Silvo Dajcman[1]

DYNAMICS OF HUNGARIAN STOCK MARKET LINKAGES WITH EUROPEAN STOCK MARKETS IN THE PERIOD 1997-2010: DCC-GARCH ANALYSIS

We examine the comovement and spillover dynamics between returns of Hungarian and 6 European stock markets (Austrian, French, German, UK, Czech and Slovene). Applying DCC-GARCH for the period 1997-2010 we find that: i) comovement between Hungarian and European stock markets is time-varying; ii) there are significant return spillovers between Hungarian and other European stock markets.

Keywords: *stock markets; comovement; DCC-GARCH; Hungary; Europe.*

JEL classification: G15; G11; F36.

Сільво Дайчман

ДИНАМІКА ЗВ'ЯЗКУ ФОНДОВОГО РИНКУ УГОРЩИНИ З ІНШИМИ ЄВРОПЕЙСЬКИМИ РИНКАМИ: DCC-GARCH-АНАЛІЗ ЗА 1997-2010 РОКИ

У статті досліджено взаємозв'язок динаміки прибутків фондового ринку Угорщини та 6 інших європейських країн - Австрії, Франції, Німеччини, Великої Британії, Чехії та Словенії. За результатами аналізу даних за 1997-2010 рр. методом DCC-GARCH зроблено висновки, що: 1) взаємозміни на угорському та інших європейських ринках залежать від фактору часу; 2) для усіх розглянутих ринків характерним є ефект пересування прибутків з ринку на ринок.

Ключові слова: *фондові ринки; взаєморух; DCC-GARCH; Угорщина; Європа.*

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Сильво Дайчман

ДИНАМИКА СВЯЗИ ФОНДОВОГО РЫНКА ВЕНГРИИ С ДРУГИМИ ЕВРОПЕЙСКИМИ РЫНКАМИ: DCC-GARCH-АНАЛИЗ ЗА 1997-2010 ГОДЫ

В статье исследована взаимосвязь динамики прибылей фондового рынка Венгрии и 6 других европейских стран – Австрии, Франции, Германии, Великобритании, Чехии и Словении. По результатам анализа данных за 1997-2010 г.г. методом DCC-GARCH сделаны выводы, что: 1) взаимоизменения венгерского и других европейских рынков зависят от фактора времени; 2) для всех рассматриваемых рынков характерным является эффект перемещения прибыли с рынка на рынок.

Ключевые слова: *фондовые рынки; взаимодвижение; DCC-GARCH; Венгрия; Европа.*

1. Introduction. International stock market linkages are of great importance for financial decisions of international investors. Since the seminal works of Markowitz (1952) 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).

[1] Department of Finance, Faculty of Economics and Business, University of Maribor, Slovenia.

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). 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 of which multivariate GARCH models proved to be very successful (Tse and Tsui, 2002; Xiao and Dhesi, 2010).

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 assets (or markets). Comovement between assets (or markets) may be time-varying (Tse and Tsui, 2002; Bae et al., 2003; Cho and Parhizgari, 2008; Xiao and Dhesi, 2010) and can be analyzed by multivariate GARCH models (MGARCH – Multivariate Generalized Autoregressive Conditional Heteroskedasticity).

There are several MGARCH models[2], of which DCC-GARCH (Dynamic Conditional Correlation GARCH) models have great popularity. They offer both flexibility of univariate GARCH models and simplicity of parametric correlation in a model (Swaray and Hamad, 2009). They are an extension of CCC-GARCH. More DCC-GARCH models have been developed: the version by Engle (2002), the version by Engle and Sheppard (2001), the model by Tse and Tsui (2002), the model by Christodoulakis and Satchell (2002), the model by Lee et al. (2006).

By applying the DCC-GARCH model of Engle and Sheppard (2001) the paper aims to: i) investigate comovement dynamics between Hungarian and some European (UK, German, the French, the Austrian, Czech and Slovenian) stock markets in the period from 1997 to 2010; ii) examine whether correlation (comovement) between the stock markets is time-varying; iii) explore what effect financial crises in the period from 1997 to 2010 exerted on comovement between these stock markets.

