A. Data

Stock indices returns are calculated as differences of logarithmic daily closing prices of indices ($\ln(P_t) - \ln(P_{t-1})$), where P is an index price). The following indices are considered: LJSEX (for Slovenia), ATX (for Austria), CAC40 (for France), DAX (for Germany), FTSE100 (for the UK), BUX (for the Hungary) and PX (for the Czech Republic). The period of observation is April 1, 1997 – May 12, 2010. Days of no trading on any of the observed stock market were left out. Total number of observations amounts to 3,060 days. Data sources of LJSEX, PX and BUX indices are their respective stock exchanges, data source of ATX, CAC40, DAX and FTSE100 indices is Yahoo Finance. Table 1 presents some descriptive statistics of the data. This is due to non-perfect positive comovement between the returns of portfolio assets. Increased comovement between asset returns can therefore diminish the advantage of internationally diversified investment portfolios (Ling and Dhesi, 2010).

TABLE 1—Descriptive statistics of indices return series

	Min	Max	Mean	Std. deviation	Skewness	Kurtosis
ATX	-0.1637	0.1304	0.0002515	0.01558	-0.40	14.91
CAC40	-0.0947	0.1059	0.0001206	0.01628	0.09	7.83
DAX	-0.0850	0.1080	0.0002071	0.01756	-0.06	6.58
FTSE100	-0.0927	0.1079	0.0000774	0.01361	0.09	9.30
BUX	-0.1803	0.2202	0.0004859	0.02021	-0.30	15.90
PX	-0.199	0.2114	0.0002595	0.01667	-0.29	24.62
LJSEX	-0.1285	0.0768	0.0003521	0.01062	-0.87	20.19
BUX	-0.1803	0.2202	0.0004859	0.02021	-0.30	15.90

SOURCE: Own calculations.

Notes: 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 (Table 2) rejects the hypothesis of normally distributed observed time series. Al indices returns are asymmetrically (left) distributed around the sample mean, kurtosis is greater than with normally distributed time series. Ljung-Box Q-statistics reject the null hypothesis of no serial correlation in stock index squared returns for all stock indices.

Since we use GARCH process to model the variance in the asset returns, we also test for the presence of the ARCH effect. The null hypothesis of no ARCH effects is rejected at 1% significance level. This suggests that GARCH parameterization might be appropriate for the conditional variance processes.

TABLE 2—Jarque-Bera, Ljung Box and ARCH effect test

	Min	Max	Mean
ATX	18,153.481***	2,759.19***	746.18***
CAC40	2,982.523***	1,495.14***	454.58***
DAX	1,635.472***	1,450.47***	436.93***
FTSE100	5,069.608***	1,939.78***	578.71***
BUX	21,260.91***	931.89***	331.68***
PX	59,654.928***	1,773.01***	686.37***
LJSEX	38,073.932***	927.09***	391.37***

SOURCE: Own calculations.

*Notes: Jarque-Bera statistics: *** indicate that the null hypothesis (of normal distribution) is rejected at the 1% significance (** that null hypothesis is rejected at the 5% significance and * that the null hypothesis is rejected at 10% significance. Ljung-Box Q^2 statistics ($Q^2(10)$) reports values of the statistics with 10 lags: *** indicate that the null hypothesis of no serial correlation can be rejected at 1% significance level. Engle (1988) ARCH test reports the value of LM test statistics at 5 lags included: *** indicate that the null hypothesis can be at 1% significance level.*

To test 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 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 reject 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 rejected for all stock indices. On the basis of the stationarity tests we conclude that time series of indices returns are stationary. Results of stationarity tests are presented in Table 3.

TABLE 3—Results of stationarity tests

	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)
ATX	0.19** (12)	0.19 (13)	-53.59*** (15)	-53.59*** (15)	- 40.60** (L=1)	- 40.61*** (L=1)
CAC40	0.11 (15)	0.25 (15)	-57.84*** (14)	-57.79*** (14)	- 36.14*** (L=2)	- 36.11*** (L=2)
DAX	0.10 (1)	0.11 (1)	-57.81*** (3)	-57.81*** (3)	- 57.69*** (L=0))	- 57.70*** (L=0)
FTSE100	0.09 (9)	0.10 (9)	-58.28*** (7)	-58.29*** (7)	-29.11*** (L=3)	- 29.11*** (L=3)
BUX	0.07 (6)	0.07 (6)	-54.30*** (6)	-54.30*** (6)	-54.30*** (L=0)	- 54.31*** (L=0)
PX	0.16* (10)	0.17 (10)	-55.02*** (10)	-55.03*** (10)	-16.68*** (L=8)	- 16.68*** (L=8)
LJSEX	0.25*** (11)	0.59** (12)	-44.10*** (0)	-43.80*** (3)	-37.23*** (L=1)	-37.13*** (L=1)

SOURCE: Own calculations.

