Analysis of stock market linkages: evidence from the selected CEE markets

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Abstract: *This paper analyses the stock market linkages of the selected Central and Eastern European (CEE) markets (Czech Republic – PX, Hungary – BUX and Poland – WIG20) with the Western European stock market represented by the German DAX and studies also the co-movement between the individual CEE countries' stock markets. The dynamic conditional correlation (DCC) models were used to model the co-movements and thereafter in some cases the smooth transition analysis was carried out in order to capture how these correlations evolve over time. The analysis was based on weekly data over the sample period January 3rd, 1997 – November 29th, 2013 (883 observations). In the first step the asymmetric univariate autoregressive conditional heteroscedasticity model of Glosten, Jagannathan and Runkle (GJR) was estimated for individual stock return series. The results of the DCC-GJR models estimated in the next step show almost in all analysed cases the increasing level of conditional correlations. In four cases (BUX_DAX, WIG20_DAX, BUX_PX and PX_WIG20) the DCC series were identified to be nonstationary – I(1) and nonlinear logistic smooth transition regression (LSTR) model was used to capture the gradual transition towards greater co-movements and to find out if the increasing level of DCC could be attributed to the accession of these countries into the European Union (EU) in May 2004.*

Keywords: *stock market linkages, dynamic conditional correlation, logistic smooth transition regression model, Central and Eastern European markets*

1. Introduction

Stock market linkages have been attracting the attention of analysts for a long time. There exist plenty of studies dealing with this issue using various ways and methods of analysis in order to capture how shocks from one market can be transmitted to another market(s). It is also known that the correlation of emerging markets with the developed markets is relatively low and returns in emerging markets are much higher than in the developed markets. These issues provide opportunities for international diversification and present one of the reasons explaining the capital inflow into the emerging markets (see e.g. [6], [9]). To analyse the co-movements of financial returns from different markets, especially to study volatility spillover, i. e. if and how the shocks from one stock market influence the volatility development of the other market is an interesting and challenging issue. Forbes and Rigobon [11] distinguish the stock market co-movement during the periods of stability and during the periods after a shock or crisis. They use the term contagion to define „a significant increase in cross-market linkages after a shock to one country (or group of countries)". So, in case that the co-movement does not increase significantly after a shock or

crisis, they speak about interdependence. They also present different methodologies for analysis of the stock market co-movements, e. g. cross-market correlation coefficients, Autoregressive Conditional Heteroscedasticity (ARCH) and Generalized ARCH (GARCH) models, cointegration techniques and direct estimation of specific transmission mechanisms. Nowadays it has become very popular the use of multivariate GARCH models. Different types of multivariate GARCH models can be found in the literature, e. g. VECH model, CCC model, BEKK model, GDC model, DCC model and AG-DCC model.1

There exist quite a lot of studies analysing the co-movements2 of Central and Eastern European (CEE) stock markets (especially V4 countries stock markets - Czech, Hungarian, Polish and Slovak) and their co-movement with the Western European stock markets using various techniques since it is commonly known that the CEE countries did during the last decades the significant steps in the area of financial reforms and also in the development of stock markets [18]. Kash-Haroutounian and Price [16] analysed the volatility of the stock markets in V4 countries using daily data based on several variants of univariate GARCH models and two types of multivariate GARCH models (CCC and BEKK). Based on the CCC model they indicated significant conditional correlations between two pairs of countries: Hungary and Poland, and Hungary and the Czech Republic. The BEKK model showed evidence of return volatility spilovers from Hungarian to Polish stock market, but not vice versa. Égert and Kočenda [10] studied co-movements between three developed (France, Germany, the UK) and three emerging (the Czech Republic, Hungary and Poland) European stock markets based on five-minute tick intraday stock price data applying the DCC-GARCH models. They detected very little systematic positive correlation between the Western European stock markets and the three CEE stock markets. Wang and Moore [20] investigated the extent of integration of three CEE stock markets with the aggregate euro-zone market based on daily data using the bivariate DCC-EGARCH model. They proved a higher level of the stock market correlation during and after the Asian and Russian crisis and also during the period after integration of the CEE countries into the EU. Baumöhl et al. [1] analysed the integration of the stock markets of V4 countries with the German market and also mutual correlations between the stock markets of individual V4 countries using the DCC-GARCH model. Horvath and Petrovski [15] analysed the stock market co-movements between Western Europe (based on STOXX Europe 600 index) and some CEE countries (the Czech Republic, Hungary and Poland) and also some South Eastern European countries (Croatia, Macedonia, Serbia). They did the analysis based on daily data using the multivariate GARCH models and confirmed a quite high level of stock market integration between the analysed CEE countries and Western Europe and significantly lower conditional correlations for the South Eastern European countries (with exception of Croatia). Chocholatá [7] analysed the stock market integration of Serbia and Slovakia with the Western European stock market (represented by the German DAX) based on the bivariate BEKK-GARCH(1,1) models using the daily data. For the Slovak stock market no stock market integration was identified, but in case of Serbian stock market the conditional correlations varied around 0,2 during the whole analysed period what can indicate the low degree of integration. The impact of the current financial crisis on the development of conditional correlation was not confirmed. Chocholatá [8] analysed the stock market integration of the CEE stock markets

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1 For an extensive survey of multivariate GARCH models and also for the references to the authors of these models see e. g. [3], [19].

2 Some authors use the term „integration" instead of „co-movement", but we similarly as Lahrech and Sylwester [17] prefer the term „co-movement". These two authors emphasize that although the analysis of evolution of correlations between equity markets is an important component in assessing whether markets are integrated, it is not the only one.

(Czech, Hungarian and Polish) vis-à-vis the Western European stock market (as a benchmark the French CAC40, German DAX and STOXX Europe 600 were used) based on BEKK-GARCH models using daily closing values of individual stock market indices and investigated was also the impact of the current global financial crisis on the corresponding conditional correlations. The values of conditional correlations from the BEKK-GARCH(1,1) models ranged during the whole analysed period between 0,415 and 0,525, no higher intensity of the stock market integration was proved during the crisis period.