2. Methodology

2.1. The DCC-GARCH model. DCC-GARCH model of Engle and Sheppard (2001) assumes that returns from k assets are conditionally multivariate normal with zero expected value (r_t)[3] and covariance matrix H_t. The returns of the asset (stocks,

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

[3] Asset return series, entering as explanatory variable in a DCC-GARCH model, have to be filtered, so that the expected (mean) value of the series is null. More methods of filtering are available. Filtering is often achieved by first estimating a bivariate Vector Autoregressive (VAR) model for the return series to initially remove potential linear structures between pairs of stock index returns, and then using the residuals of the VAR model as inputs for the DCC-GARCH model (used by e.g. Crespo-Cuaresma and Wojcik, 2006; Egart and Kocenda, 2010). The second, also popular, method is to demean the return series and then use the demeaned returns in a DCC-GARCH estimation (used by e.g. Lebo and Box-Steffensmeier (2008) or Engle (2002)). As Engle (2002) argues, the standard errors of the DCC-GARCH model will not depend on the choice of filtration, as the cross partial derivative of the log-likelihood with respect to the mean and the variance parameters has an expectation of zero when using the normal likelihood.

stock indices), given the information set available at time $t-1$, have the following distribution[4]:

$$r_t \mid \Im_{t-1} \approx N(0, H_t),$$

and

$$H_t \equiv D_t R_t D_t,$$

where D_t is the $k \times k$ 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 log-likelihood of this estimator is written as:

$$L = -\frac{1}{2}\sum_{t=1}^{T}(k\log(2\pi) + 2\log(|D_t|) + \log(|R_t|) + \in'_t R_t^{-1} \in_t),$$

where $\in_t \approx N(0, R_t)$ are the residuals standardized by their conditional standard deviation. The elements of the matrix D_t are given by the univariate GARCH model (Engle and Sheppard 2001):

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

where $i = 1, 2, ..., k$ (variables, in our case stock indices), with the usual GARCH restrictions (for non-negativity and stationarity)[5].

$$\sum_{p=1}^{P_i} \alpha_{ip} + \sum_{q=1}^{Q_i} \beta_{iq} < 1$$

The dynamic correlation structure is defined by the following equations:

$$Q_t = (1 - \sum_{m=1}^{M} \alpha_m - \sum_{n=1}^{N} \beta_n)\overline{Q} + \sum_{m=1}^{M} \alpha_m (\in_{t-m} \in'_{t-m}) + \sum_{n=1}^{N} \beta_n Q_{t-n},$$

$$R_t = Q_t^{*-1} Q_t Q_t^{*-1}$$

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:

$$(\alpha_m \geq 0, \quad \beta_n \geq 0, \quad \sum_{m=1}^{M} \alpha_m + \sum_{n=1}^{N} \beta_n < 1)$$

$\overline{Q}$ 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:

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

4 The description of the DCC-GARCH models is summarized by Engle and Sheppard (2001). We use the same notation as the authors.

5 From the GARCH model it follows that at every time, t, conditional variance equals the sum of: i) the weighted long-run variance (w_i is a constant, equal to long run variance of the GARCH model, multiplied by a factor $(1 - \alpha - \beta)$), ii) the moving average term, which is the sum of the previous lags of squared-innovations times the assigned weight α for each lagged square innovation (ARCH effect), and iii) the autoregressive term, which is the sum of the lagged variances times the assigned weight β (GARCH effect).

The elements of the matrix R_t are:

$$\rho_{ijt} = \frac{q_{ijt}}{\sqrt{q_{ii} q_{jj}}}$$

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

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

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

consequently, with the obtained residuals of the VAR model, we estimate a DCC(1,1)-GARCH(1,1) model:

$$h_{it} = \omega_i + \alpha_{i1} r_{it-1}^2 + \beta_{i1} h_{it-1}$$

$$Q_t = (1 - \alpha_1 - \beta_1)\overline{Q} + \alpha_1(\in_{t-1} \in'_{t-1}) + \beta_1 Q_{t-1}$$

3. Empirical results

3.1. Data. Data on the stock indices return are calculated as differences of logarithmic daily closing value of indices ($ln(P_t) - ln(P_{t-1})$, where P is an index value). The following indices are considered: BUX (for Hungary), PX (Czech Republic), ATX (Austria), CAC40 (France), DAX (Germany), FTSE100 (the United Kingdom) and LJSEX (Slovenia). The first day of the observations is April 1, 1997, the last day is May 12, 2010. Days of no trading on any of the observed stock market were left out. Total number of the observations amounts to 3,060 days. Data sources for LJSEX, PX and BUX indices are their respective stock exchanges; data source for ATX, CAC40, DAX and FTSE100 indices is Yahoo Finance.