*Notes: KPSS and PP tests were 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: a model with a constant and the model with a constant plus trend; number of lags to be included (L) for ADF test were selected by SIC criteria (30 was a maximum lag). Exceeded critical values for rejection of null hypothesis are marked by *** (1% significance level), ** (5% significance level) and * (10% significance level).*

B. DCC-GARCH conditional correlation results

Before estimating a DCC(1,1)-GARCH(1,1) model, time series have to be filtered to assure zero expected (mean) value of the time series. A bivariate Vector Autoregressive (VAR) model for the return series is used to initially remove potential linear structure between pairs of stock indices returns. Then the residuals of the VAR model are used as inputs for the DCC-GARCH model.

An important element of specifying a VAR model is to determine the optimal lag of the explanatory variables. More criteria can be used. In the empirical literature most frequently used 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, compares these criteria and his findings show 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) best results achieve AIC in FPE criteria, whereas for larger sample sizes (120 and more observations) best results are obtained by HQC and SIC criteria. In a similar simulation study, Ashgar and Abdi (2007) find evidence that generally support findings of Liew (2004): HQC performs the best for sample sizes of 120 observations, whereas for larger sample sizes (more than 240 observations) SIC outperforms all the other criteria. On this foundation, we use SIC criteria to select the optimal lag length of the VAR model. Results of the optimal lag selection are presented in Table 4.

TABLE 4—Optimal lag in the bi-variate VAR models

	KPPS test (a constant + trend)
LJSEX-PX	1
LJSEX-BUX	1
LJSEX-ATX	1
LJSEX-CAC40	1
LJSEX-DAX	1
LJSEX-FTSE100	1

SOURCE: Own calculations.

Notes: Optimal lag is selected by SIC criteria.

The results (Table 5) show that lagged returns of PX, BUX, ATX, CAC40, DAX and FTSE100 are statistically significantly explaining LJSEX returns. Also LJSEX lagged returns statistically significant explain returns of other stock indices. This is evidence of a feedback mechanism -- return spillovers between LJSEX and other stock markets are bi-directional.

TABLE 5—Results of the VAR models for stock indices pairs

	LJSEX-PX	LJSEX-BUX	LJSEX-ATX	LJSEX-CAC40	LJSEX-DAX	LJSEX-FTSE100
A constant	0.000264 (1.41)	0.000248 (1.33)	0.000259 (1.40)	0.000267 (1.44)	0.000261 (1.41)	0.000270 (1.46)
LJSEX (lag1)	0.20015*** (10.84)	0.19573*** (10.84)	0.17550*** (9.59)	0.19279*** (10.85)	0.19501*** (10.92)	0.19107*** (10.73)
Other index in pair (lag1)	0.04968*** (4.22)	0.06093*** (6.42)	0.10750*** (8.61)	0.10089*** (8.70)	0.08357*** (7.74)	0.12169*** (8.75)
	PX-LJSEX	BUX-LJSEX	ATX-LJSEX	CAC40-LJSEX	DAX-LJSEX	FTSE100-LJSEX
A constant	0.000287 (0.95)	0.000500 (1.37)	0.000255 (0.91)	0.000157 (0.53)	0.000241 (0.76)	0.000105 (0.43)
LJSEX (lag1)	-0.08498*** (-2.85)	-0.08646** (-2.44)	-0.02984 (-1.07)	-0.07723** (-2.73)	-0.08633*** (-2.83)	-0.07040*** (-2.98)
Other index in pair (lag1)	0.02106 (1.11)	0.02893 (1.55)	0.03664* (1.93)	-0.02388 (-1.23)	-0.03191* (-1.73)	-0.03057* (-1.66)

SOURCE: Own calculations.