In order to assess the low correlation as an indicator of low level of market integration and to check for any possible movement it shows towards integration, various authors use the Logistic Smooth Transition Regression (LSTR) models of Granger and Teräsvirta [14] which assume that market integration takes place as a gradual process. Chelley-Steeley [6] based on this methodology analysed the extent to which the CEE markets and Russia had become less segmented and found out that Hungary is becoming integrated the most quickly. The LSTR models used in their analysis also e.g. Berben and Jansen [4] who analysed the weekly data from Germany, Japan, the UK and the US and found out that correlations among the German, UK and US stock markets had doubled, whereas the Japanese correlations had remained the same during the analysed period. Lahrech and Sylwester [17] examined the stock market linkages of US and Latin American stock markets based on DCC-GARCH models and LSTR models and they inter alia pointed to the fact that through the LSTR models it is possible to observe longer-run changes in the co-movements and not to assume that the long-run relationship is stable as in case of a cointegrated system. Durai and Bhaduri [9] used the same methodology for analysis of the correlation structure of the Indian equity markets with that of world markets. Smooth transition conditional correlation models used in their analysis of stock market integration between new EU member states and the Euro-zone Savva and Aslanidis [18]. Baumöhl [2] investigated the stock market integration between CEE-4 stock marktes and the G7 markets based on AG-DCC model and LSTR model.

The main aim of this paper is to study the stock market co-movements of the selected CEE markets (Czech Republic – PX, Hungary – BUX and Poland – WIG20) with the Western European stock market represented by the German DAX and also to analyse the co-movement between the individual CEE countries' stock markets based on dynamic conditional correlation (DCC) models and LSTR models. The effect of the EU entry on the level of conditional correlations is also assessed. The paper is organised as follows: Section 2 investigates the methodological issues – univariate GJR-GARCH model, multivariate DCC-GJR model and LSTR model, Section 3 describes the data used for analysis and empirical results and Section 4 concludes.

2. Methodology

In this section we will briefly describe some methodological issues connected with the subject of the paper – the returns calculation, specification of the conditional mean equation and DCC and LSTR models used for analysis.

If we assume that P_t is e.g. the closing value of the stock index at time t and r_t denotes logarithm of the corresponding stock return, the formula for calculation of the logarithmic stock return is as follows:

$$r_t = d(\ln(P_t)) = \ln\left(\frac{P_t}{P_{t-1}}\right) \tag{1}$$

The logarithmic stock returns' equation, i.e. the conditional mean equation, can be in general written as a Box-Jenkins ARMA(m,n) model[3] of the form:

$$r_t = \omega_0 + \sum_{j=1}^{m} \phi_j r_{t-j} + \sum_{k=1}^{n} \theta_k \varepsilon_{t-k} + \varepsilon_t \qquad (2)$$

where ω_0 is unknown constant, $\phi_j \ (j=1,2,...m)$ and $\theta_k \ (k=1,2,...n)$ are the parameters of the appropriate ARMA(m,n) model, ε_t is a disturbance term.

The simplest way how to assess the stock market interdependencies is the calculation of the unconditional correlation coefficients between the pairs of returns. Since many authors have shown that international correlations are not constant over time, the models of time-varying conditional correlations will be presented. In order to model the fluctuations of correlation and volatility between the analysed pairs of stock markets in this paper the DCC model is being used. In case that the calculated bivariate dynamic conditional correlations are non-stationary a smooth transition model can be applied. The LSTR models enable to find out when the structural change occurred and also time of its duration.

2.1. Dynamic Conditional Correlation (DCC) Model

The estimation of DCC model follows in two steps: firstly the appropriate univariate GARCH model is to be estimated[4] and thereafter the DCC model is estimated. Since in this paper the asymmetric GJR(p,q,r) model of Glosten, Jaganathan, and Runkle [13] will be used to model the conditional variance, we will concentrate here just on this type of GARCH model. The conditional variance equation h_t in case of a GJR(p,q,r) is as follows:

$$h_t = \alpha_0 + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^{p} \beta_j h_{t-j} + \sum_{k=1}^{r} \gamma_k \varepsilon_{t-k}^2 I_{t-k}^- \qquad (3)$$

where $I_{t-k}^- = \begin{cases} 1, if \ \varepsilon_{t-k} < 0 \\ 0, \ if \ \varepsilon_{t-k} > 0 \end{cases}$. It seems to be clear that in this model the impact of the good news $\varepsilon_{t-k} > 0$ and the bad news $\varepsilon_{t-k} < 0$ on conditional variance is different. In case e.g. of model GJR(0,1,1) is the impact of good news represented by the value α_1 and the impact of bad news by the sum $\alpha_1 + \gamma_1$. If $\gamma_1 > 0$, it means that the negative news increase the volatility and we speak about the leverage effect. If $\gamma_1 \neq 0$, it indicates the presence of the asymmetric effect. After diagnostic checking of standardized residuals from the univariate GARCH model, it follows the estimation of the DCC model.

We denote as $\mathbf{r_t}$ the $k \times 1$ dimensional vector of stock returns and it will be furthermore assumed that it has conditional multivariate normal distribution with the zero expected value and variance-covariance matrix $\mathbf{H_t}$, i.e.

$$\mathbf{r_t} | \Omega_{t-1} \sim N(\mathbf{0}, \mathbf{H_t}) \qquad (4)$$

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[3] ARMA model = Autoregressive Moving Average model
[4] Cappiello et al. [5] pointed out the problems connected with incorrect specification of the univariate models.

where Ω_{t-1} is the information set that includes all the information up to and including time $t-1$. The specification of the variance-covariance matrix $\mathbf{H_t}$ has in case of DCC model the following form:

$$\mathbf{H_t} = \mathbf{D_t C_t D_t} \tag{5}$$

where $\mathbf{D_t}$ is the $k \times k$ diagonal matrix with the time-varying standard deviations from univariate GJR models on the diagonal and $\mathbf{C_t}$ is the time-varying correlation matrix of conditional correlation coefficients.

