Stock market integration between the CEE-4 and the G7 markets: Asymmetric DCC and smooth transition approach.

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16. January 2013

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Abstract

We study the transition process of emerging CEE-4 stock markets from segmented to integrated markets and hypothesize that this process has been gradual over time. As a proxy for integration, co-movements with developed G7 markets are estimated using the asymmetric DCC-GARCH model. A smooth transition logistic trend model is then fitted to the dynamic correlations to examine the integration process. Evidence of strengthening relationships among the markets under study is provided. In the case of Czech stock market, the results suggest that the transition began between the end of 2005 and first half of 2006. The transition midpoints for the Hungarian and Polish markets seem to overlap with the recent financial crisis. Correlations between CEE-4 and G7 markets have been approximately 0.6 in the last few years. The only exception is the Slovak stock market, which still appears to be more segmented and isolated from others in the CEE region and from the developed markets of the G7.

Keywords: stock market co-movements, G7, CEE-4, asymmetric GARCH models, ADCC, smooth transition model

JEL Classification: C32, G01, G15

I would like to thank to Tomáš Výrost and Štefan Lyócsa for their useful comments. Funding support of the Slovak Grant Agency for Science (VEGA Project No. 1/0393/12) is gratefully acknowledged.

Introduction

The area of stock market integration has been studied extensively over the last three decades, as it plays a crucial role in international portfolio diversification and thus has distinct implications for investors. Many empirical works in the 1980s observed an increase in cross-market interdependence (*inter alia*, Jaffe and Westerfield, 1985; Schöllhammer and Sand, 1985; Asprem, 1989; Eun and Shim, 1989). After the US stock market crash in October 1987, the evidence of strengthening relationships between international stock markets became even more persuasive.

The degree of stock market integration is difficult to evaluate. Since the 1980s, many emerging countries implemented financial liberalization policies to transform their segmented markets into integrated ones. The liberalization of emerging markets provides foreign investors the opportunity to invest in domestic equities and provides domestic investors the right to operate in foreign markets. However, regulatory liberalizations do not necessarily lead to market integration: "First, the market might have been integrated before the regulatory liberalization. That is, foreigners might have had the ability to access the market through other means, such as country funds and depository receipts. Second, the liberalization might have little or no effect because either foreign investors do not believe the regulatory reforms will be long lasting or other market imperfections exist that keep them out of the market" (Bekaert and Harvey, 2002). One can perceive regulatory liberalization as a necessary but not sufficient condition for stock market integration. Thus, from a quantitative perspective, it is more convenient to focus on the co-movements between stock markets (which may be viewed as a result of integration).

In this paper, stock market co-movements are used as a proxy for integration. We would like to contribute to the existing literature by estimating asymmetric dynamic conditional correlations (ADCC) between developed markets (G7) and emerging markets from the CEE region (the Czech Republic, Poland, Hungary, and Slovakia). We then determine whether the integration process may be considered gradual. Emerging markets are unique due to the potential existence of barriers that may discourage foreign investors.[1] Of course, one cannot expect that these barriers will be eliminated all at once, and therefore the transition process from segmented to integrated markets should occur gradually over time. To

[1] Bekaert (1995) distinguishes between three different categories of barriers: legal barriers, indirect barriers (based on information asymmetry, accounting standards and investor protection) and the presence of various risks (e.g., liquidity risk, political risk, economic policy risk and currency risk).

verify this hypothesis, we apply a non-linear smooth transition logistic trend regression that allows us to endogenously examine when the integration began and its pace (if at all).

The remainder of this paper is organized as follows. Section 1 presents a brief discussion of the related empirical literature. The data are described in Section 2. Section 3 explains the applied methodology, and Section 4 presents the results obtained. Finally, Section 5 presents concluding remarks.

1 Related literature

Although an extensive amount of empirical research has been conducted on stock market integration, the literature focusing on CEE markets is still rather sparse. Clearly, these markets are still relatively small in terms of market capitalization, but to some extent they have a predictive power regarding future economic activity (see, e.g., Lyócsa et al., 2011). In addition to the topic of effective international diversification, analyses of stock market co-movements may thus also provide useful insights for policy makers.

Syriopoulos (2007) examined the short- and long-run relationships among CEE-4 stock markets (the Czech Republic, Poland, Hungary and Slovakia) and developed markets (Germany and the US) on two subsamples: the pre-EMU period (1 January 1997 – 31 December 1998) and the post-EMU period (1 January 1999 – 20 September 2003). Contemporaneous correlations of the CEE markets strengthened in the post-EMU period, and few previously negative correlations became positive. Only the Slovak stock market remained isolated. Stronger linkages were found between CEE and mature markets rather that within the CEE group. Syriopoulos (2007) concluded that no dramatic impact due to the EMU has been found, and hence the transition appears to be smooth. The explanation provided in Syriopoulos (2007) stated that macroeconomic policies are already adjusted to support convergence with the EU.

Several cointegration tests and principal components analysis were also applied by Gilmore et al. (2008) using a sample of the CEE-3 stock markets[2] and developed ones (the UK and Germany) over the period from July 1995 to February 2005. The results revealed only low levels of short-term correlations and a lack of statistically significant cointegration. The authors concluded that the EU accession process had not dramatically changed the linkages between the CEE-3 stock markets and the developed European ones.

[2] The following countries constitute the CEE-3: The Czech Republic, Poland, and Hungary; the Slovak stock market is excluded in most empirical studies, primarily due to its small size, small number of actively traded stocks, low level of liquidity, near absence of initial public offerings, etc.

Contrasting results are provided by Savva and Aslanidis (2010), who applied (D)STCC-GARCH models to measure the degree of stock market integration between five Eastern European countries (the CEE-4 and Slovenia), the Euro-zone (Dow Jones Euro Stoxx50) and the US. They found increase in correlations between the Czech, Polish and Slovenian markets vis-à-vis the Euro-zone from 1997 to 2008, while the authors attributed this increase to EU-related developments.

After the EU enlargement, several empirical studies reported substantial amplification in the stock market integration exhibited by the new member states from Central and Eastern Europe. For example, Cappiello et al. (2006b) found evidence of increased integration for Hungary, the Czech Republic, Poland, Estonia, and Cyprus using daily data from January 1994 to November 2005.

Babecký et al. (2010) employed a different approach (beta- and sigma-convergence) to examine the financial integration of the CEE-3 but also confirmed the presence of integration rather than segmentation.

Wang and Moore (2008) also found an increasing level of integration of the CEE-3 towards EU markets (aggregate Euro-zone index of the 12 EMU markets) over the sample period 1994 – 2006. Conditional correlations at the end of the examined period were approximately 0.3 – 0.5.

Syllignakis and Kouretas (2011) observed a significant increase in dynamic conditional correlations between emerging European stock markets (the CEE-4, Estonia, Romania, and Slovenia) and the US, German and Russian stock markets, particularly during the financial crisis of 2007 – 2009. The average correlations between the CEE-3 markets and the US and German stock markets are around 0.5 (sample period from October 1997 to February 2009). Not surprisingly, the correlations of Slovak stock market are basically zero.

Over the period of 1998 – 2010, Baumöhl et al. (2011) showed that endogenously detected volatility breaks in weekly stock market returns are significantly associated with the estimated conditional correlations (DCCs) among the CEE-3 and developed markets (Germany and US). When breaks are linked to a decrease in volatility, the correlations between the indices also decrease. A sudden increase in volatility is similarly accompanied by an increase in DCCs and thus provides evidence for the presence of a shift contagion effect. The estimated correlations range from 0.5 to 0.7 at the end of the examined sample with a sharp peak detected during the recent financial crisis.

