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Abstract

This study examines the relationship between time-varying correlations and conditional volatility among eight European emerging stock markets and the MSCI World stock market index from January 2000 to December 2012. Correlations are estimated in the standard and asymmetric dynamic conditional correlation (DCC) model frameworks. The results can be summarized by three main findings: (1) asymmetry in volatility is not a common phenomenon in emerging markets; (2) asymmetry in correlations is found only with respect to the Hungarian stock market; and (3) the relationship between volatility and correlations is positive and significant in all countries included in the study. Thus, diversification benefits decrease during periods of higher volatility.

Key words: conditional volatility, time-varying correlations, emerging markets

JEL codes: C32, G01, G15

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Introduction

One of the most significant and discussed concepts in the field of modern finance is portfolio theory, which is based on the principle that investors can reduce the variability of portfolio returns by holding assets with low- or negative-return correlations. A common belief is that there are such asset classes in international markets, particularly in emerging markets; therefore, most studies analyze such correlations among stock market returns. The earliest empirical studies in the field of stock market co-movement (see Grubel, 1968; Ripley, 1973; Lessard, 1974) demonstrated that the equity return correlations throughout different international markets are low and can be attributed to national factors and that diversification among these markets is advisable.

A decade after the latest of these studies, many researchers noted a substantial increase in the interdependence between national stock markets (e.g., Jaffe and Westerfield, 1985; Schöllhammer and Sand, 1985; Eun and Shim, 1989; Grinold et al., 1989; Meric and Meric, 1989). In the aftermath of the October 1987 US stock market crash, co-movement between national markets increased significantly (see, King and Wadhwani, 1990; Arshanapalli and Doukas, 1993). This co-movement led to another broad area of research in the framework of stock market integration: the "contagion effect". This effect is most simply described by Forbes and Rigobon (2002, p. 2223) as “a significant increase in cross-market linkages after a shock to one country (or group of countries)”. The implications of contagion are broad; from the perspective of a practical investor, contagion leads to a weakening of diversification benefits.

Cappiello et al. (2006) examined whether the correlations between international developed equity (and bond) market movements correspond with volatilities. This relationship has several implications with respect to portfolio management and, notably, the risks are significantly larger than might be assumed by an examination of correlations or volatilities.

This paper explores possible international diversification benefits by estimating the dynamic conditional correlations (using both standard and asymmetric dynamic conditional correlation (DCC) models) among eight European emerging markets and the MSCI World stock market index during the period from January 2000 to December 2012. The study will link the correlations to conditional volatility to examine whether the correlations are correspondingly higher during periods of high volatility (or vice versa). If the relationship between conditional volatility and the correlations is positive, this suggests that diversification benefits decrease during volatile periods, i.e., during the times when they are most valuable.

The remainder of this paper is organized as follows. The next section provides a short review of the empirical studies. Section 2 describes the data and methodology, and Section 3 presents the results of the study. Section 4 presents conclusions.

1. The related literature

The evidence concerning increasing stock market linkages depends on the study period and on the methodology employed; however, most studies indicate that international stock market linkages have increased in recent decades. Lahrech and Sylwester (2011) applied a smooth transition logistic trend model to establish the degree of stock market integration between the US and Latin American stock markets from December 1988 to March 2004. The smooth transition model was fitted to the standard DCCs between the US equity market and the Argentina, Brazil, Chile, and Mexico markets. The results demonstrated an increase in the degree of co-movements among these markets; however, the speed and magnitude of integration varied with the country examined. A similar approach was utilized by Durai and Bhaduri (2011), who studied the correlations from July 1997 to August 2006 among the following sample markets: the US, the UK, Germany, India, Malaysia, Indonesia, Singapore, South Korea, Japan, and Taiwan. The results showed that the correlations are higher among developed markets and lower between the returns of the Indian stock market with the developed and Asian stock markets. The low correlations of the Indian market continue to suggest the possibility of international diversification benefits.

Guesmi and Nguyen (2011) concluded that emerging market regions (Latin America, Asia, Southeastern Europe, and the Middle East) are segmented from other world markets. With the exception of the Latin American region, calculated DCCs did not exhibit a significant increase from March 1996 to March 2008.