*Notes: In parentheses under the parameter estimation, t-statistics are given. *** (**/*) denote rejection of the null hypothesis that parameter is equal to zero at 1% (5%/10%) significance level. The first index (for example LJSEX in LJSEX-PX pair) in the indices pairs represents dependent variable in a bivariate VAR model regression.*

Next, a test of Engle and Sheppard (2001) for constant correlation was applied in order to determine whether the correlation between every pair of stock indices is time-varying or not.

The hypotheses of the test are:

$$H_o = R_t = \overline{R} \qquad \textbf{\textit{(12)}}$$

$$H_1 = vech^u(R_t) = vech^u(R_t) + \beta_1 vech^u(R_{t-1}) + \ldots + \beta_p vech^u(R_{t-p}),$$

where $vech^u$ is a modified $vech$ which only selects elements above the diagonal.

The testing procedure is as follows. First the univariate GARCH processes are estimated, and then residuals are standardized. Then the correlation of the standardized residuals is estimated, and the vector of univariate standardized residuals is jointly standardized by the symmetric square root decomposition of the $\overline{R}$. Under the null of constant correlation, these residuals should be IID with a variance covariance matrix given by I_k. The artificial regressions will be a regression of the outer products of the residuals on a constant and lagged outer products. The vector autoregression is:

$$Y_t = \alpha + \beta_1 Y_{t-1} + \ldots + \beta_s Y_{t-s} + \eta_t \qquad \textbf{(13)}$$

where $Y_t = vech^u\left[(\overline{R}^{-0.5} D^{-1}\varepsilon_t)(\overline{R}^{-0.5} D^{-1}\varepsilon_t)' - I_k\right]$ and $\overline{R}^{-0.5} D_t^{-1}\varepsilon_t$ is a $k \times 1$ vector of residuals jointly standardized under the null hypothesis.

Under the null hypothesis the intercept and all of the lag parameters in the model should be zero. The test can then be conducted as $\frac{\hat{\delta} X' X \hat{\delta}'}{\hat{\sigma}^2}$, which is asymptotically $\chi^2_{(s+1)}$, where $\hat{\delta}$ are estimated regression parameters and X is a matrix consisting of regressors.

The null hypothesis of constant correlation was rejected for the next stock indices pairs -- LJSEX-PX, LJSEX-BUX, LJSEX-DAX and LJSEX-FTSE100 (See Table 6). For LJSEX-ATX and LJSEX-CAC40 pairs we cannot reject the null hypothesis of constant correlation. For the former pairs, a DCC(1,1)-GARCH(1,1) model is estimated, for the later a DCC(1,1)-GARCH(1,1) and a CCC-GARCH(1,1) model.

TABLE 6—A test of constant correlation for stock indices pairs

Parameter	LJSEX-PX	LJSEX-BUX	LJSEX-ATX	LJSEX-CAC40	LJSEX-DAX	LJSEX-FTSE100
χ^2	33.7127	34.1908	9.3114	7.6732	24.7153	22.4866
p-value	0.0004***	0.0003****	0.5932	0.7422	0.0100***	0.0209**

SOURCE: Own calculations.

Notes: A constant correlation model test of Engle and Sheppard (2001) with 10 lags is estimated. The test statistic is χ^2 *with 10 +1 degress of freedom. *** denote rejection of the null hypothesis of constant correlation at 1% significance (**at 5% significance, and * at 10% significance) level..*

The results for the DCC(1,1)-GARCH(1,1) model are presented in Table 7 and for the CCC-GARCH(1,1) model in Table 8. All estimated GARCH model parameters ($\omega_{\text{LJSEX - other index}}$, $\omega_{\text{other index - LJSEX}}$, $\alpha_{\text{LJSEX - other index}}$, $\alpha_{\text{other index - LJSEX}}$, $\beta_{\text{LJSEX - other index}}$ and $\beta_{\text{other index - LJSEX}}$) are statistically significant. Conditional variance of LJSEX returns is influenced by past return innovations in the foreign index in the pair ($\alpha_{\text{LJSEX - other index}}$ and $\alpha_{\text{other index - LJSEX}}$) and by its lagged variances ($\beta_{\text{LJSEX - other index}}$ and $\beta_{\text{other index – LJSEX}}$). Statistically significant parameters $\beta_{\text{LJSEX - other index}}$ and $\beta_{\text{other index - LJSEX}}$ indicate, that volatility transmission is bi-directional between the indices in pairs (so they are transmitted to Slovenian stock market and, vice versa, from the Slovenian stock market to the other markets). The DCC parameter β is statistically significant in all cases, while α is significant only for stock indices pairs LJSEX-PX, LJSEX-BUX and LJSEX-ATX. If we also consider that $\beta > \alpha$ for all indices pairs, we can argue, that behavior of current variances is more affected by magnitude of past variances as by past return innovations. Having value β close to 1 indicates high persistance in the time series of correlation, R_t. The sum of the