Horvath and Petrovski (2012) compared stock market co-movements between Western Europe (Stoxx Europe 600) and the markets of countries in the CEE-3 and South

Eastern Europe (Croatia, Macedonia and Serbia) over the period 2006 – 2011. Comparing these two groups of emerging European markets, the authors conclude that the degree of integration is much higher in the CEE-3 countries (conditional correlations vary around 0.6 with no visible pattern).

Gjika and Horvath (2012) used daily data from the period 2001 – 2011 to examine time-varying correlations between the CEE-3 and Euro-zone (Stoxx50) estimated in the ADCC model framework. The conditional correlations increased significantly after EU entry (May 2004) and remained at these high levels (approximately 0.6 – 0.7) during the recent financial crisis.

Several empirical works exploited high frequency data from the CEE-3 stock markets. Černý and Koblas (2008) performed Granger causality and cointegration analysis between CEE-3 and developed markets. Hanousek et al. (2009) and Hanousek and Kočenda (2011) analyzed stock market price responses to macroeconomic news and spillover effects. Égert and Kočenda (2011) obtained the most surprising results using intraday data from the CEE-3. Over a sample period from June 2003 to January 2006, they found very low (close to zero) conditional correlations within the CEE-3 group and between the CEE-3 and French stock market. A possible explanation of this noteworthy difference from the previously mentioned studies is provided by Büttner and Hayo (2011): "… markets in the CEE-3 are too slow in their reaction, possibly because of low liquidity and less advanced trading platforms".

Finally, studies employing the smooth transition logistic trend models should be mentioned, as they served as a methodological basis for this paper. To the best of our knowledge, Chelley-Steeley (2004) was the first to apply the smooth transition logistic trend model in the field of stock market integration. She used a sample of Asia-Pacific emerging markets (Korea, Taiwan, Thailand, and Singapore) and developed markets (US, UK, Canada, France, Germany, and Japan) over the period from January 1990 – January 2002. Chelley-Steeley (2005) analyzed the integration of equity markets in the CEE-3 and Russia with respect to the US, the UK, Germany, Japan, and France during the period from July 1994 – December 1999. In both papers, she applied the smooth transition logistic trend model (as described in Section 3) to bivariate correlations, which have been calculated for each month using the daily returns within the corresponding month.

However, the time series of the correlations obtained in this manner may be distorted, as correlation coefficients tend to be biased upward when volatility increases. Since the work of Ronn (1998), Boyer et al. (1999), Loretan and English (2000) and, most notably, Forbes and Rigobon (2002), it has been shown that correlation coefficients suffer from distortion due to heteroskedasticity in the data.[3] This finding is particularly important for studies of stock market co-movements in periods of high volatility (e.g., crises). When correlation analyses are conducted using a sub-sample exhibiting high volatility, the correlation coefficient estimates are biased upward, and thus may provide misleading results. Moreover, calculating correlations using daily returns within one month will likely obscure potential correlation dynamics.

A smooth transition logistic trend model was also applied by Lahrech and Sylwester (2011) to establish the degree of stock market integration between the US and Latin American stock markets in the period from December 1988 – March 2004. In this case, a smooth transition model was fitted to the standard DCCs, which overcome the above-stated distortion of simple unconditional correlations. The same approach is utilized by Durai and Bhaduri (2011) on a sample of markets in the US, UK, Germany, India, Malaysia, Indonesia, Singapore, South Korea, Japan, and Taiwan over the period from July 1997 – August 2006.

In this paper, we will follow these works in estimating the smooth transition model, but the dynamic conditional correlations will be calculated using an asymmetric DCC-GARCH model framework. We account for the asymmetries in the correlations and conditional variances.

2 Data description

Our dataset comprises daily closing prices of the stock market indices from G7 countries, namely, the US (S&P500), Canada (S&P/TSX Composite, TSE henceforth), German (DAX30, DAX henceforth), the United Kingdom (FTSE100, FTSE henceforth), France (CAC40, CAC henceforth), Italy (FTSE/MIB, MIB henceforth) and Japan (Nikkei225, N225 henceforth). Indices from the developed G7 stock markets are complemented by indices from emerging countries of CEE-4, namely, the Czech Republic (PX), Poland (WIG), Hungary (BUX) and Slovakia (SAX). All indices are obtained from Datastream and are denominated in local currencies, and thus do not reflect swings in the exchange rates. To avoid non-synchronous trading effects[4] and possible day-of-the-week effects, weekly returns

[3] To the best of our knowledge, Rob Stambaugh first mentioned correlation bias resulting from changes in volatility in his discussion of the Karolyi and Stulz (1995) paper at the May 1995 NBER Conference on Financial Risk Assessment and Management. Nevertheless, to the best of our knowledge, the first notice can be found in King and Wadhwani (1990): "we might expect that the contagion coefficients would be an increasing function of volatility" (p. 20). However, no formal proof or corrections were proposed in their work.

[4] For further information about non-synchronous trading effects I and II (the first is induced by differing numbers of observations in the stock market indices, and the second is related to the different time zones in which respective markets operate), see Baumöhl and Výrost (2010).

were computed by averaging the daily observations within the corresponding week[5]. The dataset covers the period from 4 January 1998 to 5 August 2012.

Prior to the analyses, all of the series were subjected to unit-root testing using the ADF-GLS test with finite sample critical values computed via the response surfaces of Cheung and Lai (1995). The testing procedure is based on adding the augmented terms in the auxiliary regression until the null hypothesis of no autocorrelation of the residuals cannot be rejected at the 5% critical level using the Ljung-Box test with up to 12 lags and maximal lag order selected according to Schwert's rule of thumb (Schwert, 1989), k_{max} = int[12(T/100)$^{1/4}$], where T is the sample size. Based on the test results, all logarithmic prices are non-stationary (model with trend and constant) and the logarithmic differences (i.e., returns) are mean stationary. Surprisingly, the Italian MIB appears to be mean non-stationary even in logarithmic differences. We have therefore decided to run the KPSS test, where the long-run variance was estimated using the quadratic spectral kernel weighting scheme and the bandwidth was selected according to the automatic bandwidth selection of Newey and West (1994).[6] The KPSS test concludes that all differenced series may be assumed to be mean stationary. See appendices 1A and 1B for detailed results.

Table 1: Unconditional correlations (Pearson)

	TSE	DAX	FTSE	CAC	MIB	N225	BUX	WIG	PX	SAX
S&P500	0.813	0.826	0.847	0.843	0.768	0.617	0.561	0.590	0.583	0.064
TSE		0.730	0.754	0.755	0.691	0.600	0.557	0.604	0.603	0.065
DAX			0.838	0.922	0.842	0.621	0.590	0.594	0.591	0.033
FTSE				0.889	0.814	0.613	0.582	0.590	0.583	0.076
CAC					0.889	0.631	0.592	0.592	0.605	0.045
MIB						0.590	0.591	0.548	0.591	0.035
N225							0.467	0.521	0.522	0.024
BUX								0.669	0.690	0.116
WIG									0.669	0.063
PX										0.091

Notes: For iid samples, the 5% critical value (two-tailed) is 0.0711 for sample size T = 791.

Table 1 presents the unconditional (Pearson) correlations among all of the examined stock market indices. Correlations between the CEE countries and developed ones are slightly lower than the correlations within the G7 group. The only exception is the Slovak SAX index,

[5] Baumöhl and Lyócsa (2012) show that the method of constructing the weekly returns from daily data matters, as the conclusions of the analyses might be different. The Friday-to-Friday method provides the most diverse returns that are the least correlated with Wednesday-to-Wednesday returns or averaged returns within the corresponding week. As we wish to determine the representative price for a given week, the averaged returns are selected.