Using a sample of CEE-3 countries (the Czech Republic, Poland, and Hungary), Germany, and the US, Baumöhl et al. (2011) demonstrated that endogenously detected unconditional volatility breaks in stock market returns are significantly associated with DCCs. When the breaks are linked to a decrease in volatility, the correlations between the indices also decrease. Similarly, a sudden increase in volatility is accompanied by an increase in DCCs, which supports the presence of a shift contagion effect. Kenourgios et al. (2011) also provide evidence of contagion on a sample of emerging markets (Brazil, Russia, India, China) and two developed markets (UK and US) from 1995 to 2006 using an asymmetric time-varying framework (AG-DCC). In a separate study, Kenourgios and Samitas (2011) examine the correlations of Balkan emerging stock markets (Turkey, Romania, Bulgaria, Croatia, and

Serbia) with developed European markets (UK, Germany, and Greece) from January 2000 to February 2009 and provide evidence that the dependence increased between the Balkans and the developed equity markets, which supports the presence of herding behavior that appeared to be evident during the 2008 stock market crash period.

Samarakoon (2011) conducted an extensive study of stock market integration and contagion among 62 emerging and frontier markets and the US market from April 2000 to September 2009. Using shock models, Samarakoon (2011) found that shocks are more likely driven by the US market during periods of tranquility, whereas shocks from emerging markets impact the US during periods of crisis. There are important interdependencies among emerging and frontier markets with the US market that do not offer US investors an effective hedge against US shocks and periods of crisis.

Syllignakis and Kouretas (2011) applied a rolling regression analysis of conditional correlations with conditional volatility. Their results imply that the usefulness of the Central and Eastern European stock markets as a diversification tool has diminished in recent years, most notably during the recent financial crisis and the 2008 stock market crash. This particular sample included the stock markets of the US, Germany, Russia, the Czech Republic, Estonia, Hungary, Poland, Romania, Slovakia, and Slovenia from October 1997 to February 2009.

Horvath and Petrovski (2013) compared the CEE-3 market correlations with those of Southeastern Europe (Croatia, Macedonia, and Serbia). These authors found that the degree of co-movement with the Stoxx Europe 600 index is much higher with respect to the CEE-3 countries during their study period from January 2006 to May 2011.

The asymmetric DCC model was used in the study by Gjika and Horvath (2013) to estimate the correlations between the CEE-3 stock markets and the aggregate Euro-zone index Stoxx 50 from December 2001 to October 2011. This study observed a significant increase in correlations after the entry of the CEE-3 countries into the European Union; moreover, the correlations remained at higher levels (approximately 0.6) during the recent financial crisis. Although asymmetries in volatility were present in all cases, an asymmetry in correlations was significant only for the BUX (Hungary) and WIG (Poland) pair of indices; these authors also linked the correlations to conditional volatility but not all relationships were significant.

2. Data and methodology

Our dataset consists of the daily closing prices of eight European (the Czech Republic, Hungary, Poland, Croatia, Estonia, Latvia, Lithuania, and Romania) emerging market indices and the MSCI World stock market index from January 2000 to December 2012. The corresponding period includes the recent financial crisis that spread globally and the European debt crisis, and it implies a relationship between correlations and volatility during periods in which diversification was most required.

Because of non-synchronous trading effects (for further discussion see Baumöhl and Výrost, 2010), each series of daily closing prices was individually synchronized with the daily values of the MSCI World stock market index and continuous returns were then computed from weekly averages. The data were obtained from the Thomson Reuters Datastream database. Table 1 summarizes all the countries and national stock market indices used in this study.

Table 1 Countries and stock market indices that are included in the sample.

Country	**RIC**	**Country**	**RIC**
Czech Republic	.PX	Estonia	.OMXTGI
Hungary	.BUX	Latvia	.OMXRGI
Poland	.WIG	Lithuania	.OMXVGI
Croatia	.CRBEX	Romania	.BETC

Note: RIC stands for the Reuters Instrument Code.