DCC parameters ($\alpha + \beta$) is larger than zero (meaning that conditional correlation between the pairs of indices returns is not constant); actually, values close to 1 are observed, indicating that conditional variances are highly persistent and only slowly mean-reverting (Lebo and Box-Steffensmeier, 2008). Results of the Ljung-Box statistics do not reject the null hypothesis of no serial correlation in squared residuals of estimated DCC-GARCH model, suggesting a DCC(1,1)-GARCH(1,1) model is appropriately specified.

TABLE 7—Results of the DCC(1,1)-GARCH(1,1) model for stock market indices

	LJSEX-PX	LJSEX-BUX	LJSEX-ATX	LJSEX-CAC40	LJSEX-DAX	LJSEX-FTSE100
$\omega_{\text{LJSEX- other index}}$	4.37e-06 (3.45)***	4.50e-06 (3.54)***	4.54e-6*** (3.18)	4.40e-6*** (2.76)	4.37e-6*** (3.26)	4.43e-6*** (2.85)
$\alpha_{\text{LJSEX-other index}}$	0.3571*** (6.19)	0.3532 (5.90)***	0.3541*** (5.40)	0.3363*** (4.44)	0.3429*** (5.29)	0.3362*** (4.52)
$\beta_{\text{LJSEX - other index}}$	0.6429*** (12.37)	0.6468*** (12.42)	0.6459*** (10.83)	0.6637*** (9.53)	0.6571*** (11.37)	0.6638*** (9.88)
Ljung-Box $Q^2(10)$ statistics	12.81	14.57	16.25*	13.91	13.88	13.66
$\omega_{\text{other index - LJSEX}}$	7.55e-06*** (4.39)	1.55e-05** (2.05)	3.49e-6*** (3.76)	2.39e-6*** (2.76)	3.32e-6*** (3.06)	1.32e-6*** (3.15)
$\alpha_{\text{other index -LJSEX}}$	0.1389*** (8.60)	0.1550*** (2.66)	0.1202*** (5.72)	0.0930*** (7.01)	0.1140*** (6.83)	0.0948*** (8.09)
$\beta_{\text{other index -LJSEX}}$	0.8367*** (57.42)	0.8117*** (12.47)	0.8666*** (42.38)	0.9022*** (67.19)	0.8802*** (55.22)	0.9018*** (78.99)
Ljung-Box $Q^2(10)$ statistics	11.42	6.26	13.61	8.74	11.12*	9.77
α	0.0235*** (2.55)	0.0304*** (2.45)	0.0039** (1.70)	0.0029* (1.45)	0.0143* (1.56)	0.0169 (0.67)
β	0.9181*** (25.58)	0.8687*** (14.23)	0.9927*** (172.83)	0.9948*** (211.22)	0.9541*** (25.73)	0.9275*** (5.83)

SOURCE: Own calculations.

*Notes: Parameters $\omega_{LJSEX\text{-}other\ index}$, $\alpha_{JSEX\text{-}other\ index}$, $\beta_{LJSEX\text{-}other\ index}$ are estimated parameters of a univariate GARCH (1,1) model, with residuals input from the estimated bivariate Vector Autoregressive (VAR) model with LJSEX returns as dependent variable and the other index returns as explanatory variable. $\omega_{other\ index–LJSEX}$, $\alpha_{other\ index\ –LJSEX}$, $\beta_{other\ index–LJSEX}$ are estimated parameters of a univariate GARCH (1,1) model, with residuals input from the estimated bivariate Vector Autoregressive (VAR) model with LJSEX returns as explanatory variable and the other index returns as dependent variable. In parentheses under the parameter estimation, t-statistics are given: *** (**/*) denote rejection of the null hypothesis that parameter is equal zero at 1% (5%/10%) significance level. Ljung-Box $Q^2(10)$ statistics reports the value of the statistics at lag 10: ***(**/*) indicate that the null hypothesis of no serial correlation in squared residuals of estimated DCC-GARCH model can be rejected at 1% (5%/10%) significance level.*