[6] This procedure was recommended in Hobijn et al. (2004).

where the reported correlations are close to zero. The Slovak stock market may be considered inefficient and not very influential in terms of turnover, market capitalization and the shareholder structure (the stock exchange in Slovakia is practically a state-owned institution; the major shareholder is the National Property Fund of the Slovak Republic with a share slightly greater than 75%, and three financial institutions hold approximately 20%). The Bratislava stock exchange is therefore often neglected in empirical research, but to make some general conclusions regarding the (non-) integration of the Slovak stock market, we decided to include SAX in our sample.

3 Methodology

To estimate the time-varying conditional correlations, an asymmetric DCC (ADCC) model introduced by Cappiello et al. (2006a) is applied. In the standard two-step DCC model proposed by Engle and Sheppard (2001) and Engle (2002), the returns $\mathbf{r}_t$, $t = 1,2,\ldots,T$, of k assets are assumed to follow a conditional multivariate normal distribution with zero expected value and the variance-covariance matrix $\mathbf{H}_t$:

$$\mathbf{r}_t \mid \Omega_{t-1} \sim N(\mathbf{0}, \mathbf{H}_t) \tag{1}$$

$$\mathbf{H}_t = \mathbf{D}_t \mathbf{R}_t \mathbf{D}_t \tag{2}$$

where Ω_{t-1} is the information set at time $t - 1$. The decomposition of $\mathbf{H}_t$ is realized as in (2), where $\mathbf{D}_t$ is the $k \times k$ diagonal matrix of time-varying conditional standard deviations from univariate GARCH models and $\mathbf{R}_t$ is the time-varying correlations matrix:

$$\mathbf{R}_t = diag\{\mathbf{Q}_t^*\}^{-1} \mathbf{Q}_t diag\{\mathbf{Q}_t^*\}^{-1} \tag{3}$$

with its typical element ($\mathbf{Q}_t^*$ is a diagonal matrix with the square root of the i-th diagonal element of $\mathbf{Q}_t$ on its i-th diagonal position):

$$\rho_{ij,t} = \frac{q_{ij,t}}{\sqrt{q_{ii,t}\, q_{jj,t}}},\ i, j = 1,2,\ldots,n; i \neq j \tag{4}$$

Conditional variance $\sigma_{i,t}^2$ is obtained in the first step of the DCC estimation procedure using univariate GARCH models. As stated by Cappiello et al. (2006a), the correlation estimates are inconsistent when univariate models are not well specified. Therefore, to minimize the risk, we implemented a rather extensive model selection procedure. The following models were included:

1. GARCH (Bollerslev, 1986)
2. AVGARCH (Taylor, 1986)
3. NGARCH (Higgins and Bera, 1992)
4. EGARCH (Nelson, 1991)
5. GJR-GARCH (Glosten, et al., 1993)
6. APARCH (Ding et al., 1993)
7. NAGARCH (Engle and Ng, 1993)
8. TGARCH (Zakoian, 1994)
9. FGARCH (Hentschel, 1995)
10. CSGARCH (Lee and Engle, 1999).

In all models, we allow the inclusion of up to 5 lags of innovation and 5 lags of volatility, and the same lag structure was allowed in the mean equations (ARMA models). The autocorrelation and remaining ARCH effects of the standardized residuals were controlled at the 5% significance level using Ljung-Box test with up to int[0.05T] lags. To ensure that the model specification is correct (meaning all possible asymmetric effects are included), the Sign Bias test proposed by Engle and Ng (1993) is applied. After appropriate models were found, we selected the one that best fits the data according to the Bayesian information criterion (BIC).[7] Instead of the normality condition on the distribution of errors, we utilized a generalized error distribution (GED) following Nelson (1991). To overcome some optimization problems and to speed up the procedure, we employed variance targeting in all models.

After the univariate GARCH models are fitted, in the second step of the DCC model, standardized residuals $s_{i,t} = r_{i,t} / \sigma_{i,t}$ are used to estimate the correlations. The correlation dynamics of $\mathbf{Q}_t$ (in the case of standard DCC (1,1) model) is given by:

$$\mathbf{Q}_t = (1-\varphi-\psi)\overline{\mathbf{Q}} + \varphi\left(\mathbf{s}_{t-1}\mathbf{s}_{t-1}^T\right) + \psi\,\mathbf{Q}_{t-1} \tag{5}$$

where $\overline{\mathbf{Q}} = [\mathbf{s}_t\mathbf{s}_t^T]$ is the unconditional correlation matrix of standardized residuals. The restrictions, which ensure that matrix $\mathbf{Q}_t$ is a positive definite, are imposed: scalar parameters $\varphi, \psi \geq 0$ and $\varphi + \psi < 1$.

In the ADCC model developed by Cappiello et al. (2006a), asymmetries in the correlation dynamics are introduced as follows:

$$\mathbf{Q}_t = (1-\varphi-\psi)\overline{\mathbf{Q}} - \xi\,\overline{\mathbf{N}} + \varphi\left(\mathbf{s}_{t-1}\mathbf{s}_{t-1}^T\right) + \psi\,\mathbf{Q}_{t-1} + \xi\left(\mathbf{n}_{t-1}\mathbf{n}_{t-1}^T\right) \tag{6}$$

[7] Following Cappiello et al. (2006a).

where $\overline{\mathbf{N}} = [\mathbf{n}_t \mathbf{n}_t^T]$, $\mathbf{n}_t = I[\mathbf{s}_t < 0] \circ \mathbf{s}_t$, while $I[.]$ is a $k \times 1$ indicator function that takes the value of 1 if the argument is true (0 otherwise) and "$\circ$" indicates the Hadamard product. All other variables are the same as in the DCC model. The positive definiteness of $\mathbf{Q}_t$ is also ensured in a similar manner: $\varphi, \psi, \xi \geq 0$ and $\varphi + \psi + \delta\xi < 1$, where δ=maximum eigenvalue $[\overline{\mathbf{Q}}^{-1/2}\overline{\mathbf{N}}\overline{\mathbf{Q}}^{-1/2}]$ can be estimated on the sample data (for more details, see, Cappiello et al., 2006a). The entire analysis is conducted with R software using the rmgarch (Ghalanos, 2012a) and rugarch (Ghalanos, 2012b) packages.

After conditional correlations are obtained, we verify whether stock market integration[8] can be considered a gradual process, as the underlying theory suggests. The non-linear smooth transition logistic model suggested by Granger and Teräsvirta (1993) seems to be a suitable choice. The model takes the following form[9]:

$$\rho_{ij,t} = \alpha + \beta S_t(\gamma, \tau) + \upsilon_t \tag{7}$$

where $\rho_{ij,t}$ are the estimated dynamic conditional correlations, α, β are regression parameters and υ_t is the error term. The logistic function $S_t(\gamma, \tau)$ is defined as:

$$S_t(\gamma, \tau) = (1 + \exp(-\gamma(t - \tau T)))^{-1}, \gamma > 0 \tag{8}$$

where T is the sample size, the parameter τ determines the transition midpoint between two regimes and γ measures the speed of transition. For small values of γ, we may consider the integration from the first regime α to $\alpha + \beta$ to be slow and gradual. For larger values of γ, the shift between the two regimes occurs more quickly. If the parameter $\beta < 0$, the estimated co-movements between the two markets declined under the second regime, i.e., after the endogenously detected break in correlations (at date τT). After the smooth transition model is fitted, the residuals are checked for stationary using the ADF-GLS test (the same procedure is applied as described in Section 2).

[8] It is worth recalling from the Introduction that we use only correlations as a proxy for real stock market integration, which is difficult to evaluate.

[9] Our model specification is the same as that of Chelley-Steeley (2005). The same approach was subsequently used by Lahrech and Sylwester (2011), who also discussed the possible estimation bias introduced by the DCC procedure.