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

Table 1. **Descriptive statistics of the indices return series**

	Min	Max	Mean	Std. deviation	Skewness	Kurtosis
BUX	-0.1803	0.2202	0.0004859	0.02021	-0.30	15.90
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
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

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 more to the right. Kurtosis: The kurtosis of the normal distribution is 3. Fat-tailed distributions have a kurtosis greater than 3; distributions that are less outlier-prone than normal distributions have a kurtosis less than 3.

3.2. Some preliminary tests of the time series. Jarque-Bera test (Table 2) rejects the hypothesis of normally distributed time series, all indices returns are asymmetrically (left) distributed around the sample mean, kurtosis is greater than with normally distributed time series. Ljung-Box Q-statistics rejects 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 the 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 tests**

	Jarque-Bera statistics	Ljung-Box Q^2 statistics ($Q^2(10)$)	ARCH effect (5)
BUX	21,260.91***	931.89***	331.68***
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***
PX	59,654.928***	1,773.01***	686.37***
LJSEX	38,073.932***	927.09***	391.37***

Notes: Jarque-Bera statistics: *** indicate that the null hypothesis (of normal distribution) is rejected at the 1% significance level (** for the 5% significance level and * for the 10% significance level). Ljung-Box Q^2 statistics (Q2(10)) reports values of the statistics with 10 lags: *** indicate that the null hypothesis of no serial correlation can be rejected at the 1% significance level. Engle ARCH test reports the value of the LM test statistics at 5 lags included: *** indicate that the null hypothesis can be at the 1% significance level.

To test stationarity of stock index return time series Augmented Dickey-Fuller (ADF) test, Phillips-Peron (PP) and Kwiatkowski-Philips-Schmidt-Shin (KPSS) test were applied. The test results are presented in Table 3.

Table 3. **The results of stationarity tests of time series**

	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)
BUX	0.065 (6)	0.065 (6)	-54.295*** (6)	-54.304*** (6)	-54.301*** (L=0)	- 54.310*** (L=0)
PX	0.158* (10)	0.170 (10)	-55.022*** (10)	-55.029*** (10)	-16.676*** (L=8)	- 16.676*** (L=8)
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)
LJSEX	0.249*** (11)	0.591** (12)	-44.099*** (0)	-43.795*** (3)	-37.229*** (L=1)	-37.128*** (L=1)

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. 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 a 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).

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 was not significantly different from zero in all the stationarity tests, 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 except LJSEX) at the 1% significance level. The null hypothesis of PP and ADF tests is rejected for all the stock indices. On the basis of stationarity tests we conclude that all indices return time series are stationary.

3.3. DCC-GARCH time-varying conditional correlation analysis results. Before estimating a DCC(1,1)-GARCH(1,1) model, time series had to be filtered to assure zero expected (mean) value of the time series. A bivariate vector autoregressive (VAR) model for return series was used to initially remove potential linear structure between the pairs of stock index returns. Then the residuals of the VAR model are used as inputs for the DCC-GARCH model.