To estimate the DCCs, we employed the standard two-step DCC model of Engle and Sheppard (2001) and Engle (2002), in addition to the asymmetric version that was proposed by Cappiello et al. (2006). It is known that for higher dimensions, the estimated parameters in the DCC model are downward biased, see Hafner and Reznikova (2012). We therefore estimated the DCC model for each pair of markets separately, which allowed the estimation of different parameters for the equations modeling the bivariate variance-covariance matrices.

First, ARMA-GARCH models are estimated to obtain standardized residuals. Our model selection procedure includes the following GARCH-class models:

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).

Our procedure permitted the inclusion of up to five lags of innovation and volatility in all models, and the same lag structure was permitted in the mean equations. The autocorrelation and ARCH effects of the standardized residuals were tested at the 5% significance level using the Ljung-Box test up to $int[0.05T]$ lags. The sign bias test proposed by Engle and Ng (1993) was applied to ensure that the model specification was correct (all possible asymmetric effects are included). After appropriate models were found consistent with Cappiello et al. (2006), we selected the model that best fit the data according to the Bayesian information criterion (BIC). We utilized a generalized error distribution (GED) instead of the normality condition on the distribution of errors. To overcome certain optimization problems and to speed up the procedure, we employed variance targeting in all models.

After the univariate GARCH models were fitted, in the second step of the DCC model, standardized residuals were used to estimate the correlations. It is assumed that the variance-covariance matrix of paired residuals can be decomposed to $\mathbf{D}_t\mathbf{R}_t\mathbf{D}_t$, where $\mathbf{D}_t$ is a diagonal matrix of time-varying conditional standard deviations from univariate GARCH models. Given this assumption, the DCC (1, 1) model takes the following form:

$$\mathbf{R}_t = diag\{\mathbf{Q}_t\}^{-1/2}\mathbf{Q}_t diag\{\mathbf{Q}_t\}^{-1/2} \tag{1}$$

$$\mathbf{Q}_t = (1-\alpha-\beta)\overline{\mathbf{Q}} + \alpha\boldsymbol{\varepsilon}_{t-1}\boldsymbol{\varepsilon}_{t-1}^T + \beta\mathbf{Q}_{t-1} \tag{2}$$

$$\rho_{ij,t} = \frac{q_{ij,t}}{\sqrt{q_{ii,t}\, q_{jj,t}}},\ i, j = 1,2,\ldots,n; i \neq j \tag{3}$$

where $\mathbf{R}_t$ is the time-varying correlation matrix, $\overline{\mathbf{Q}}$ is the unconditional correlation matrix in the dynamic correlation structure $\mathbf{Q}_t$, and $\boldsymbol{\varepsilon}_t$ is a vector of standardized residuals. $\overline{\mathbf{Q}}$ is estimated via the moment estimator $T^{-1}\sum_{t=1}^{T}\hat{\boldsymbol{\varepsilon}}_t\hat{\boldsymbol{\varepsilon}}_t^{\mathrm{T}}$. The following restrictions are imposed to ensure that the matrix $\mathbf{Q}_t$ is positive definite: the scalar parameters $\alpha, \beta \geq 0$, and $\alpha + \beta < 1$. A typical element of $\mathbf{R}_t$ takes the form of $\rho_{ij,t}$, which are the estimated DCCs. The asymmetric version of the DCC model is:

$$\mathbf{Q}_t = (1-\alpha-\beta)\overline{\mathbf{Q}} - \xi\,\overline{\mathbf{N}} + \alpha\boldsymbol{\varepsilon}_{t-1}\boldsymbol{\varepsilon}_{t-1}^{\mathrm{T}} + \beta\mathbf{Q}_{t-1} + \xi\,\mathbf{n}_{t-1}\mathbf{n}_{t-1}^{\mathrm{T}} \tag{4}$$

where $\overline{\mathbf{N}} = T^{-1}\sum_{t=1}^{T}\mathbf{n}_t\mathbf{n}_t^{\mathrm{T}}$, $\mathbf{n}_t = I[\boldsymbol{\varepsilon}_t < 0]\circ\boldsymbol{\varepsilon}_t$, $I[.]$ is a k × 1 indicator function that takes the value of 1 if the argument is true (and 0 otherwise), and "$\circ$" represents the Hadamard product. The positive definiteness of $\mathbf{Q}_t$ is similarly ensured: α, β, $\xi \geq 0$, and $\alpha + \beta + \delta\xi < 1$, where δ = the maximum eigenvalue $[\overline{\mathbf{Q}}^{-1/2}\overline{\mathbf{N}}\overline{\mathbf{Q}}^{-1/2}]$ (for more details, see Cappiello et al., 2006). If the asymmetric term in the correlation dynamics is significant, the estimated correlations from the bivariate asymmetric DCC model will be used in a subsequent analysis; otherwise, the correlations from the bivariate standard DCC model are employed.