4 Results

This section is divided into two subsections. First, in Section 4.1, the results from the univariate GARCH models and estimated dynamic conditional correlations are briefly described. Second, Section 4.2 presents the results from the smooth transition model.

4.1 Description of estimated correlations

Various univariate GARCH models have been selected according to the selection procedure described in Section 3. For the sake of brevity, Table 2 summarizes the representation and basic statistics of the fitted models (detailed results are available upon request). At the 5% significance level, no autocorrelation or remaining ARCH effects are present in our models. The Sign Bias test also confirmed that no other asymmetric terms should be included.

Table 2: Fitted univariate GARCH models

Index	Mean equation	Variance equation	LB	LB^2	BIC	SB stat
S&P500	ARMA(1,1)	NAGARCH(1,1)	0.1534(9)	0.4752(2)	-5.1505	4.1894
TSE	ARMA(1,1)	NAGARCH(1,1)	0.182(8)	0.2923(2)	-5.1259	5.1380
DAX	ARMA(1,1)	NAGARCH(1,1)	0.2059(3)	0.0708(2)	-4.4727	1.7120
FTSE	ARMA(1,1)	NAGARCH(1,1)	0.2813(14)	0.5171(1)	-5.1282	1.8449
CAC	ARMA(1,1)	NAGARCH(1,1)	0.1747(3)	0.1207(18)	-4.6710	2.7228
MIB	ARMA(1,1)	TGARCH(1,2)	0.2196(4)	0.2609(1)	-4.5578	4.9291
N225	ARMA(5,2)	EGARCH(1,1)	0.0765(26)	0.4782(2)	-4.4670	0.6111
BUX	ARMA(2,1)	GJR-GARCH(1,1)	0.1399(3)	0.4386(1)	-4.2037	1.7006
WIG	ARMA(1,1)	GJR-GARCH(1,1)	0.1194(14)	0.0924(4)	-4.4160	4.7839
PX	ARMA(3,1)	NAGARCH(1,1)	0.1433(14)	0.8612(1)	-4.5339	0.1047
SAX	ARMA(3,1)	EGARCH(1,1)	0.1238(25)	0.5181(1)	-4.9478	1.6249

Notes: "LB" represents minimal p-values recorded by the Ljung-Box test of standardized residuals (testing for autocorrelation) and corresponding lag (in parentheses) from the entire set of int[0.05T] lags. Column "LB^2" is conducted in the same manner but on the squares of the standardized residuals (testing for remaining ARCH effects). "BIC" is the Bayesian information criterion, and "SB stat" corresponds to the test statistic of joint hypothesis in the Sign Bias test of Engle and Ng (1993). All hypotheses (joint, sign bias, positive bias, and negative bias) cannot be rejected at the 5 % significance level.

Asymmetries in volatility are found in all indices, as according to the BIC, asymmetric GARCH models fit the data best. Once the univariate GARCH models are estimated, we may proceed to the ADCC estimation, which is presented in Table 3. Note that the asymmetry in correlations is significant, which is in contrast to the results of Gjika and Horvath (2012), who estimated bivariate ADCC between the PX, BUX, WIG and Stoxx50 indices.

Table 3: Estimation of ADCC

Parameter	Estimate	SE	*t*-value	*p*-value
φ	0.0128	0.0044	2.9187	0.0035
ψ	0.9132	0.0406	22.5066	0.0000
ξ	0.0151	0.0058	2.5871	0.0097

Notes: "SE" stands for standard errors.

Changes in the correlations are captured in the figures in Appendix 3. Minimal and maximal values of the estimated correlations between the CEE-4 and G7 markets are presented in Table 4. With few exceptions, minimal correlations were found at the beginning of our sample and maximal correlations at the end of it, suggesting that integration occurred over the examined sample period. It is also noteworthy that in many cases the highest correlations occurred in the week ending 19 October 2008. On 15 October 2008, the US stock market experienced its largest decline since the stock market crash of 1987. The increasing correlations of the CEE-4 markets (except Slovakia) after this shock suggest the presence of contagion. The same result was also obtained by Baumöhl et al. (2011).

Table 4: Minimal and maximal correlations between CEE-4 and G7

		S&P500	TSE	DAX	FTSE	CAC	MIB	N225
BUX	min	0.3950	0.3580	0.4426	0.4415	0.4411	0.4049	0.1941
	(date)	06.07.2003	08.07.2007	07.06.1998	14.06.1998	07.06.1998	08.07.2007	14.06.1998
	max	0.6652	0.6376	0.6760	0.6875	0.7121	0.6502	0.6215
	(date)	**19.10.2008**	25.6.2006	**19.10.2008**	**19.10.2008**	**19.10.2008**	24.01.1999	**19.10.2008**
WIG	min	0.4223	0.4641	0.4120	0.3945	0.4193	0.3254	0.1686
	(date)	23.04.2000	26.09.1999	14.06.1998	23.01.2000	14.06.1998	10.05.1998	05.04.1998
	max	0.6671	0.6486	0.7068	0.7117	0.7129	0.6533	0.5791
	(date)	21.08.2011	27.01.2008	21.08.2011	21.08.2011	**19.10.2008**	**19.10.2008**	**19.10.2008**
PX	min	0.3062	0.3521	0.3380	0.3223	0.3806	0.3012	0.2716
	(date)	15.08.1999	16.01.2000	17.05.1998	27.02.2000	17.05.1998	17.05.1998	15.02.1998
	max	0.6162	0.6142	0.6433	0.6435	0.6618	0.6367	0.5502
	(date)	21.08.2011	01.03.2009	**19.10.2008**	30.05.2010	**19.10.2008**	01.03.2009	**19.10.2008**
SAX	min	-0.0011	-0.0231	-0.0314	-0.0198	-0.0557	-0.0697	-0.0270
	(date)	09.08.2009	13.08.2000	21.06.1998	28.09.2008	22.03.1998	14.05.2000	28.09.2008
	max	0.2528	0.2403	0.2308	0.2944	0.2223	0.2242	0.2014
	(date)	06.06.2010	30.05.2010	06.06.2010	30.05.2010	30.05.2010	06.06.2010	06.06.2010

Notes: Highlighted (bold) dates correspond to the week ending 19 October 2008, during which the large decline in the US stock market occurred.

The results for the Slovak SAX are as expected. The correlations with developed markets are low, and the minimal values are negative. Surprisingly, one spike occurred in all of SAX's relationships within the two-week period (the weeks ending 30 May and 6 Jun

2010). Table 5 presents the correlations within the CEE group, and in this case the same dates exhibit maximal correlations for the SAX index. We did not find any significant event on Slovak stock exchange, although the European Financial Stability Facility was created in May 2010 as a response to the EU debt crisis. However, we will not speculate on the potential causes of such a sudden increase in correlations.

Table 5: Minimal and maximal correlations within the CEE-4 group

	BUX–WIG	BUX–PX	WIG–PX
min	0.4955	0.4727	0.4493
(date)	03.12.2000	14.06.1998	16.09.2001
max	0.7576	0.7320	0.7302
(date)	21.08.2011	27.03.2005	21.08.2011
	BUX–SAX	WIG–SAX	PX–SAX
min	0.0098	-0.0356	0.0039
(date)	22.06.2003	19.03.2006	29.06.2003
max	0.3029	0.2298	0.2805
(date)	06.06.2010	30.05.2010	30.05.2010

The correlations among the CEE-4 markets are markedly high (except for the Slovak SAX). The highest correlations for BUX-WIG and WIG-PX are reported in the same week. This is another interesting date that also appears frequently in Table 4; as in August 2011, there was a sharp decline in stock markets across the world due to fears that the sovereign debt crisis would spread (and likely accompanying events such as a downgrade of the US credit rating by Standard & Poor's for the first time since 1941 or the banning of short-selling in various EU countries).