The evolution of the correlation in the DCC model can be described as follows (see e.g. [20]):

$$\mathbf{Q_t} = (1 - q_a - q_b)\overline{\mathbf{Q}} + q_a \boldsymbol{\varepsilon}_{t-1} \boldsymbol{\varepsilon}_{t-1}^{\mathbf{T}} + q_b \mathbf{Q_{t-1}} \tag{6}$$

where $\mathbf{Q_t} = \{q_{ij,t}\}$ is the $k \times k$ conditional variance-covariance matrix of residuals, $\overline{\mathbf{Q}} = E(\boldsymbol{\varepsilon_t}\boldsymbol{\varepsilon_t^T})$ the unconditional (i.e. time-invariant) variance-covariance matrix and the symbols q_a, q_b denote the non-negative scalar parameters which fulfil the condition $q_a + q_b < 1$. Taking into account the fact that the matrix $\mathbf{Q_t}$ from the formula (6) does not have unit diagonal elements, it is necessary to scale it and we will receive the correlation matrix $\mathbf{C_t}$ of the form (see e.g. [20]):

$$\mathbf{C_t} = diag(\mathbf{Q_t})^{-1/2} \mathbf{Q_t} diag(\mathbf{Q_t})^{-1/2} \tag{7}$$

The typical element of matrix $\mathbf{C_t}$, i.e. the conditional correlation coefficient is as follows:

$$\rho_{ij,t} = \frac{q_{ij,t}}{\sqrt{q_{ii,t}\, q_{jj,t}}}, \ i,j = 1,2,...,n \ \text{a} \ i \neq j. \tag{8}$$

2.2. Logistic Smooth Transition Regression (LSTR) Model

The LSTR model can be applied to measure the stock market co-movements between the analysed stock markets. This model enables to capture the smooth transition between two correlation regimes unlike the structural break models supposing the instantaneous regime change. Before application of the LSTR model it is useful to test the conditional correlations for stationarity. If the conditional correlations are stationary, there is no indication of a structural break and therefore no indication of a change in the degree of market co-movement. In such a case there is no reason to use the LSTR model. Otherwise, in case that the conditional correlations are I(1), it is appropriate to apply the LSTR model (see e.g. [6], [17]).

The LSTR model for the bivariate conditional correlations calculated based on formula (8) is as follows [6]:

$$\rho_{ij,t} = \alpha + \beta S_t(\gamma,\tau) + v_t \tag{9}$$

where α and β are parameters and v_t is a stationary zero mean process. The logistic smooth transition function $S_t(\gamma,\tau)$ which controls the transition between the two correlation regimes has the following form:

$$S_t(\gamma, \tau) = \left(1 + \exp\left(-\gamma\left(t/T - \tau\right)\right)\right)^{-1} \tag{10}$$

where T is the sample size, parameter τ determines the timing of transition midpoint and parameter γ measures the speed of the transition between the two correlation regimes. The small value of γ indicates a slow gradual movement towards integration, the large value of γ speaks for an abrupt change between the two correlation regimes. The parameter α measures the degree of market co-movement in the first regime and the sum of parameters $\alpha + \beta$ the degree of market co-movement in the second regime. The values $\beta < 0$ also indicate the decrease of market co-movement, whereas the values $\beta > 0$ indicate that the conditional correlations move upward. After estimation of the LSTR model, it is necessary to test the residuals for stationarity (for more information see e.g. [17]).

3. Data and empirical results

The analysed data set consists of weekly data of stock price indices of CEE countries - the Czech PX, Hungarian BUX, Polish WIG20 and the German DAX which was used as a benchmark for Western European stock markets. We used the above mentioned weekly data spanning from January 3rd, 1997 to November 29th, 2013 (i.e. 883 observations for each index) in order to avoid the problems connected with the use of the daily data like different trading hours, national holidays or day-of-week effects. All the data were retrieved from the web-page http://stooq.com ([22], [23], [24], [25]) and the analysis was carried out in econometric software EViews.[5]

Since one of the typical features of the financial time series is the non-stationarity, we started the analysis by the unit root testing of individual logarithmic stock price indices based on the Augmented Dickey – Fuller (ADF) test. At 1 % significance level we failed to reject the null hypothesis about the existence of unit root, i. e. all the series were identified to be non-stationary. The first differences of all analysed logarithmic stock indices, i. e. logarithmic stock returns, were already stationary[6]. In further analysis we also concentrated on modelling of logarithmic returns. Individual logarithmic stock indices (prefix "L") and logarithmic returns (prefix "DL")[7] are graphically depicted on the Figure 1(a) – (d). Concerning the logarithmic return series there is a clear evidence of volatility clustering, i.e. that large (small) returns tend to be followed by another large (small) returns.

The summary descriptive statistics of logarithmic returns together with the values of Jarque – Bera test statistics are given in Table 1. The highest weekly percentage return was provided by Hungarian market (0,170%), followed by the German, Czech and Polish market with 0,134%, 0,073% and 0,066%, respectively. Concerning the standard deviations, the most volatile is the Hungarian market (4,08 %) followed by the Polish (3,72 %), German (3,43 %) and the Czech market (3,26 %). From the Table 1 it is furthermore clear that all the analysed series are negatively skewed with higher kurtosis than the normal distribution which has the kurtosis of 3. The non-normality of the distribution is also indicated by the values of the Jarque-Bera test statistics.

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[5] Programs for estimation of DCC and LSTR models were written with the help of advice provided on the web-page of EViews User Forum [21].

[6] The results are available from the author upon request.