Table 4. **Results of VAR models for stock indices in pair with BUX**

	BUX-PX	BUX-ATX	BUX-CAC40	BUX-DAX	BUX-FTSE100	BUX-LJSEX
A constant	0.000475 (1.299420)	0.000471 (1.289885)	0.000484 (1.329369)	0.000476 (1.304285)	0.000519 (1.426564)	0.000500 (1.299420)
BUX (lag1)	0.015589 (0.719063)	-0.012126 (-0.579731)	-0.031274 (-1.522126)	-0.010063 (-0.476162)	-0.037915 *(lag1) (-1.814996) 0.007834 (lag2) (0.374804) -0.069702*** (lag3) (-3.360802)	0.028934 (1.5528)
Other index in pair (lag1)	0.004965 (0.000475)	0.077127*** (2.842034)	0.126846*** (4.971175)	0.061935** (2.545739)	0.174776 (lag1)*** (5.647530) -0.029814 (lag2)*** (-0.955813) 0.049410 (lag3)*** (1.591083)	-0.086464** (-2.4391)
	PX-BUX	ATX-BUX	CAC40-BUX	DAX-BUX	FTSE100-BUX	LJSEX-BUX
A constant	0.000243 (0.807626)	0.000231 (0.822140)	0.000135 (0.458596)	0.000215 (0.675958)	0.000102 (0.414727)	0.000248 (1.334087)
BUX (lag1)	0.058368*** (3.270285)	0.045543*** (2.824619)	-0.009093 (-0.547788)	-0.003917 (-0.213254)	-0.003387 (lag1) (-0.240806) 0.001024 (lag2) (-0.072792) -0.014339 (lag3) (-1.026963)	0.060933*** (6.422511)
Other index in pair (lag1)	-0.034571 (-1.596790)	0.000586 (0.028005)	-0.028634 (-1.388997)	-0.040537* (-1.917106)	-0.049222*** (lag1) (-2.362459) -0.070443***(lag2) (-3.354446) -0.083981***(lag3) (-4.016922)	0.195731*** (10.843982)

Notes: In parentheses under the parameter estimation, t-statistics are given. *** (**/*) denote rejection of the null hypothesis that parameter is equal to zero at the 1% (5%/10%) significance level. The first index (for example BUX in the BUX-CAC40 pair) in the indices pairs represents dependent variable in a bivariate VAR model regression equation. Schwarz Information Criterion was used to select optimal lag of the explanatory variables in VAR.

The results of the VAR model (Table 5) show that the lagged returns of LJSEX, ATX, CAC40, DAX and FTSE100 significantly explain BUX returns, while the lagged BUX returns may be used to forecast LJSEX, PX and ATX returns. Based on these results, we may note that there are significant spillovers between the Hungarian and European stock markets.

Next, a test for constant correlation was applied in order to determine whether the correlation between every pair of stock indices is time-varying or not. The test proposed by Engle and Sheppard (2001) was used. The results (not presented here, but obtainable from the author) prove that the null hypothesis of a constant correlation is rejected for all stock indices pairs. Therefore, a DCC(1,1)-GARCH(1,1) model was given advantage over CCC-GARCH(1,1) model.

DCC(1,1)-GARCH(1,1) models results are presented in Table 5. The DCC parameters α and β are significant for all stock indices pairs. $\beta > \alpha$ for all indices pairs, so the current variances of returns are more affected by magnitude of past variances as by past return innovations. A high persistence in the series of correlations R_t is observed (as β is close to 1). The sum of the DCC parameters ($\alpha + \beta$) is very close to 1 in all cases, indicating that conditional variances are higly persistent and only slowly mean-reverting. 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.

By examining the conditional correlation graphs from DCC-GARCH results (Figures 1 and 2), main findings may be summarized as:

- A rising trend of correlation can be observed between the returns of Hungarian and European stock markets, suggesting that comovement between Hungarian and European stock markets has increased in the observed period. This finding is in accordance with the recent literature on measuring the stock market comovements (Forbes and Rigobon, 2002; Phylaktis and Ravazzolo, 2005; Syriopoulos, 2007; Gilmore et al., 2008; Kizys and Pierdzioch, 2009), suggesting also that correlation between stock market returns is time-varying.

- A time path of conditional correlations between BUX and other indices returns (Figures 1 and 2) is highly volatile. Volatility increases at times of events that disrupt global financial markets. We graphically abbreviated times of the past events that according to economic literature had a major impact on European economies: Russian financial crisis, the dot-com financial crisis, the attack on the World Trade Center, Hungary entering the European Union and the recent global financial crisis.

- The rising trend of DCC-GARCH conditional correlation between Hungarian and European stock market returns is especially noticeable since 2002, as the real and financial integration in the European Union already took place before the de-facto entrance into the European Union. In the empirical literature, there is plenty evidence that European integration leads to increased interdependence of financial markets[6].