4.2 Smooth transition model

In the Introduction, we hypothesized that the integration of emerging stock markets with developed ones should be described as a gradual process. We employed stock market co-movements, modeled by utilizing the ADCC approach, as a proxy for integration. To verify the hypothesis, a smooth transition logistic model is fitted to the estimated conditional correlations. The estimation results for the CEE-4 and G7 correlations are presented in Appendix 2.A, and the results within the CEE-4 group are presented in Appendix 2.B. After fitting the smooth transition model, the residuals were tested for the presence of a unit-root using the ADF-GLS test procedure described above (see Section 2). The results are available in Appendix 2.C. Visualizations of the conditional correlations and fitted smooth transition models are presented in Appendix 3.

In most of the relations between the Hungarian BUX and Polish WIG, the transition midpoint is dated during the financial crisis and not around May 2004, i.e., following the accession of the CEE-4 countries to the EU. The increase attributed to the second regime (β) is rather small, and it is possible that second regime in estimated co-movements is caused by increased correlations during the recent financial crisis (contagion) and not by lasting interdependence between markets. Unfortunately, the smooth transition approach cannot distinguish between these two cases. Moreover, the model only considers one break in the mean of the series, and after observations are added in the future, the correlations may regress to the levels in first regime (α). The speed adjustment coefficient (γ) is frequently larger than 1, suggesting a sudden increase in co-movements. However, as is evident from the figures in Appendix 3, the smooth transition model may not be an appropriate choice for explaining all of the relationships.

The apparent existence of two correlation regimes is observable in the Czech PX's relationships. Here, the transition occurs earlier, from the end of 2005 to midway through 2006 (the only exception is N225-PX in August 2007). The "smoothest" increase in correlations is reported for S&P500-PX and CAC-PX, with γ coefficients close to zero. The most rapid increase is obtained in the case of DAX-PX.

For the Slovak SAX, the use of a smooth transition model is clearly not justified. The correlations are trending near zero and no regimes are visible. Even within the CEE group, (see Appendix 2.B) the integration of the Slovak stock market cannot be considered gradual. It is more likely that this market is not at all integrated with the developed or the other CEE markets. Note that decreases in the correlations between SAX and the other CEE markets are estimated in the second regime.

The remaining results within the CEE group are also not convincing, as the speed adjustment coefficient is not significant in any of the cases. The estimated correlations between BUX-WIG and BUX-PX do not contain any observable pattern, or any notable regime shifts. The increase in the correlations in the second regime is small (around 0.03). The existence of a second regime is more likely to be observed in the case of WIG-PX, where the increase in correlations is slightly higher (nearly 0.07).

5. Concluding remarks

In this paper, an ADCC-GARCH model was used to investigate the degree of stock market integration between the CEE-4 and G7 countries. By estimating univariate GARCH models, we have found that asymmetric models provide the best fit to the data; thus the leverage effect is observable in the CEE-4 stock market returns. In addition to the asymmetries in volatilities, significant asymmetry in the correlations was also observed. This provides evidence that the correlations between the returns increase more following a joint negative shock (both returns being negative) than after a positive shock of the same size.

The minimal conditional correlations were generally observed at the beginning of our sample, and the maximal conditional correlations were observed at the end of it, suggesting that integration surged (or the co-movements were at least strengthened) over the examined period. The reported correlations between the CEE-4 and G7 markets over the last few years are approximately 0.6, which may be considered extensive due to the nature, size, and brief existence of the emerging markets examined. The only exception is the Slovak stock market, which still appears to be more segmented and isolated from the others in the CEE region, and from the developed markets of the G7.

To establish the speed of integration, a smooth transition logistic trend model was fitted to the dynamic conditional correlations. In the case of the Czech PX, the results suggest that the transition began from the end of 2005 to midway through 2006 (the only exception is the relationship with the Japanese N225, i.e., in August 2007). In most of the relations between the Hungarian BUX and the Polish WIG, the transition midpoint was dated during the recent financial crisis and not near their accession to the EU in May 2004. Such findings imply that global shocks caused increased co-movements of the BUX and WIG with developed markets than integration to the EU per se.

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Appendix 1.A: Results from ADF-GLS test

		stat	5 %	10 %	lag	LB
LOGDATA	SPX	-1.8484	-2.8575	-2.5700	4	0.0822
	TSE	-2.2369	-2.8593	-2.5716	3	0.1856
	DAX	-1.6256	-2.8645	-2.5762	0	0.0847
	FTSE	-2.1175	-2.8628	-2.5747	1	0.1183
	CAC	-1.0552	-2.8645	-2.5762	0	0.1747
	MIB	-1.1948	-2.8593	-2.5716	3	0.0700
	N225	-2.1625	-2.8378	-2.5522	14	0.0748
	BUX	-2.0684	-2.8593	-2.5716	3	0.1546
	WIG	-1.9380	-2.8557	-2.5683	5	0.1593
	PX	-1.2710	-2.8520	-2.5650	7	0.8108
	SAX	-0.7594	-2.8593	-2.5716	3	0.1313
DIFFLOG	SPX	-7.3564	-1.9646	-1.6439	6	0.1002
	TSE	-3.2934	-1.9634	-1.6429	7	0.2894
	DAX	-21.8629	-1.9713	-1.6499	0	0.3348
	FTSE	-2.8273	-1.9573	-1.6374	12	0.0852
	CAC	-24.2837	-1.9713	-1.6499	0	0.5819
	MIB	-1.2121	-1.9560	-1.6362	13	0.2803
	N225	-6.4900	-1.9560	-1.6362	13	0.0644
	BUX	-2.9426	-1.9610	-1.6407	9	0.0514
	WIG	-10.7743	-1.9669	-1.6460	4	0.1818
	PX	-2.7893	-1.9573	-1.6374	12	0.2446
	SAX	-2.5576	-1.9534	-1.6339	15	0.1241

Notes: In the case of log prices (“LOGDATA”), the test includes constant and trend, while in the case of returns (“DIFFLOG”) only the constant is included. The “stats” column contains the test statistics; “5%” and “10%” are the computed critical values from the response surfaces of Cheung and Lai (1995) at a given significance level; “lag” specifies the number of lags included in the auxiliary regression; “LB” is the minimal p-value of the Ljung-Box test from up to 12 lags.

Appendix 1.B: Results from KPSS test

		stat	5 %	10 %	BW
LOGDATA	S&P500	0.1909	0.148	0.119	13
	TSE	0.2357	0.148	0.119	13
	DAX	0.408	0.148	0.119	13
	FTSE	0.3807	0.148	0.119	13
	CAC	0.2381	0.148	0.119	13
	MIB	0.4268	0.148	0.119	13
	N225	0.3453	0.148	0.119	13
	BUX	0.4577	0.148	0.119	13
	WIG	0.3844	0.148	0.119	13
	PX	0.6071	0.148	0.119	13
	SAX	0.8322	0.148	0.119	13
DIFFLOG	S&P500	0.0754	0.46	0.348	4
	TSE	0.0605	0.46	0.348	8
	DAX	0.0679	0.46	0.348	7
	FTSE	0.0624	0.46	0.348	2
	CAC	0.1905	0.46	0.348	6
	MIB	0.3181	0.46	0.348	2
	N225	0.0735	0.46	0.348	5
	BUX	0.0853	0.46	0.348	9
	WIG	0.0901	0.46	0.348	7
	PX	0.1623	0.46	0.348	8
	SAX	0.4496	0.46	0.348	6

Notes: In the case of log prices (“LOGDATA”), the test includes constant and trend, while in the case of returns (“DIFFLOG”) only the constant is included. The “stats” column contains the test statistics; “5%” and “10%” are the critical values at a given significance level; “BW” is the bandwidth parameter.