[7] Logarithmic returns were calculated as the first differences of logarithmic index series (see (1)) and thereafter multiplied by 100%.
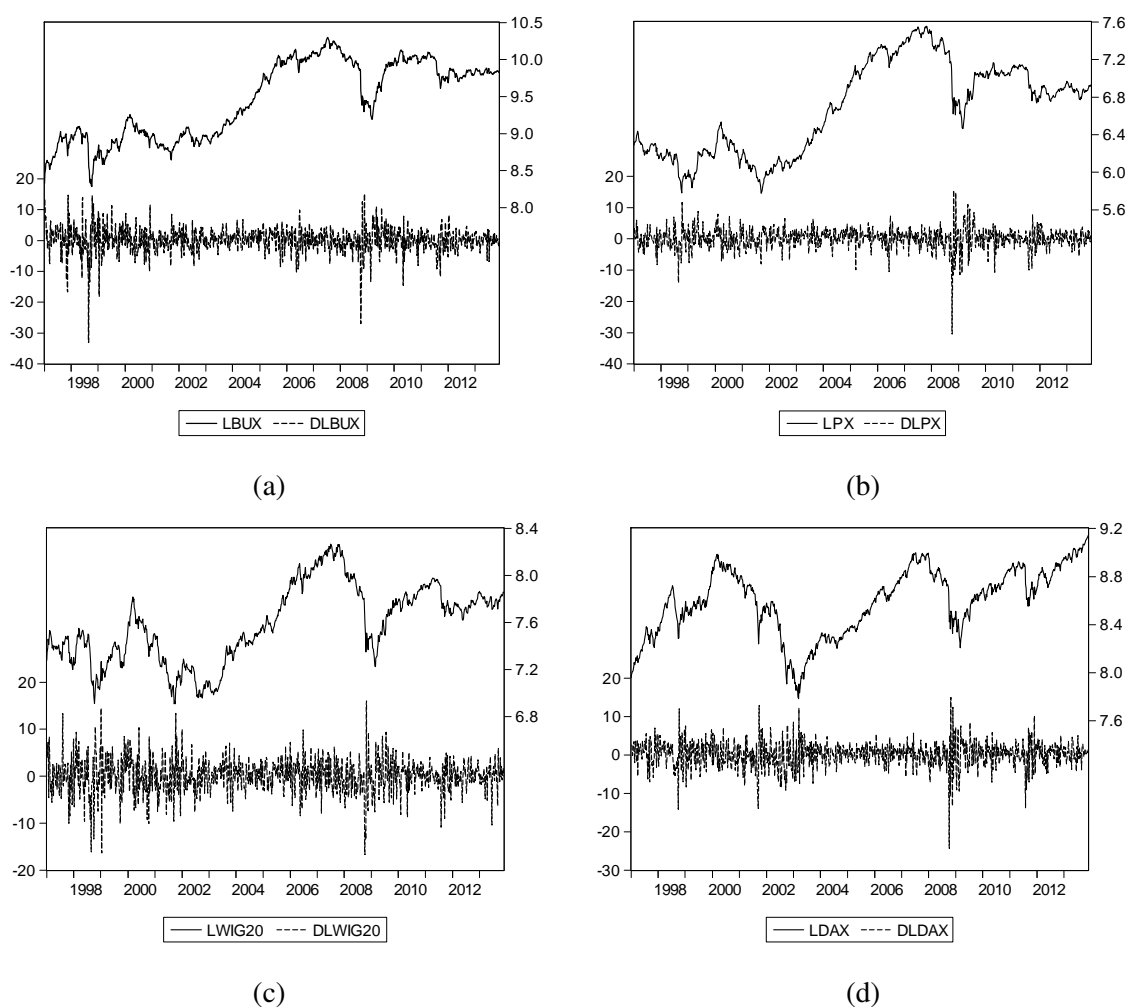
(a)

(b)

(c)

(d)

Figure 1. Logarithmic indices and logarithmic return series.
Source: Own calculations in econometric software EViews.

Table 1. Descriptive statistics of logarithmic returns

	DLBUX	DLPX	DLWIG20	DLDAX
Mean	0,169942	0,072862	0,065830	0,134345
Std. Dev.	4,082434	3,267682	3,723509	3,432103
Skewness	-1,066868	-1,072662	-0,246356	-0,640427
Kurtosis	11,42798	13,32422	5,211695	7,454353
Jarque-Bera	2777,700***	4086,301***	188,6878***	789,4578***

Note: Symbol *** denotes rejection of the normality hypothesis at 1% significance level.
Source: Own calculations in econometric software EViews.

Table 2. Unconditional correlation coefficients for the whole analysed period

	DLBUX	DLPX	DLWIG20	DLDAX
DLBUX	1,000000	0,640948	0,636964	0,556778
DLPX		1,000000	0,613074	0,536131
DLWIG20			1,000000	0,547422
DLDAX				1,000000

Source: Own calculations in econometric software EViews.

The unconditional correlation coefficients between the pairs of returns for the whole analysed period are presented in Table 2. As we can see, the unconditional correlations of individual CEE markets with the German market reach quite high values – varying between 0,536 and 0,557. Even higher values of unconditional correlations spanning from 0,613 to 0,641 were achieved for the pairs of CEE markets.