TABLE 8—Results of the DCC(1,1)-GARCH(1,1) model for stock market indices

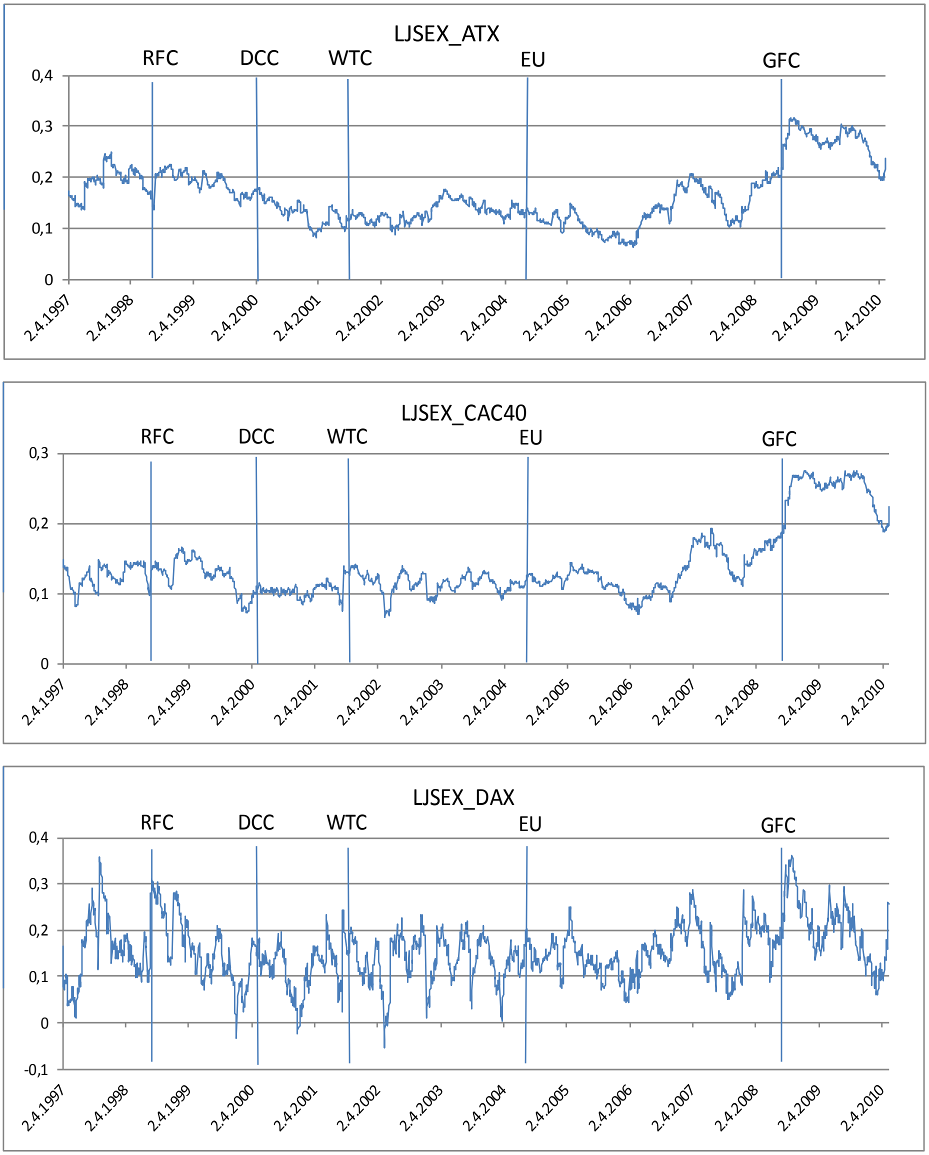
Parameter	LJSEX-ATX	LJSEX-CAC40
$\omega_{\text{LJSEX - other index}}$	4.56e-06*** (3.18)	4.40e-06*** (2.76)
$\alpha_{\text{LJSE - other index}}$	0.3541*** (5.40)	0.3363*** (4.44)
$\beta_{\text{LJSEX - other index}}$	0.6459*** (10.83)	0.6637*** (9.53)
$\omega_{\text{other index - LJSEX}}$	3.49e-06*** (3.76)	2.39e-06*** (2.76)
$\alpha_{\text{other index - LJSEX}}$	0.1202*** (5.72)	0.0930*** (7.02)
$\beta_{\text{other index - LJSEX}}$	0.866595*** (42.38)	0.9022*** (67.1917)
Constant correlation estimation	0.1678	0.1412
Parameter	LJSEX-ATX	LJSEX-CAC40

SOURCE: Own calculations.
Notes: See notes for table 7.