Appendix 2.A: Estimation of the smooth transition model for CEE-4 markets

BUX	***α***		***β***		***γ***		***T***		**Transition midpoint**
S&P500	**0.5147**	***	**0.0446**	***	**1.2608**	*	**0.6829**	***	30.12.2007
	[0.0055]	(0.0000)	[0.0108]	(0.0000)	[0.7146]	(0.0781)	[0.0008]	(0.0000)	
TSE	**0.5077**	***	**0.0168**	*	**0.8383**		**0.5278**	***	02.10.2005
	[0.0062]	(0.0000)	[0.0095]	(0.0773)	[1.2817]	(0.5133)	[0.0027]	(0.0000)	
DAX	**0.5493**	***	**0.0364**	***	**0.1891**		**0.6915**	***	10.02.2008
	[0.0064]	(0.0000)	[0.0112]	(0.0012)	[0.2495]	(0.4489)	[0.0083]	(0.0000)	
FTSE	**0.5484**	***	**0.0428**	***	**1.1895**	*	**0.6831**	***	30.12.2007
	[0.0060]	(0.0000)	[0.0099]	(0.0000)	[0.6571]	(0.0707)	[0.0008]	(0.0000)	
CAC	**0.5601**	***	**0.0465**	***	**0.6962**	**	**0.6809**	***	16.12.2007
	[0.0057]	(0.0000)	[0.0085]	(0.0000)	[0.3373]	(0.0394)	[0.0010]	(0.0000)	
MIB	**0.5352**	***	**0.0462**	***	**0.3297**		**0.6866**	***	20.01.2008
	[0.0059]	(0.0000)	[0.0085]	(0.0000)	[0.3210]	(0.3047)	[0.0027]	(0.0000)	
N225	**0.3540**	***	**0.0616**	***	**0.3238**		**0.6682**	***	14.10.2007
	[0.0064]	(0.0000)	[0.0139]	(0.0000)	[0.2056]	(0.1156)	[0.0028]	(0.0000)	

WIG	***α***		***β***		***γ***		***T***		**Transition midpoint**
S&P500	**0.5389**	***	**0.0334**	***	**0.4750**		**0.4547**	***	05.09.2004
	[0.0077]	(0.0000)	[0.0104]	(0.0013)	[0.3868]	(0.2198)	[0.0026]	(0.0000)	
TSE	**0.5421**	***	**0.0170**	*	**0.0433**		**0.6307**	***	25.03.2007
	[0.0057]	(0.0000)	[0.0088]	(0.0543)	[0.1628]	(0.7901)	[0.1125]	(0.0000)	
DAX	**0.5610**	***	**0.0527**	***	**0.2479**		**0.7115**	***	25.05.2008
	[0.0048]	(0.0000)	[0.0110]	(0.0000)	[0.1510]	(0.1010)	[0.0036]	(0.0000)	
FTSE	**0.5528**	***	**0.0627**	***	**0.5415**	***	**0.6737**	***	11.11.2007
	[0.0062]	(0.0000)	[0.0093]	(0.0000)	[0.1943]	(0.0055)	[0.0011]	(0.0000)	
CAC	**0.5602**	***	**0.0567**	***	**0.3642**	*	**0.6735**	***	11.11.2007
	[0.0048]	(0.0000)	[0.0084]	(0.0000)	[0.1940]	(0.0609)	[0.0017]	(0.0000)	
MIB	**0.4950**	***	**0.0597**	***	**0.4983**	***	**0.6758**	***	18.11.2007
	[0.0059]	(0.0000)	[0.0096]	(0.0000)	[0.1858]	(0.0075)	[0.0013]	(0.0000)	
N225	**0.1215**		**0.2737**	*	**0.0491**	**	**0.0324**		26.07.1998
	[0.1493]	(0.4157)	[0.1507]	(0.0698)	[0.0214]	(0.0217)	[0.0342]	(0.3440)	

PX	***α***		***β***		***γ***		***T***		**Transition midpoint**
S&P500	**0.4444**	***	**0.0887**	***	**0.0379**	**	**0.5896**	***	20.08.2006
	[0.0089]	(0.0000)	[0.0136]	(0.0000)	[0.0178]	(0.0337)	[0.0226]	(0.0000)	
TSE	**0.4761**	***	**0.0556**	***	**0.1000**		**0.5529**	***	05.02.2006
	[0.0078]	(0.0000)	[0.0106]	(0.0000)	[0.1071]	(0.3505)	[0.0154]	(0.0000)	
DAX	**0.4941**	***	**0.0584**	***	**0.7884**		**0.5679**	***	30.04.2006
	[0.0080]	(0.0000)	[0.0111]	(0.0000)	[0.5337]	(0.1400)	[0.0010]	(0.0000)	
FTSE	**0.4785**	***	**0.0810**	***	**0.0789**	*	**0.5398**	***	04.12.2005
	[0.0087]	(0.0000)	[0.0116]	(0.0000)	[0.0456]	(0.0842)	[0.0117]	(0.0000)	
CAC	**0.5054**	***	**0.0733**	***	**0.0382**	*	**0.5888**	***	20.08.2006
	[0.0084]	(0.0000)	[0.0123]	(0.0000)	[0.0223]	(0.0862)	[0.0292]	(0.0000)	
MIB	**0.4830**	***	**0.0690**	***	**0.1561**		**0.5470**	***	08.01.2006
	[0.0087]	(0.0000)	[0.0112]	(0.0000)	[0.1262]	(0.2165)	[0.0067]	(0.0000)	
N225	**0.3685**	***	**0.0673**	***	**0.5870**	**	**0.6565**	***	12.08.2007
	[0.0050]	(0.0000)	[0.0111]	(0.0000)	[0.2372]	(0.0135)	[0.0011]	(0.0000)	

SAX	***α***		***β***		***γ***		***T***		**Transition midpoint**
S&P500	**0.0888**	***	**-0.0129**		**2.4193**		**0.4451**	***	18.7.2004
	[0.0067]	(0.0000)	[0.0094]	(0.1696)	[3.5318]	(0.4936)	[0.0013]	(0.0000)	
TSE	**0.0643**	***	**0.0245**	***	**0.7586**		**0.1895**	***	5.11.2000
	[0.0067]	(0.0000)	[0.0087]	(0.0051)	[0.7809]	(0.3316)	[0.0019]	(0.0000)	
DAX	**0.0356**	***	**0.0379**	***	**2.9893**		**0.7636**	***	1.3.2009
	[0.0048]	(0.0000)	[0.0135]	(0.0050)	[2.9762]	(0.3155)	[0.0006]	(0.0000)	
FTSE	**0.1283**	***	**-0.0315**		**0.7552**		**0.1268**	***	5.12.1999
	[0.0185]	(0.0000)	[0.0194]	(0.1044)	[1.1227]	(0.5014)	[0.0032]	(0.0000)	
CAC	**0.0372**	***	**0.0376**	***	**0.0504**		**0.7864**	***	28.6.2009
	[0.0053]	(0.0000)	[0.0143]	(0.0088)	[0.1043]	(0.6286)	[0.0553]	(0.0000)	
MIB	**0.0256**	***	**0.0476**	***	**0.4971**		**0.9192**	***	29.5.2011
	[0.0055]	(0.0000)	[0.0150]	(0.0015)	[0.4120]	(0.2280)	[0.0025]	(0.0000)	
N225	**0.0224**		**0.0213**		**0.0265**		**0.1169**		17.10.1999
	[0.0193]	(0.2459)	[0.0221]	(0.3343)	[0.0516]	(0.6081)	[0.1195]	(0.3282)	