Since the unconditional correlations for the whole analysed period are not able to detect the increasing co-movement of stock markets, the calculations were carried out separately for individual years (see also [6]). Figure 2 (a) – (b) represent the results and it is clear, that the values of unconditional correlations were in individual years very different and unlike Chelley-Steeley [6], who did her analysis for the period 1995-1999, there is no clear tendency of growing correlation during the whole analysed period in neither case. Concerning the values of unconditional correlations Forbes and Rigobon [11] accented the limitations connected with these coefficients which are biased and inaccurate due to heteroscedasticity in market returns. In further analysis we therefore concentrated on the analysis of conditional correlations based on DCC models.
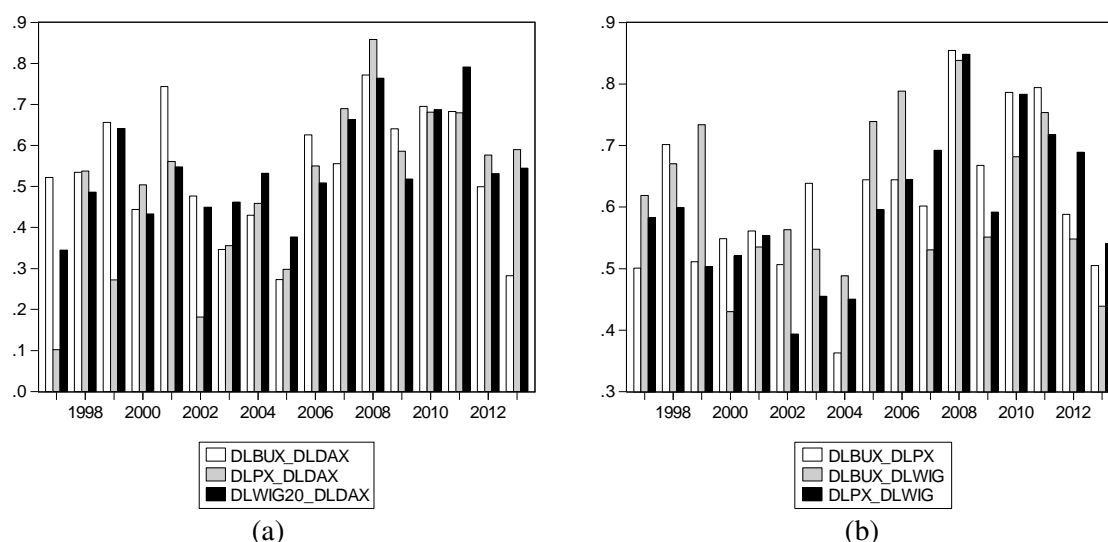

Figure 2. Unconditional correlations for individual analysed years.
Source: Own calculations in econometric software EViews.

3.1. Univariate GJR models

As it was already mentioned in section 2, the first step in estimation of the DCC model is the selection and estimation of an appropriate univariate GARCH model.

Foremost the individual logarithmic return series were modelled as ARMA models as follows:

DLBUX – AR(2)   DLWIG20 – without AR, MA components
DLPX – AR(1), AR(2), AR(7)   DLDAX – AR(3)

The residuals from these ARMA models were then tested for uncorrelatedness (Ljung – Box Q – statistics) and for normality (Jarque – Bera test statistics). The results show that the residuals are till the lag 200 (maximal possible lag in EViews)[8] uncorrelated and non-normally distributed (see Table 3).

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[8] Corresponding critical value is $\chi^2_{0,01}(200) = 249,44$.

The squared residuals however exhibit significant autocorrelation (the values of the Ljung – Box Q – statistics till the lag 12 are summarized in Table 4). Since the occurrence of the second order dependence of squared series, it is adequate to apply an appropriate ARCH-class model.

Table 3. Ljung – Box Q – statistics for residuals and values of Jarque-Bera statistics

	DLBUX+ AR(2)	DLPX+ AR(1, 2, 7)	DLWIG20	DLDAX+ AR(3)
Q(200)	210,38	197,57	184,97	209,17
Jarque-Bera	2671,201***	3830,253***	188,6878***	748,37***

Note: Symbol *** denotes rejection of the normality hypothesis at 1% significance level.
Source: Own calculations in econometric software EViews.

Table 4. Ljung – Box Q – statistics for squared residuals

lag	DLBUX+AR(2)	DLPX+ AR(1, 2, 7)	DLWIG20	DLDAX+ AR(3)
1	8,2426	5,3771	39,065***	25,754
2	23,957***	16,943	66,918***	81,392***
3	30,521***	66,765	96,221***	116,89***
4	31,474***	71,193***	101,90***	122,63***
5	36,238***	94,139***	108,20***	137,83***
6	38,522***	97,721***	113,51***	170,55***
7	64,546***	119,72***	118,42***	199,20***
8	64,596***	121,90***	120,20***	206,47***
9	66,923***	122,09***	121,17***	208,53***
10	67,886***	122,37***	121,20***	209,96***
11	68,400***	122,56***	124,22***	212,02***
12	77,320***	124,36***	132,58***	224,21***

Note: Symbol *** denotes rejection of the no autocorrelation hypothesis at 1% significance level.
Source: Own calculations in econometric software EViews.

Table 5. Estimated parameters of univariate GJR models

	DLBUX+ AR(2)	DLPX+ AR(1, 2, 7)	DLWIG20	DLDAX+ AR(3)
Model type	GJR(1,0,1)	GJR(1,1,1)	GJR(1,0,1)	GJR(1,0,1)
α_0	0,659273	0,679051	0,440847	1,095590
α_1	-	0,076560	-	-
γ_1	0,147830	0,127660	0,101456	0,387025
β_1	0,882861	0,793385	0,912989	0,705407
Diagnostic test results of standardized residuals				
Q(200)	204,57	197,22	175,62	183,12
Q^2(200)	94,003	216,67	158,48	156,17
ARCH-LM	0,0056	0,0109	0,0052	0,2861
Jarque-Bera	1397,864***	434,844***	103,062***	206,068***