The DCCs are then regressed on a constant, time trend, and conditional volatility:

Model 1: $\rho_{ij,t} = \gamma_{ij,0} + \gamma_{ij,1} t + \sum_{k=1}^{p} \rho_{ij,t-k} + \pi_{ij,1}\sigma_{i,t} + \pi_{ij,2}\sigma_{j,t} + \varepsilon_{ij,t}$ (5)

where $\rho_{ij,t}$ are the bivariate DCCs between the MSCI World stock market index (i) and the index from the emerging markets group (j), σ_i is the conditional standard deviation of the MCSI index and σ_j is the conditional standard deviation of the emerging market. The time trend (t) is also included in our models because several DCCs may exhibit a strong trend that is manifested by an increasing integration among markets. Model 1 requires further discussion. In the studies by Syllignakis and Kouretas (2011) and Gjika and Horvath (2013), a specification with no time trend and with $p = 0$ was used. DCCs are stationary by construction but typically highly persistent (the sum of $\alpha + \beta$ approaches 1). Conditional volatilities also have high persistence. In such cases, the specification with $p = 0$ leads to high autocorrelation of residuals. In our case, the first order autocorrelation coefficient is often larger than 0.9, and size distortions are thus substantial (see Granger et al., 2001 or Su, 2008). Although Newey-West standard errors – particularly with pre-whitening – reduce the size distortions, the model remains miss-specified and requires lagged dependent variables. Therefore, we employed the following approach. We estimated (5) with $p = 1$. The presence of autocorrelation in residuals was tested via the Peña and Rodríguez (2006) procedures. If the null of autocorrelation was rejected, we estimated $p = 2$, and the procedures were repeated until the null of autocorrelation was not rejected.We then tested for the presence of heteroskedasticity using the White (1980) test with a nonparametric unweighted bootstrap as in Cribari-Neto and Zarkos (1999). If the null of homoskedasticity was rejected, we used the HC3 standard errors, consistent with MacKinnon and White (1985).

Finally, as $\sigma_{i,t}$ and $\sigma_{j,t}$ are often highly correlated, we estimated two alternative specifications with only one conditional volatility included:

Model 2 (developed market): $\rho_{ij,t} = \gamma_{ij,0} + \gamma_{ij,1} t + \sum_{k=1}^{p} \rho_{ij,t-k} + \pi_{ij,1}\sigma_{i,t} + \varepsilon_{ij,t}$ (6)

Model 3 (emerging market): $\rho_{ij,t} = \gamma_{ij,0} + \gamma_{ij,1} t + \sum_{k=1}^{p} \rho_{ij,t-k} + \pi_{ij,1}\sigma_{j,t} + \varepsilon_{ij,t}$ (7)

3. Results and discussion

The preferred univariate ARMA-GARCH models are presented in Table 2. Although asymmetry in volatility is a widespread phenomenon in developed stock markets, not all the emerging markets exhibit such volatility behavior. Asymmetry in volatility did not occur in four indices, namely, those from Croatia, Estonia, Latvia, and Romania. Asymmetry in correlations is even rarer: the asymmetric term in the bivariate DCC models were found significant only for the Hungarian BUX. [1] All other dynamic conditional correlations are thus estimated in a standard DCC model framework.

Table 2 ARMA-GARCH specifications.