*Notes: Robust standard errors based on quadratic spectral kernel with the automatic bandwidth selection of Newey and West (1994) are reported in brackets. P-values are reported in parentheses. Significance codes are *, **, and *** for the 10%, 5%, and 1% significance levels, respectively.*

Appendix 2.B: Estimation of the smooth transition model within the CEE-4 group

	α		β		γ		T		Transition midpoint
BUX-WIG	**0.6106**	***	**0.0311**	***	**1.9072**		**0.5577**	***	5.3.2006
	[0.0056]	(0.0000)	[0.0092]	(0.0007)	[1.2580]	(0.1299)	[0.0006]	(0.0000)	
BUX-PX	**0.6041**	***	**0.0321**	***	**0.1223**		**0.7064**	***	4.5.2008
	[0.0066]	(0.0000)	[0.0098]	(0.0011)	[0.1760]	(0.4875)	[0.0143]	(0.0000)	
WIG-PX	**0.5545**	***	**0.0662**	***	**0.0435**		**0.5401**	***	4.12.2005
	[0.0084]	(0.0000)	[0.0118]	(0.0000)	[0.0328]	(0.1851)	[0.0231]	(0.0000)	
BUX-SAX	**0.1762**	***	**-0.0730**	***	**0.0695**		**0.0640**	***	10.1.1999
	[0.0230]	(0.0000)	[0.0250]	(0.0036)	[0.0490]	(0.1569)	[0.0237]	(0.0072)	
WIG-SAX	**0.1319**	***	**-0.0811**	***	**0.1099**		**0.0675**	***	31.1.1999
	[0.0213]	(0.0000)	[0.0224]	(0.0003)	[0.0688]	(0.1106)	[0.0119]	(0.0000)	
PX-SAX	**0.1204**	***	**-0.0277**	**	**2.4343**		**0.2408**	***	5.8.2001
	[0.0124]	(0.0000)	[0.0136]	(0.0427)	[3.1640]	(0.4419)	[0.0007]	(0.0000)	

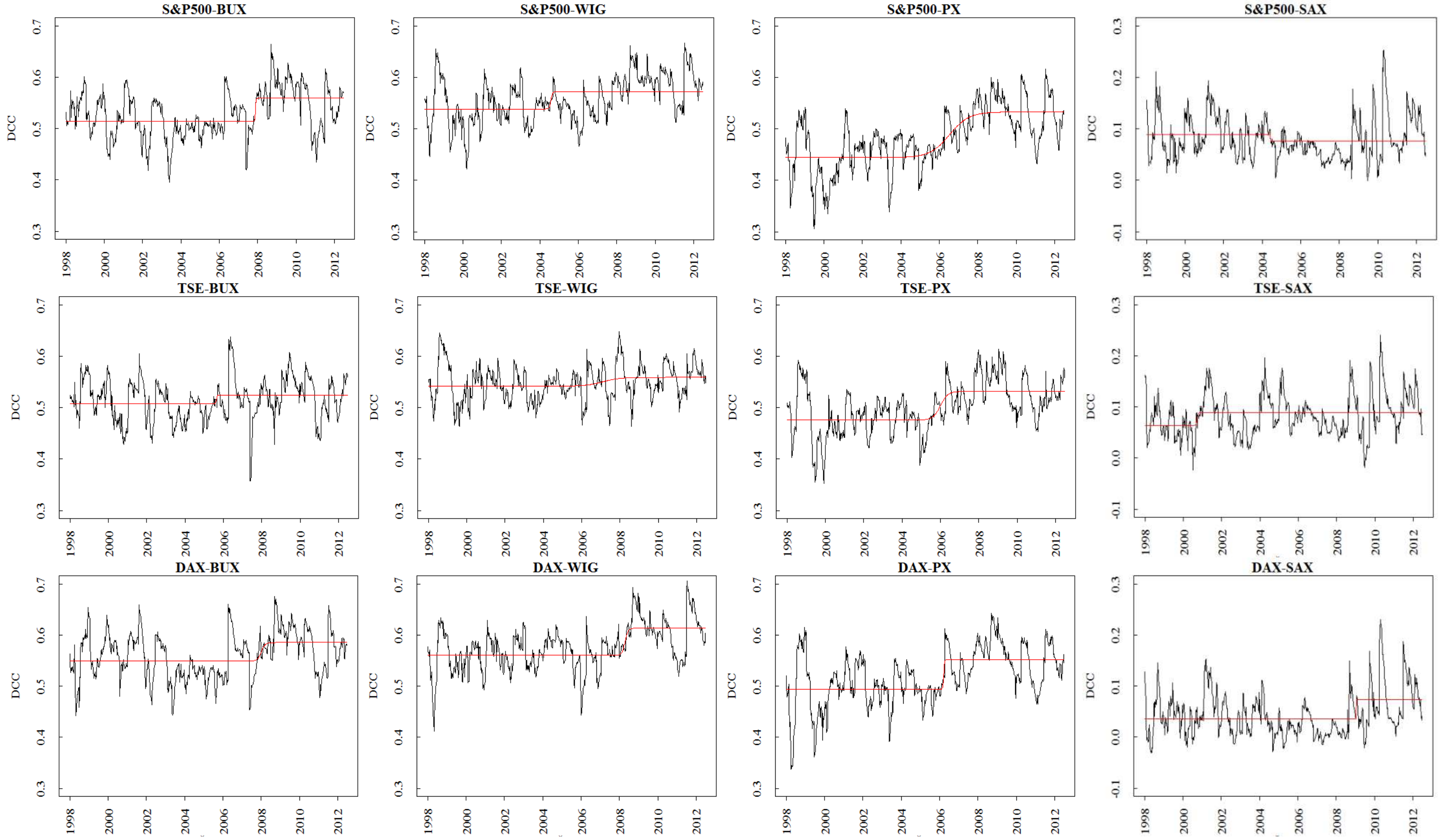
*Notes: Robust standard errors based on quadratic spectral kernel with the automatic bandwidth selection of Newey and West (1994) are presented in brackets. P-values are reported in parentheses. Significance codes are *, **, and *** for the 10%, 5%, and 1% significance levels, respectively.*