- Financial market crises covered by our study (Russian financial crisis, dot-com and the global financial crisis) lasted shortly (of about 100-400 days) effect on the

[6] Empirical studies of the effects of European integration on interdependence of the developed European stock markets, confirm this assumption, e.g. Koch and Koch (1991), Kasa (1992), Longin and Solnik (1995) and Bessler and Yang (2003). For the CEE stock markets, this was confirmed by studies of Syllignakis and Kouretas (2006), Harrison and Moore (2009), Allen et al. (2010), Caporale and Spagnolo (2010).

Table 5. **Results of a DCC(1,1)-GARCH (1,1) models for indices in pair with BUX**

Parameter	BUX-PX	BUX-ATX	BUX-CAC40	BUX-DAX	BUX-FTSE100	BUX-LJSEX
$\omega_{BUX - other index}$	1.564940e-05** (2.1176)	1.562665e-05** (2.0824)	1.575592e-05** (2.0951)	1.568158e-05** (2.1026)	1.722471e-05** (2.1309)	4.369636e-06*** (3.4461)
$\alpha_{BUX - other index}$	0.159238*** (2.7525)	0.159189*** (2.6953)	0.156398*** (2.6926)	0.157180*** (2.7292)	0.158555** (2.7156)	0.357100*** (6.1872)
$\beta_{BUX - other index}$	0.807847*** (12.6097)	0.807992*** (12.3669)	0.809988*** (12.5474)	0.809179*** (12.6017)	0.803222*** (12.2241)	0.642898*** (12.3724)
Ljung-Box $Q^2(10)$ statistics	4.41	5.70	4.40	8.85	4.36	6.26
$\omega_{other index - BUX}$	7.518040e-06*** (4.3790)	3.514911e-06*** (3.7920)	2.364951e-06*** (2.7007)	3.322459e-06*** (3.0542)	1.311132e-06*** (3.1204)	7.546223e-06*** (4.3904)
$\alpha_{other index -BUX}$	0.1338*** (8.6676)	0.118507*** (5.9100)	0.094441*** (6.7704)	0.114296*** (6.7170)	0.093314*** (8.1319)	0.138853*** (8.5966)
$\beta_{other index - BUX}$	0.8408 *** (58.8184)	0.867938*** (44.2360)	0.901342*** (64.1602)	0.880049*** (54.2586)	0.903238*** (80.2921)	0.836669*** (57.4213)
Ljung-Box $Q^2(10)$ statistics	8.35	13.26*	3.77	5.72	7.34	14.57
α	0.034941** (2.1874)	0.032434 * (1.4832)	0.031757 ** (1.8284)	0.047663*** (3.5616)	0.031595*** (2.9764)	0.023455*** (2.5499)
β	0.937888*** (24.8776)	0.942426*** (19.1555)	0.944527*** (27.8519)	0.921698*** (38.3278)	0.939361*** (38.4189)	0.9181218*** (25.5845)

Notes: Parameters ω BUX – other index, α BUX – other index, βBUX – other index are the estimated parameters of a univariate GARCH (1,1) model, with residuals input from the estimated bivariate vector autoregressive (VAR) model with BUX returns as dependent variable and the other index return as explanatory variable. other index – BUX, α other index – BUX, β other index – BUX are the estimated parameters of a univariate GARCH (1,1) model, with residuals input from the estimated bivariate vector autoregressive (VAR) model with BUX returns as dependent variable and the other index returns as explanatory variable. In parenthesis under the parameter estimation, t-statistics are given: *** (**/*) denote rejection of the null hypothesis that parameter is equal zero at the 1% (5%/10%) significance levels. In the parentheses, t-statistics, calculated from the robust standard errors are given. Ljung-Box Q2(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 GARCH model can be rejected at the 1% (5%/10%) significance levels.