Czech Republic	ARMA(5,1)-NAGARCH(1,1)	MSCI	ARMA(1,1)-NAGARCH(1,1)
Hungary	ARMA(1,1)-NAGARCH(1,1)	MSCI	ARMA(1,1)-NAGARCH(1,1)
Poland	ARMA(5,1)-NAGARCH(1,1)	MSCI	ARMA(1,1)-NAGARCH(1,1)
Croatia	ARMA(1,1)-GARCH(1,1)	MSCI	ARMA(1,1)-NAGARCH(1,1)
Estonia	ARMA(1,1)-GARCH(1,1)	MSCI	ARMA(1,1)-NAGARCH(1,1)
Latvia	ARMA(1,1)-GARCH(1,1)	MSCI	ARMA(1,1)-NAGARCH(1,1)
Lithuania	ARMA(1,1)-GJRGARCH(1,1)	MSCI	ARMA(1,1)-TGARCH(1,1)
Romania	ARMA(1,1)-GARCH(1,1)	MSCI	ARMA(4,2)-GJRGARCH(1,1)

Note: We allow the ARMA-GARCH specification of the MSCI to be different because the series are individually synchronized with the MSCI World index as a result of the non-synchronous trading effects.

The descriptive statistics of the DCCs are presented in Table 3. The highest average correlations are reported for Poland (0.606), Hungary (0.583), and the Czech Republic (0.558). The stock market returns from Southeastern Europe exhibit lower correlations with the returns of the MSCI World stock market index. Figure 1 demonstrates that for several of these markets, the DCCs swing below 0.5 (Estonia, Latvia, and Lithuania).

Table 3 Descriptive statistics of the estimated DCCs.

Country	**Mean**	**Std.**	**Min**	**(date)**	**Max**	**(date)**
Czech Republic	0.558	0.132	0.258	04.07.2003	0.787	15.05.2009
Hungary	0.583	0.074	0.317	04.07.2003	0.816	26.05.2006
Poland	0.606	0.124	0.316	26.04.2002	0.824	20.08.2010
Croatia	0.359	0.161	0.028	14.10.2005	0.695	15.05.2009
Estonia	0.378	0.066	0.140	25.02.2000	0.547	17.10.2008
Latvia	0.207	0.068	0.037	03.08.2001	0.380	17.10.2008
Lithuania	0.293	0.107	-0.176	03.08.2007	0.688	17.10.2008
Romania	0.317	0.263	-0.193	13.12.2002	0.797	09.07.2010

With respect to portfolio diversification opportunities, among the eight series of DCCs, seven of the cases had maximal DCCs that were identified after 2007. Moreover, in three of the cases (Baltic States), October 2008 (when the American stock market reported its highest decrease since the 1987 stock market crash) is the month in which maximal DCCs were obtained.

We follow Cappiello et al. (2006), Syllignakis and Kouretas (2011), and Gjika and Horvath (2013) and estimate the relationship among DCCs and volatilities. Table 4 summarizes the results from Model 1, which explains the DCCs in terms of conditional volatilities of both stock market returns. In the five cases (the Czech Republic, Croatia, Estonia, Latvia, and Lithuania), the volatility of the MSCI World index is significant and

[1] Gjika and Horvath (2013) found asymmetric effects in correlations between the Hungarian BUX and Polish WIG.

positive at the 10% significance level at least. Domestic volatility of the emerging markets is significant and positive in four of the cases (Hungary, Poland, Lithuania, and Romania).

Table 4 Results from Model 1.

Country	*Constant*	*Time*	σ_i	σ_j	R^2	R^2*
Czech Republic	0.017[a]	3.8E-05[a]	0.300[c]	0.201	0.961	0.638
Hungary	0.055[a]	9.1E-06	0.100	0.896[b]	0.848	0.340
Poland	0.020[a]	4.1E-05[a]	0.154	0.522[b]	0.956	0.638
Croatia	-0.007[c]	2.1E-05[a]	0.573[a]	0.116	0.976	0.491
Estonia	0.040[a]	2.4E-05[a]	0.690[a]	-0.075	0.836	0.361
Latvia	0.005[b]	1.3E-05[a]	0.274[a]	-0.015	0.930	0.457
Lithuania	0.055[a]	4.5E-05[a]	1.049[b]	1.481[b]	0.476	0.196
Romania	-0.020[a]	6.0E-05[a]	0.059	0.541[b]	0.977	0.699