Note: Symbol *** denotes rejection of the normality hypothesis at 1% significance level.
Source: Own calculations in econometric software EViews.
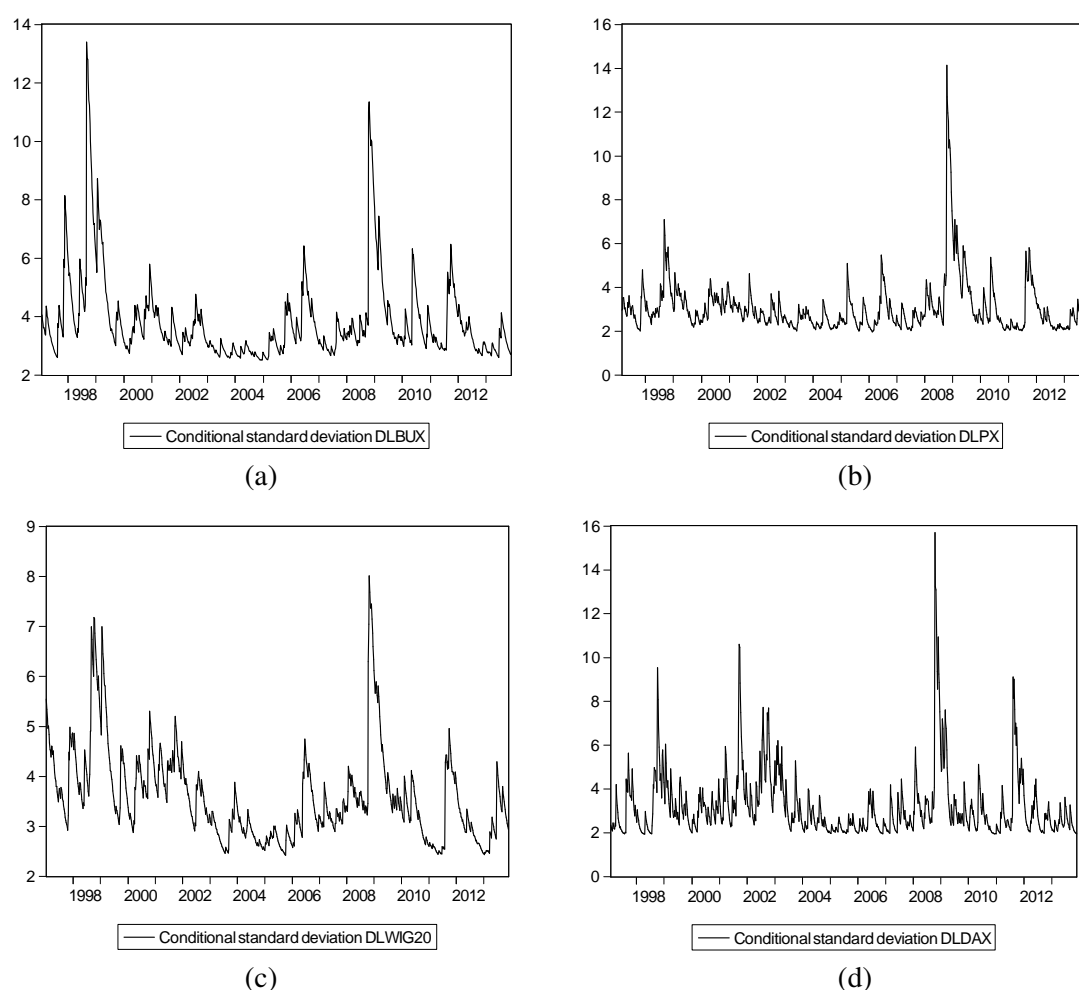
(a)

(b)

(c)

(d)

Figure 3. Conditional standard deviations from GJR models.
Source: Own calculations in econometric software EViews.

Concerning the possible asymmetric effects in conditional variance, the conditional variance was modelled by the asymmetric GJR-GARCH model (3). Information about the type of estimated GJR models together with the values of estimated parameters from the conditional variance equations and the diagnostic tests of standardized residuals are in Table 5. All the parameters were statistically significant at 1% significance level, there was no autocorrelation in the standardized residuals and squared standardized residuals till the lag 200 at 1% significance level and also no remaining heteroscedasticity was detected by the ARCH-LM test (critical value $\chi^2_{0,01}(1) = 6,635$). However the normality assumption was not fulfilled for the standardized residuals, so the estimates are consistent only as quasi-maximum likelihood estimates (see e.g. [12]).

The development of conditional standard deviations from univariate GJR models is graphically depicted on the Figure 3 (a) – (d). The highest values of conditional standard deviations were recorded for the second half of 1998 and the first months of 1999 and during the last quarter of 2008[9].

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[9] The same conclusion can be taken also from the development of logarithmic returns depicted on the Figure 1 (a)-(d).

3.2. Modelling of Dynamic Conditional Correlations (DCC)

After the estimation of univariate GJR models and adequate diagnostic check it followed the construction and estimation of multivariate DCC models. The estimated parameters[10] together with descriptive statistics of conditional correlations (8), the Jarque-Bera and ADF test results are summarized in Table 6. All the series were non-normally distributed, four series (DCC_BUX_DAX, DCC_WIG_DAX, DCC_BUX_PX, DCC_PX_WIG) were non-stationary I(1) and the remaining two conditional correlations were stationary I(0). Graphically the conditional correlations are plotted on the Figure 4 (a) – (f). For the non-stationary conditional correlations the LSTR models were applied.

Table 6. Estimated parameters of DCC models and descriptive statistics

	DCC_BUX_ DAX	DCC_PX_ DAX	DCC_WIG_ DAX	DCC_BUX_ PX	DCC_BUX_ WIG	DCC_PX_ WIG
q_a	0,017458	0,042888	0,011112	0,008838	0,035232	0,010131
q_b	0,976763	0,922430	0,989437	0,990793	0,922186	0,990177
Descriptive statistics						
Mean	0,516883	0,459542	0,527514	0,585251	0,574011	0,550901
Maximum	0,760553	0,844715	0,711276	0,744401	0,817725	0,728139
Minimum	0,292822	0,064643	0,361900	0,435862	0,277275	0,380693
Std. Dev.	0,094888	0,133903	0,090457	0,089105	0,082968	0,101974
Skewness	0,320024	-0,365403	0,439111	0,335593	-0,189191	0,269625
Kurtosis	3,072519	3,241297	1,951304	1,724765	3,381397	1,529412
Jarque-Bera	15,23100***	21,74243***	68,68264***	76,23276***	10,59539***	90,06101***
ADF test - conclusion	I(1)	I(0)	I(1)	I(1)	I(0)	I(1)

Note: Symbol *** denotes rejection of the normality hypothesis at 1% significance level.
Source: Own calculations in econometric software EViews.