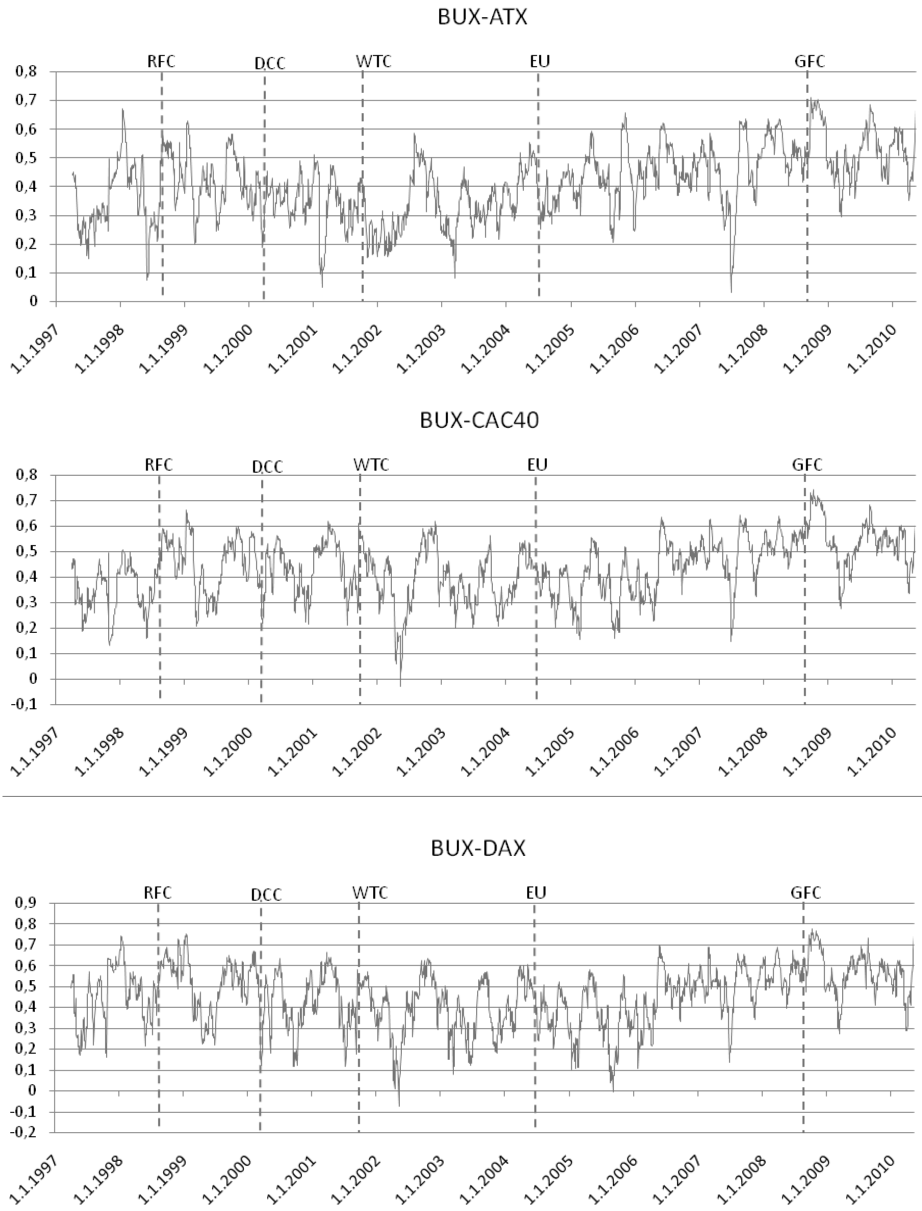
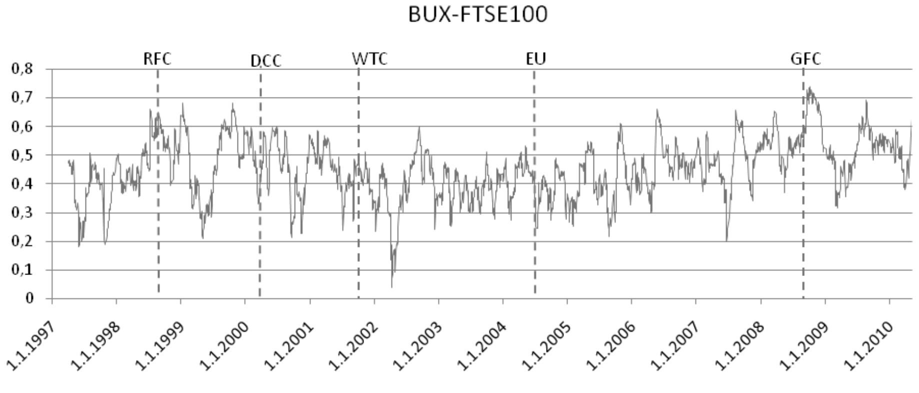
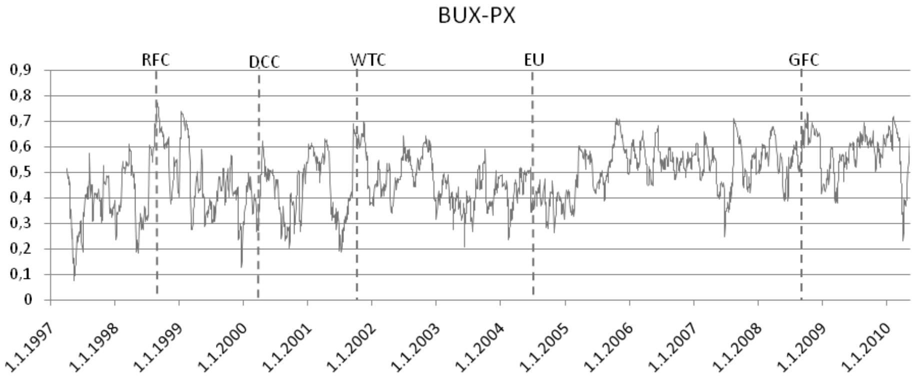