Note: Superscripts a, b, and c denote significance at the 1%, 5%, and 10% level, respectively. We do not present coefficients of the lagged dependent variable; however, first lags are significant at the 1% level in all cases with coefficient estimates of approximately 0.9 on average. In most models, one lag was sufficient to capture autocorrelation structure. Two lags were required only for Hungary. R^2 is the adjusted R-squared without a lagged dependent variable in the regression model.*

The results from Model 1 suggest that there may yet be emerging markets for international investors that might provide diversification benefits in times of higher volatility. Unfortunately, the correlations among conditional volatilities were high in many instances and the resulting standard errors might have been inflated. We therefore checked our results by estimating Model 2 with the conditional volatility of the MSCI World stock market index and Model 3 with the conditional volatility of domestic stock market returns. Table 5 presents the results from these models.

Table 5 Results from Models 2 and 3.

Country	*Model 2 (MSCI volatility)*					*Model 3 (domestic volatility)*				
	Constant	*Time*	σ_i	R^2	R^2*	*Constant*	*Time*	σ_j	R^2	R^2*
Czech Republic	0.018[a]	0.483[a]	0.483[a]	0.961	0.634	0.017[a]	0.404[a]	0.404[a]	0.961	0.631
Hungary	0.059[a]	0.705[a]	0.705[a]	0.845	0.285	0.057[a]	0.980[a]	0.980[a]	0.848	0.338
Poland	0.024[a]	0.489[a]	0.489[a]	0.956	0.631	0.019[a]	0.667[a]	0.667[a]	0.956	0.635
Croatia	-0.005[c]	0.640[a]	0.640[a]	0.976	0.470	-0.004	0.379[a]	0.379[a]	0.976	0.462
Estonia	0.039[a]	0.652[a]	0.652[a]	0.836	0.361	0.032[a]	0.353	0.353	0.830	0.240
Latvia	0.005[b]	0.261[a]	0.261[a]	0.930	0.410	0.006[b]	0.039	0.039	0.928	0.308
Lithuania	0.069[a]	1.596[a]	1.596[a]	0.464	0.158	0.062[a]	1.807[a]	1.807[a]	0.471	0.148
Romania	-0.011[b]	0.381[b]	0.381[b]	0.977	0.676	-0.020[a]	0.586[a]	0.586[a]	0.977	0.699

Note: Superscripts a, b, and c denote significance at the 1%, 5%, and 10% level, respectively. We do not present coefficients of the lagged depended variable; however, first lags are significant at the 1% level in all cases with coefficient estimates of approximately 0.9 on average. In all models, one lag was sufficient to capture autocorrelation structure. R^2 is the adjusted R-squared without a lagged dependent variable in the regression model.*

These results are less ambiguous. From eight markets included in our sample, all cases demonstrated that the conditional volatility of the MSCI World stock market index were significant and positive at the 5% significance level at least. With respect to Model 3, the volatility of domestic markets was significant and positive in six of the analyzed countries, which is a considerable increase compared to previous results. The only exception is Estonia and Latvia, where domestic volatility remains insignificant.

These results demonstrate that when the volatility (domestic and/or foreign) increases, the correlations between emerging markets and developed markets are also likely to increase. Consequently, despite the lower correlations of emerging markets with developed markets, diversification benefits decrease during more volatile periods, which is the time when investors most need them.

We included the time trend in the specifications of all models because several studies have indicated an overall increase in DCCs (e.g., Guesmi and Nguyen, 2011; Lahrech and Sylwester, 2011; Gjika and Horvath, 2013). The trend captures the long-run increase in the DCCs that was confirmed for the majority of emerging markets. The corresponding coefficient was significant and positive for 7, 8, and 6 countries in Models 1, 2, and 3, respectively. These results suggest that the stock market integration of emerging markets is gradual and increasing over time. To test whether an increase in correlations at the end of our sample is not simply a manifestation of contagion, we employed a fourth specification that expanded Model 1 with a dummy variable for a recent financial crisis. This variable took the value of 1 after July 15, 2007 and 0 otherwise. However, this variable was significant only in the regression models of Romania.[2]

4. Conclusions

This paper examined the time-varying correlations of eight European emerging markets with developed markets that were represented by the MSCI World index on a sample of weekly returns during the period from January 2000 to December 2012. Our findings have implications for risk management, international finance, and particularly for portfolio management; they are summarized as follows:

(i) The asymmetric behavior of volatility, often observed for developed stock markets, is not present in all analyzed emerging stock market indices.