3.3. Smooth transition analysis

Table 7 presents the estimated parameters of the LSTR models and contains also the information about the transition midpoint. All the estimated parameters were statistically significant at 1% significance level, the only exception was the parameter γ in LSTR_BUX_DAX which was significant only at 13,11% significance level. All the parameters β were non-negative, indicating an increase of the mean correlation in the „new" correlation regime. Higher increases were reached between the CEE markets correlations whereas the correlation increases with DAX were not so high. The values of γ were in individual cases quite different - the higher the value of γ was, the sharper was the transition between correlation regimes.

Graphically the fitted correlations are depicted together with the actual correlations on Figure 4 (a), (c), (d), (f). The most abrupt change between the two correlation regimes was identified for the pair BUX_DAX, followed by WIG_DAX, PX_WIG and BUX_PX. In all the four cases the transition midpoint occurred later after the entrance of the CEE countries to the EU. The residuals of the LSTR models were tested for stationarity via ADF test (for

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[10] All the parameters were statistically significant at 1% significance level.

more information see e.g. [6], [17]). All the residual series were identified to be stationary, i.e. the use of the LSTR model was justified.[11]
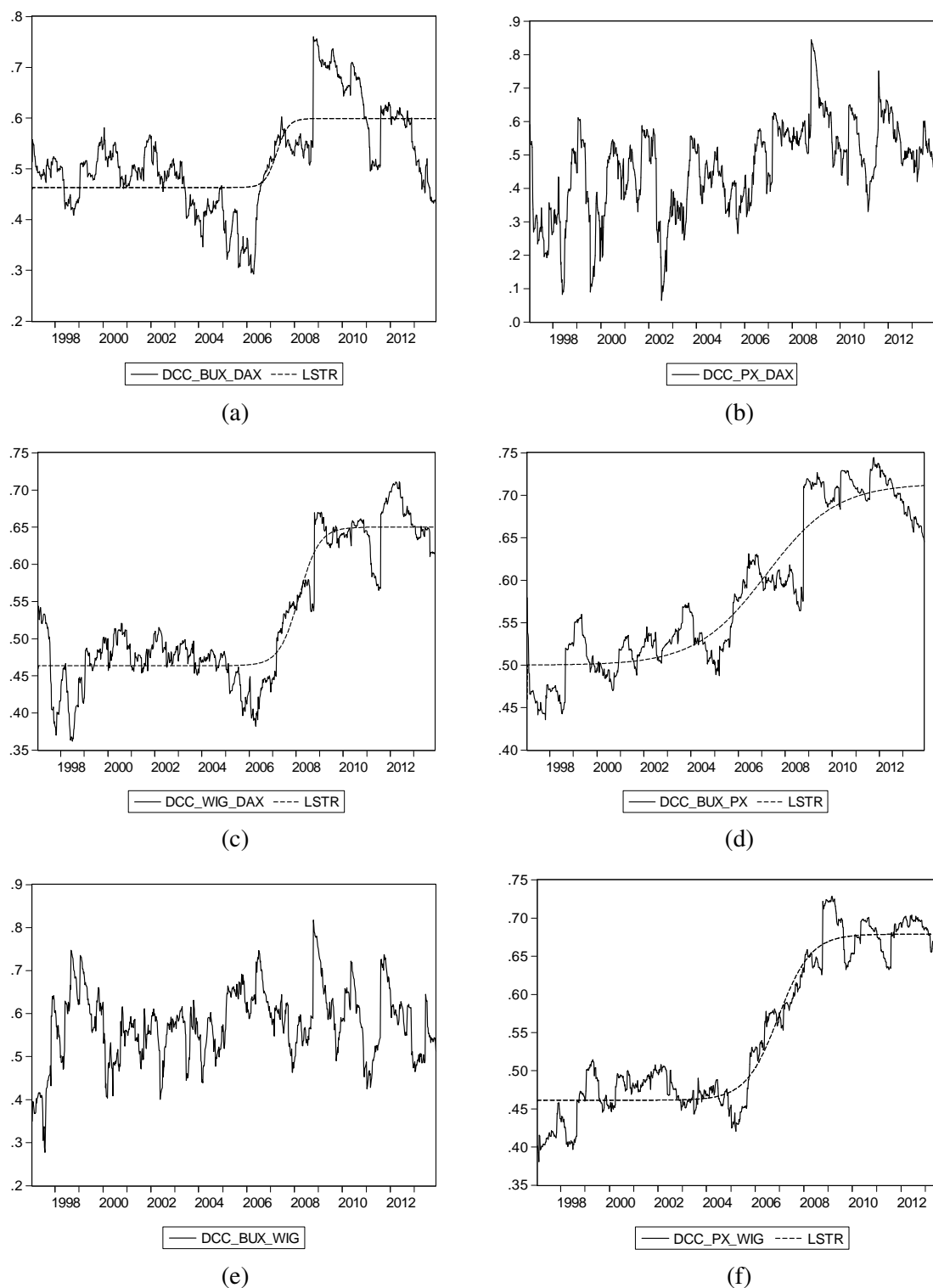

(a)

(b)

(c)

(d)

(e)

(f)

Figure 4. Dynamic conditional correlations and Logistic Smooth Transition Regression models.
Source: Own calculations in econometric software EViews.

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[11] The results are available from the author upon request.

Table 7. Estimated parameters of LSTR models

	LSTR BUX_DAX	LSTR WIG_DAX	LSTR BUX_PX	LSTR PX_WIG
α	0,463199	0,463587	0,499916	0,461293
β	0,135941	0,186453	0,213906	0,217631
γ	69,08097	39,59171	11,30365	25,15060
τ	0,606789	0,658933	0,603615	0,589181
Transition midpoint	April 6th, 2007	February 22nd, 2008	March 16th, 2007	December 15th, 2006

Source: Own calculations in econometric software EViews.