Figure 1. **Conditional correlation between BUX and other stock indices returns**

Notes: On the time axis the financial crises are denoted: RFC = Russian financial crisis (outbreak on August 13, 1998), DCC = Dot-Com crisis (March 24, 2000 is taken, as the date 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 Hungary joined the European Union (May 1, 2004), GFC = global financial crisis (September 16, 2008). The vertical dotted lines indicate these events.





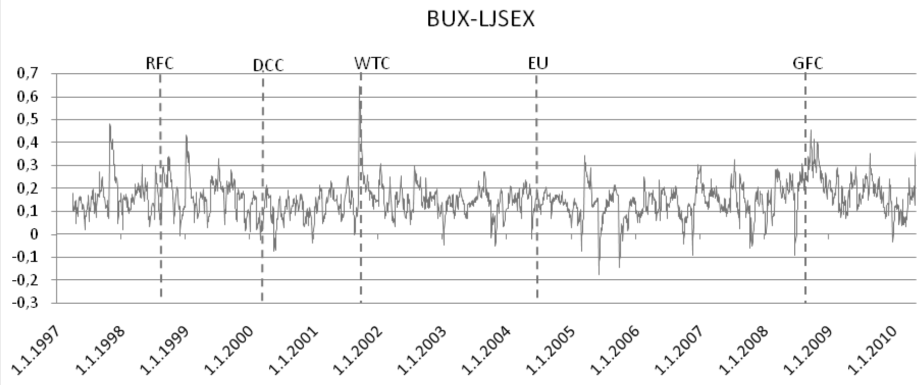


Figure 1. **Conditional correlation between BUX and other stock indices returns (continued)**

For acronyms see Notes to Fig. 1.

increased stock market comovement. Also the recent global financial crisis (collapse of Lehman Brothers on 16 September, 2008 is taken as the major event that spread the financial crisis from the US to other financial markets) had only a temporary impact on Hungarian stock market comovement with European stock markets.

4. Conclusion. In this paper we examine the comovement and spillover dynamics between Hungarian and 6 European stock markets (the United Kingdom, German, French, Austrian, Czech and Slovene) in the period April, 1997 – May, 2010. A DCC-GARCH model proves to be a statistically appropriate model to study the return comovement and spillovers between these markets, and the key findings from the model results are: (1) The comovement between Hungarian and European stock markets in the observed period has increased. (2) Financial market crises covered by our study (Russian financial crisis, dot-com and the global financial crisis) had only a short-term (of about 100-400 days) effect on the increased stock market comovement between Hungarian and European stock markets. (3) The European integration led to the long-term increase in the comovement with European stock markets.

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