(ii) Asymmetry in correlations is likely to be scarce because it was only detected in the Hungarian BUX. Therefore, the correlations were changing symmetrically, regardless of whether the previous innovation was positive or negative. This result is by contrast to the results of Cappiello et al. (2006) who found asymmetric effects in correlations for developed stock market returns.

[2] Results available upon request.

(iii) The linkages among emerging markets with developed markets have increased over time, which implies that diversification opportunities in international markets are slowly decreasing.

(iv) We found evidence that the relationship between correlations and volatility might be considered positive. This further reduces diversification possibilities because diversification benefits decrease during periods of higher volatility.

These results raise several issues with respect to hedging in international equity markets, such as whether different strategies are required in periods of tranquility and crisis, or whether different asset classes should be used when hedging equity portfolios.

Literature

Arshanapalli, B., Doukas, J., 1993. International Stock Market Linkages: Evidence from the Pre- and Post-October 1987 period. Journal of Banking & Finance. 17, 193–208.

Baumöhl, E., Lyócsa, Š., Výrost, T., 2011: Shift Contagion with Endogenously Detected Volatility Breaks: The Case of CEE Stock Markets. Applied Economics Letters. 18, 1103–9.

Baumöhl, E., Výrost, T., 2010. Stock Market Integration: Granger Causality Testing with respect to Nonsynchronous Trading Effects. Czech Journal of Economics and Finance. 60, 414–25.

Bollerslev, T., 1986. Generalized Autoregressive Conditional Heteroskedasticity. Journal of Econometrics. 31, 307–27.

Büttner, D., Hayo, B., 2011. Determinants of European stock market integration. Economic Systems. 35, 574–85.

Cappiello, L., Engle, R.F., Sheppard, K., 2006. Asymmetric dynamics in the correlations of global equity and bond returns. Journal of Financial Econometrics. 4, 537–72.

Cribari-Neto, F., Zarkos, S.G., 1999. Bootstrap methods for heteroskedastic regression models: evidence on estimation and testing. Econometric review. 18, 211–25.

Ding, Z., Engle, R.F., Granger, C.W.J., 1993. A Long Memory Property of Stock Market Returns and a New Model. Journal of Empirical Finance. 1, 83–106.

Durai, S.R.S., Bhaduri, S.N., 2011. Correlation dynamics in equity markets: evidence from India. Research in International Business and Finance. 25, 64–74.

Engle, R.F., Ng, V.K., 1993. Measuring and Testing the Impact of News On Volatility. Journal of Finance. 48, 1749–78.

Eun, CH.P., Shim, P., 1989. International Transmission of Stock Market Movements. Journal of Financial & Quantitative Analysis. 24, 241–56.

Gjika, D., Horvath, R., 2013. Stock Market Comovements in Central Europe: Evidence from Asymmetric DCC Model. Economic Modelling. 33, 55–64.

Glosten, L.R., Jagannathan, R., Runkle, D.E., 1993. On the Relationship Between the Expected Value and the Volatility of the Nominal Excess Return on Stocks. Journal of Finance. 48, 1779–1801.

Granger, C.W.J., Hyung, N., Jeon, Y., 2001. Spurious regressions with stationary series. Applied Economics. 33, 899–904.

Grinold, R., Rudd, A., Stefek, D., 1989. Global Factors: Facts and Fiction. Journal of Portfolio Management. 16, 79–88.

Grubel, H.G., 1968. Internationally Diversified Portfolios: Welfare Gains and Capital Flows. American Economic Review. 58, 1299–314.

Guesmi, K., Nguyen, D.K., 2011. How strong is the global integration of emerging market regions? An empirical assessment. Economic Modelling. 28, 2517–27.