We can observe a highly volatile time path of conditional correlation between pairs of stock indices returns (Figure 1).

DCC-GARCH CONDITIONAL CORRELATION BETWEEN RETURN OF THE LJSEX AND OTHER EUROPEAN STOCK INDICES

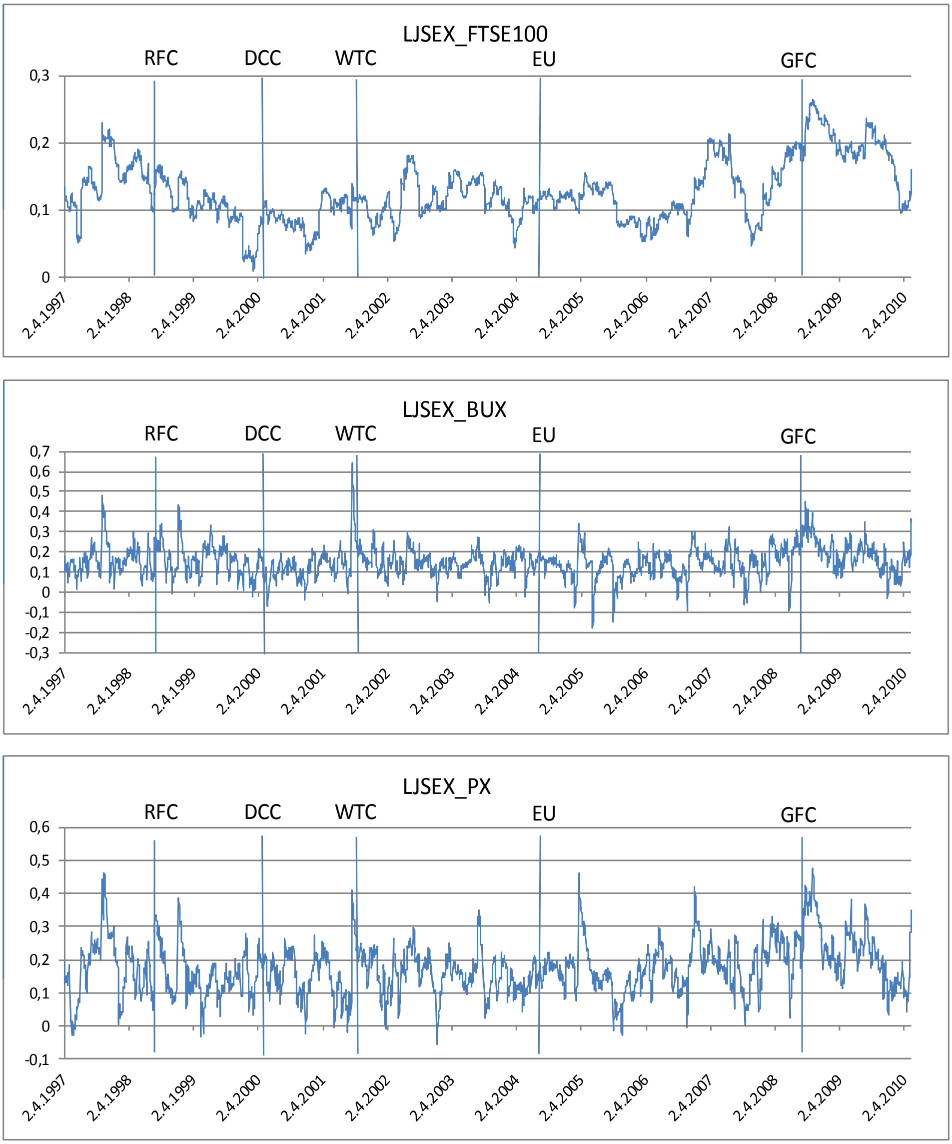
FIGURE 1



SOURCE: Author

DCC-GARCH CONDITIONAL CORRELATION BETWEEN RETURN OF THE LJSEX AND OTHER EUROPEAN STOCK INDICES (CONTINUED)