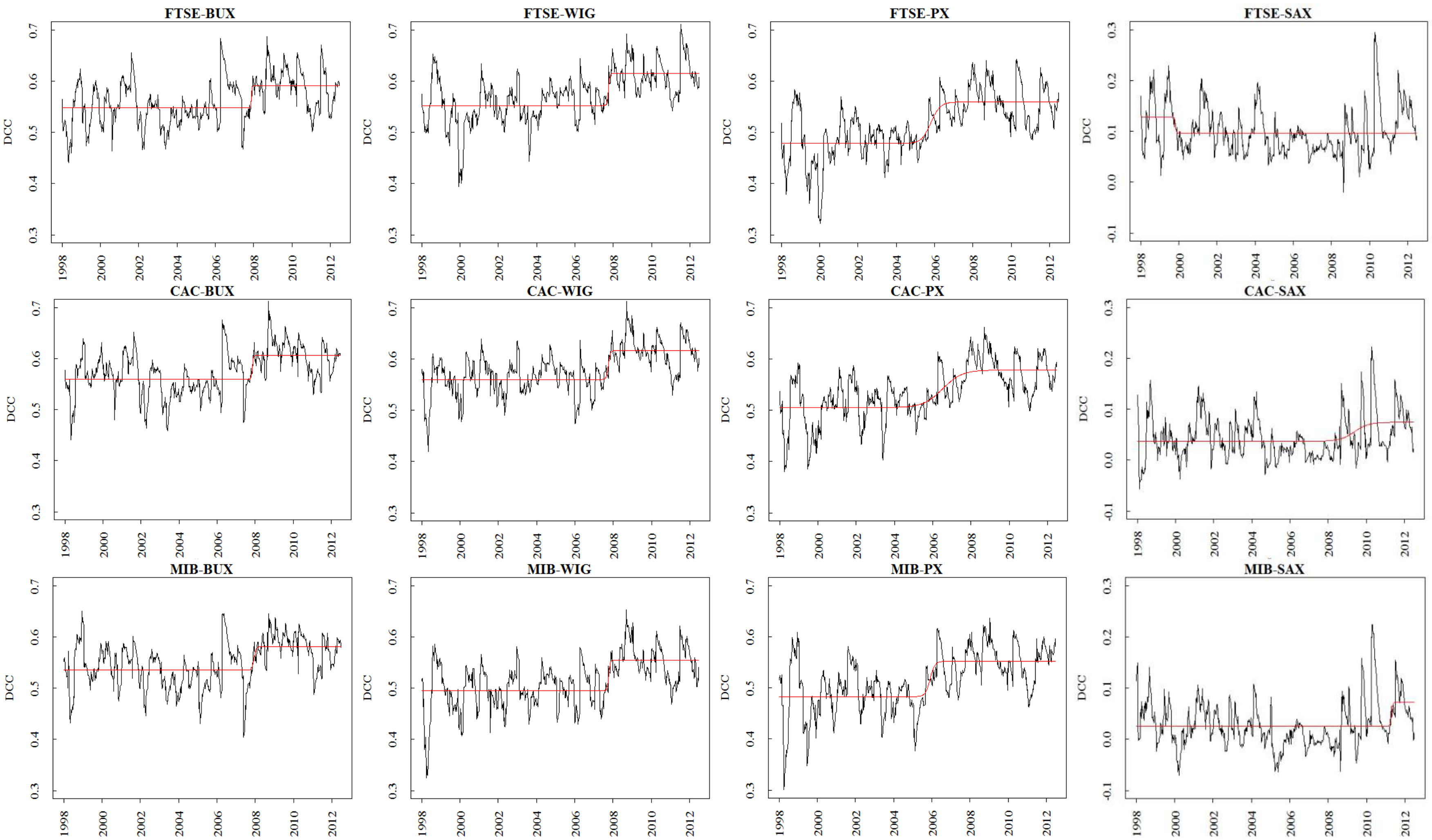
Appendix 2.C: ADF-GLS test on residuals from smooth transition models

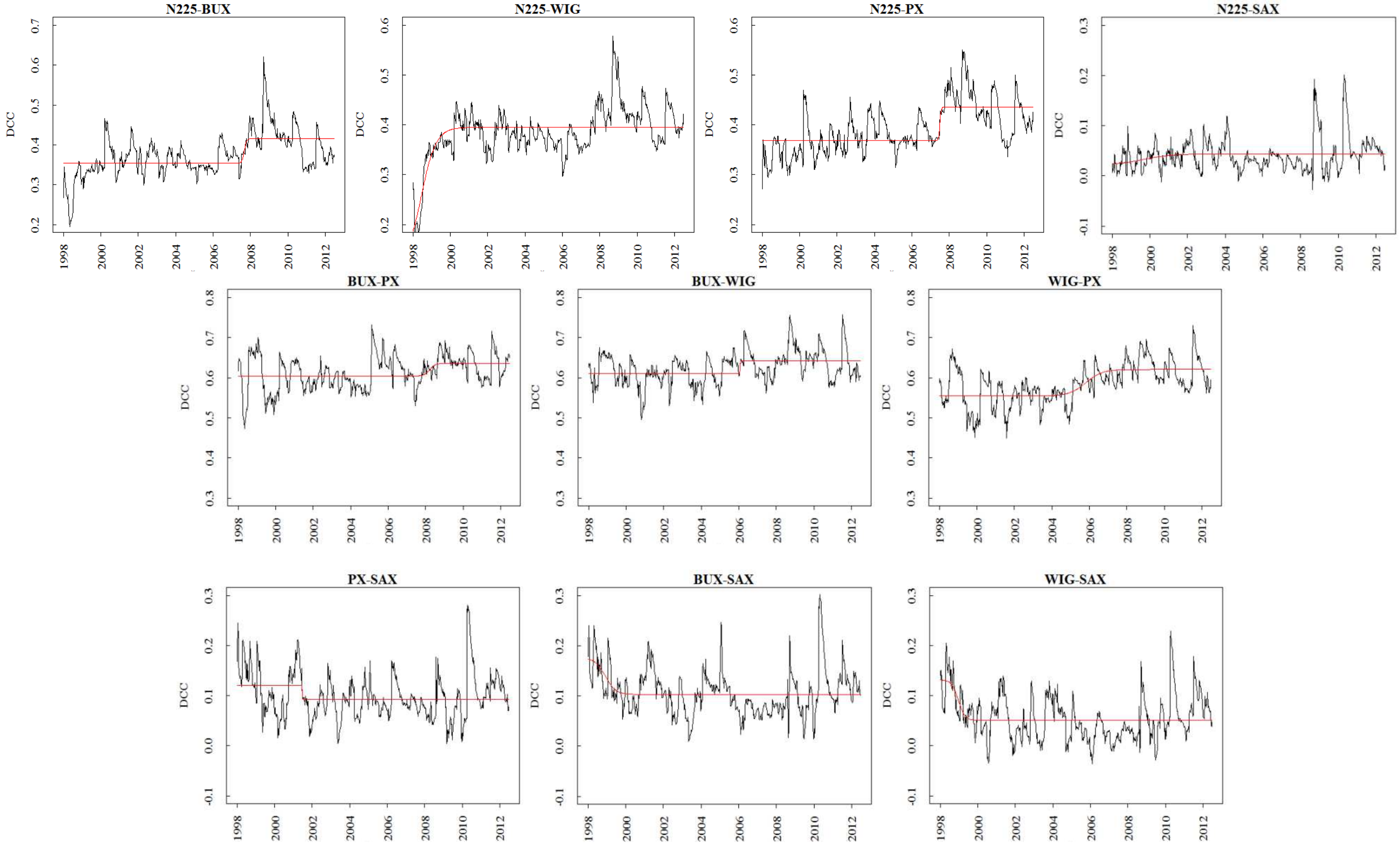
	SPX	TSE	DAX	FTSE	CAC	MIB	N225	BUX	WIG	PX
BUX	-4.8888	-5.6001	-4.9729	-5.0258	-5.1648	-5.4515	-2.1792	-	-	-
WIG	-2.9417	-5.9032	-5.1663	-4.4389	-5.3060	-5.2392	-2.0375	-4.5892	-	-
PX	-3.8668	-4.2461	-3.3127	-3.7741	-4.1081	-4.1611	**-1.8587**	-4.8486	-3.9319	-
SAX	-3.1550	-2.1747	-2.3003	-3.4279	-2.3254	-2.2887	-5.9600	-5.4081	-5.5855	-3.7811

Notes: The table contains test statistics from the ADF-GLS test procedure (as described above). The computed critical values from the response surfaces of Cheung and Lai (1995) are the same for all cases: -1.9714 and -1.6500 for the 5% and 10% significance levels. The null hypothesis of a unit-root in the residuals from the N225-PX model can only be rejected at the 10% level.

Appendix 3: ADCC and fitted smooth transition models




FTSE-BUX
FTSE-WIG
FTSE-PX
FTSE-SAX
CAC-BUX
CAC-WIG
CAC-PX
CAC-SAX
MIB-BUX
MIB-WIG
MIB-PX
MIB-SAX
DCC
1998 2000 2002 2004 2006 2008 2010 2012



Notes: The charts use different scaling for better visualization of the correlations. Most notably, relations with SAX index are ranged between -0.1 and 0.3.