4. Summary and conclusion

The analysis of the stock market co-movement builds an important issue in order to design the optimal portfolio and also for policy makers. The high correlations indicate that equity market disturbances in one country have a tendency to be transmitted into another country.

In this paper we analysed the stock market co-movement of the CEE countries with German DAX and also the stock market linkages between the individual CEE countries based on DCC and LSTR models. The dynamic conditional correlations were in four analysed cases (DCC_BUX_DAX, DCC_WIG_DAX, DCC_BUX_PX, DCC_PX_WIG) non-stationary with the transition midpoints calculated by LSTR models located between December 2006 and February 2008. The conditional correlations had in these cases the increasing tendency with notable increase during the years 2006 and 2007, but the most rapid increase in the degree of the stock market co-movement was recorded in October 2008 and can be attributed to the global financial crisis. The conditional correlations of the remaining pairs, i.e. DCC_PX_DAX and DCC_BUX_WIG were stationary with no significant shifts in the level of conditional correlation.

Taking into account the results of our study, we can conclude, similarly as Chelley-Steeley [6], that the most rapid progress in the degree of stock market co-movement between the CEE country and DAX was achieved for Hungary and Poland followed by only the slight progress in case of the Czech Republic.

Concerning the conditional correlations between the individual CEE stock markets, the co-movement of Hungarian and Polish market measured by the DCC values was around the mean 0,517 during the whole analysed period. Very interesting is the conclusion about the remaining two pairs Hungarian BUX with the Czech PX and Polish WIG20 with the Czech PX, since in both these cases it was recorded quite a significant progress in the degree of co-movement.

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References

[1]   Baumöhl E., Farkašovská M. and Výrost T.: Integrácia akciových trhov: DCC MV-GARCH model. Politická ekonomie, Vol. 2010(4), 2010, 488-503.

[2]   Baumöhl E.: Stock market integration between the CEE-4 and the G7 markets: Asymmetric DCC and smooth transition approach. Available online at http://mpra.ub.uni-muenchen.de/43834/, 2013, 26 p.

[3]   Bauwens L., Laurent S. and Rombouts J. V. K.: Multivariate GARCH Models: A Survey. Journal of Applied Econometrics, Vol. 21, 2006, 79-109.

[4]   Berben R.P. and Jansen W.J.: Comovement in international equity markets: a sectoral view. DNB Staff Reports 2002, 2002, No. 83, 28p.

[5]   Cappiello L., Engle R.F. and Sheppard K.: Asymmetric Dynamics in the Correlations Of Global Equity and Bond Returns. Journal of Financial Econometrics, Vol. 4(4), 2006, 537-572.

[6]   Chelley-Steeley P.L.: Modelling equity market integration using smooth transition analysis: a study of Eastern European stock markets. Journal of International Money and Finance, Vol. 24, 2005, 818–831.

[7]   Chocholatá M. Stock Market Integration: A Case Study for Serbia and Slovakia. Strategic management: International Journal of Strategic management and Decision Support Systems in Strategic Management. Serbia: University of Novi Sad, Vol. 18(4), 2013, 35-42.

[8]   Chocholatá M. The global financial crisis and stock returns: evidence from the Czech Republic, Hungary and Poland. Mathematical methods in economics 2013: proceedings of the 31st international conference: Jihlava, September 2013, 315-320.

[9]   Durai S.R.S. and Bhaduri S.N.: Correlation dynamics in equity markets: evidence from India. Research in International Business and Finance, Vol. 25(1), 2011, 64-74.

[10] Égert B. and Kočenda E.: Time-Varying Comovements in Developed and Emerging European Stock Markets: Evidence from Intraday Data. William Davidson Institute Working Paper 861, 2007.

[11] Forbes K. J. and Rigobon R.: No Contagion, Only Interdependence: Measuring Stock Market Comovements. Journal of Finance, Vol. LVII(5), 2002, 2223–2262.

[12] Franses P.H. and Dijk, D. van: Non-Linear Time Series Models in Empirical Finance. Cambridge: Cambridge University Press, 2000. 298 p.

[13] Glosten L.R., Jagannathan R. and Runkle D. E.: On the Relationship Between the Expected Value and the Volatility of the Nominal Excess Return on Stocks. Journal of Finance, Vol. 48(5), 1993, 1779-1801.

[14] Granger C.W.J. and Teräsvirta T.: Modelling Nonlinear Economic Relationships. Oxford University Press, 1993.

[15] Horvath R. and Petrovski D.: International Stock Market Integration: Central and South Eastern Europe Compared. William Davidson Institute Working Papers Series, wp 1028, 2012.

[16] Kash-Haroutounian M. and Price S.: Volatility in the transition markets of Central Europe. Applied Financial Economics, Vol. 11(1), 2001, 93-105.

[17] Lahrech A. and Sylwester K.: U.S. and Latin American stock market linkages. Journal of International Money and Finance, Vol. 30(7), 2011, 1341-57.

[18] Savva Ch.S. and Aslanidis N.: Stock market integration between new EU member states and the Euro-zone. Empirical Economics, Vol. 39(2), 2010, 337-51.

[19] Silvennoinen A. and Teräsvirta T.: Multivariate GARCH models. SSE/EFI Working Paper Series in Economics and Finance No. 669, 2008.

[20] Wang P. and Moore T.: Stock Market Integration for the Transition Economies: Time-Varying Conditional Correlation Approach. The Manchester School Vol. 76 (1), 2008, 116–133.

[21] http://forums.eviews.com/ [valid to November 30th, 2013]

[22] http://stooq.com/q/d/?s=%5Ebux&c=0&i=w [valid to November 30th, 2013]

[23] http://stooq.com/q/d/?s=%5Edax&c=0&i=w [valid to November 30th, 2013]

[24] http://stooq.com/q/d/?s=%5Epx&c=0&i=w [valid to November 30th, 2013]

[25] http://stooq.com/q/d/?s=wig20&c=0&i=w [valid to November 30th, 2013]