FIGURE 2



SOURCE: Author

Notes: On the time axis the financial crises are denoted: RFC = Russian financial crisis (outbreak on August 13, 1998), DCC = Dot-Com crisis (the date, March 24, 2000, is taken, when the peak of S&P500 was reached, before the dot-com crisis began), WTC = attack on WTC in New York (September 11, 2001), EU = the date when the Slovenia joined European Union (May 1, 2004), GFC = Global financial crisis (September 16, 2008). The vertical dotted lines indicate these events.

The main findings of figure 1 are the following. First of all, one can observe high volatility of conditional correlations between LJSEX and European stock indices returns, meaning correlation (comovement) between Slovenian and European stock markets returns is time-varying. The finding of time varying comovement between stock markets is in accordance with the empirical literature on measuring international stock market comovements (Forbes and Rigobon, 2002; Phylaktis and Ravazzolo, 2005; Syriopoulos, 2007; Gilmore et al., 2008; Kizys and Pierdzioch, 2009).Secondly, the trend of correlation between Slovenian and developed European stock markets (Austrian, German, French, the UK) in observed period is rising, indicating that Slovenian stock market has become more interdependent with these stock markets.

Further, comovement between Slovenian and the Central and Eastern European stock markets (PX and BUX) during the observed period was more volatile than with developed European stock markets. Considering the whole observed period, no increasing trend of conditional correlation can be confirmed between Slovenian and Central and Eastern European stock markets. Financial crises, especially the global financial crisis of 2007-2008, had a major impact on increased comovement of Slovenian stock market with European stock markets. Our findings confirm mounting evidence that correlations among international markets tend to increase when stock returns fall precipitously (Lin et al., 1994; Longin and Solnik, 1995; Karolyi and Stulz, 1996; Chesnay and Jondeau, 2001; Ang and Bekaert, 2002; Baele, 2005).

IV. CONCLUSION

In this paper the comovement and spillover dynamics between returns of the Slovenian and six European stock markets (the United Kingdom, German, French, Austrian, Hungarian and the Czech stock market) were studied. A DCC-GARCH model proved to be a statistically appropriate model to study return comovement and spillovers between these markets, and the key results obtained are: (1) Statistically significant bi-directional volatility spillovers were identified between Slovenian and European stock markets; (2) Volatilities of stock indices´ returns were more affected by magnitude of past variances as by past return innovations; (3) Conditional correlations between LJSEX and European stock indices returns in the observed period were highly volatile; (4) Comovement between Slovenian and developed European stock markets in the observed time period has generally increased (a rising trend of comovement could be indentified), while comovement with Central and Eastern European stock markets did not; (5) Financial crises, especially the global financial crisis of 2007-2008, had a major impact on increased comovement of Slovenian stock market with European stock markets.

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ODVISNOST IZMEĐU SLOVENSKOG I EUROPSKIH DIONIČKIH TRGOVA – DCC-GARCH ANALIZA

SAŽETAK

U ovom radu se analizira dinamika kretanja donosa i prijenosa volatilnosti između dioničkih trgova Slovenije i pojedinih europskih država (Velike Britanije, Njemačke, Austrije, Madžarske i Češke republike). Upotrijebljena je DCC-GARCH analiza na podacima dnevnih donosa dioničkih trgova za period između aprila 1997 i maja 2010 kako bi se odgovorilo na sledeča pitanja: i) Da li je korelacija između donosima slovenskog i europskih dioničkih trgova dinamična; ii) Postoje li prijenos donosa i volatilnosti između slovenskog i europskih dioničkih trgova; iii) Kako su financijske krize u Europi i svijetu u istraživanom periodu utjecale na korelaciju donosa dioničkih trgova? Rezultati pokazuju, kako je korelacija između donosima slovenskog i europskih dioničkih trgova dinamična i da postoje prijenos donosa i volatilnosti između slovenskog i europskih dioničkih trgova. Financijske krize su vodile u porast u međusobni odvisnosti slovenskog i europskih dioničkih trgova.

KLJUČNE RIJEČI: *DCC-GARCH, dionički trg, analiza kretanja donosa, prijenos volatilnosti*