Hafner, C.M., Reznikova, O., 2012. On the estimation of dynamic conditional correlation models. Computational Statistics and Data Analysis. 56, 3533–45.

Hamilton, J., 1994. Time Series Analysis. Princeton University Press, New Jersey.

Hardouvelis, G., Malliaropulos, D., Priestley, R., 2006. EMU and European Equity Market Integration. Journal of Business. 79, 365–92.

Hentschel, L., 1995. All in the family: Nesting symmetric and asymmetric GARCH models. Journal of Financial Economics. 39, 71–104.

Higgins, M.L., Bera, A.K., 1992. A Class of Nonlinear ARCH Models. International Economic Review. 33, 137–58.

Horvath, R., Petrovski, D., 2013. International Stock Market Integration: Central and South Eastern Europe Compared. Economic Systems. 37, 81–91.

Jaffe, J., Westerfield, R., 1985. The Weekend Effect in Common Stock Returns: the International Evidence. Journal of Finance. 40, 433–54.

Kenourgios, D., Samitas, A., 2011. Equity market integration in emerging Balkan markets. Research in International Business and Finance. 25, 296–307.

Kenourgios, D., Samitas, A., Paltalidis, N., 2011. Financial crises and stock market contagion in a multivariate time-varying asymmetric framework. Journal of International Financial Markets, Institutions & Money. 21, 92–106.

King, M.A., Wadhwani, S., 1990. Transmission of Volatility between Stock Markets. Review of Financial Studies. 3, 5–33.

Lahrech, A., Sylwester K., 2011. U.S. and Latin American stock market linkages. Journal of International Money and Finance. 30, 1341–57.

Lee, G.J., Engle, R.F., 1999. A permanent and transitory component model of stock return volatility, in: Engle, R.F., White, H. (Eds.), Cointegration Causality and Forecasting: A Festschrift in Honor of Clive W. J. Granger. Oxford University Press, New York. pp. 475–97.

Lessard, D.R., 1974. World, National, and Industry Factors in Equity Return. Journal of Finance. 29, p. 379–91.

MacKinnon, J.G., White, H., 1985. Some heteroskedasticity-consistent covariance matrix estimators with improved finite sample properties. Journal of Econometrics. 29, 305–25.

Meric, I., Meric, G., 1989. Potential Gains from International Diversification and Intertemporal Stability and Seasonality in International Stock Market Relationships. Journal of Banking & Finance. 13, 627–40.

Nelson, D.B., 1991. Conditional Heteroskedasticity in Asset Returns: A New Approach. Econometrica. 59, 347–70.

Peña, D., Rodríguez, J., 2006. The log of the determinant of the autocorrelation matrix for testing goodness of fit in time series. Journal of Statistical Planning and Inference. 136, 2706–18.

Ripley, D.M., 1973. Systematic Elements in the Linkage of National Stock Market Indices. Review of Economics & Statistics. 55, 356–61.

Samarakoon, L.P., 2011. Stock market interdependence, contagion, and the U.S. financial crisis: The case of emerging and frontier markets. Journal of International Financial Markets, Institutions and Money. 21, 724–42.

Schöllhammer, H., Sand, O., 1985. The Interdependence among the Stock Markets of Major European Countries and the United States: An Empirical Investigation of Interrelationships Among National Stock Price Movements. Management International Review. 25, 17–26.

Su, J.J., 2008. A note on spurious regressions between stationary series. Applied Economics Letters. 15, 1225–30.

Syllignakis, M.N., Kouretas, G.P., 2011. Dynamic correlation analysis of financial contagion: Evidence from the Central and Eastern European markets. International Review of Economics and Finance. 20, 717–32.

Taylor, S.J. 1986. Modeling Financial Time Series. John Wiley & Sons, Chichester.

Wang, P., Moore, T., 2008. Stock Market Integration for the Transition Economies: Time-varying Conditional Correlation Approach. The Manchester School. 76, 116–33.

White, H., 1980. A heteroskedasticity-consistent covariance matrix estimator and a direct test for heteroskedasticity. Econometrica. 48, 817–38.

Zakoian, J-M., 1994. Threshold Heteroskedastic Models. Journal of Economic Dynamics and Control. 18, 931–55.

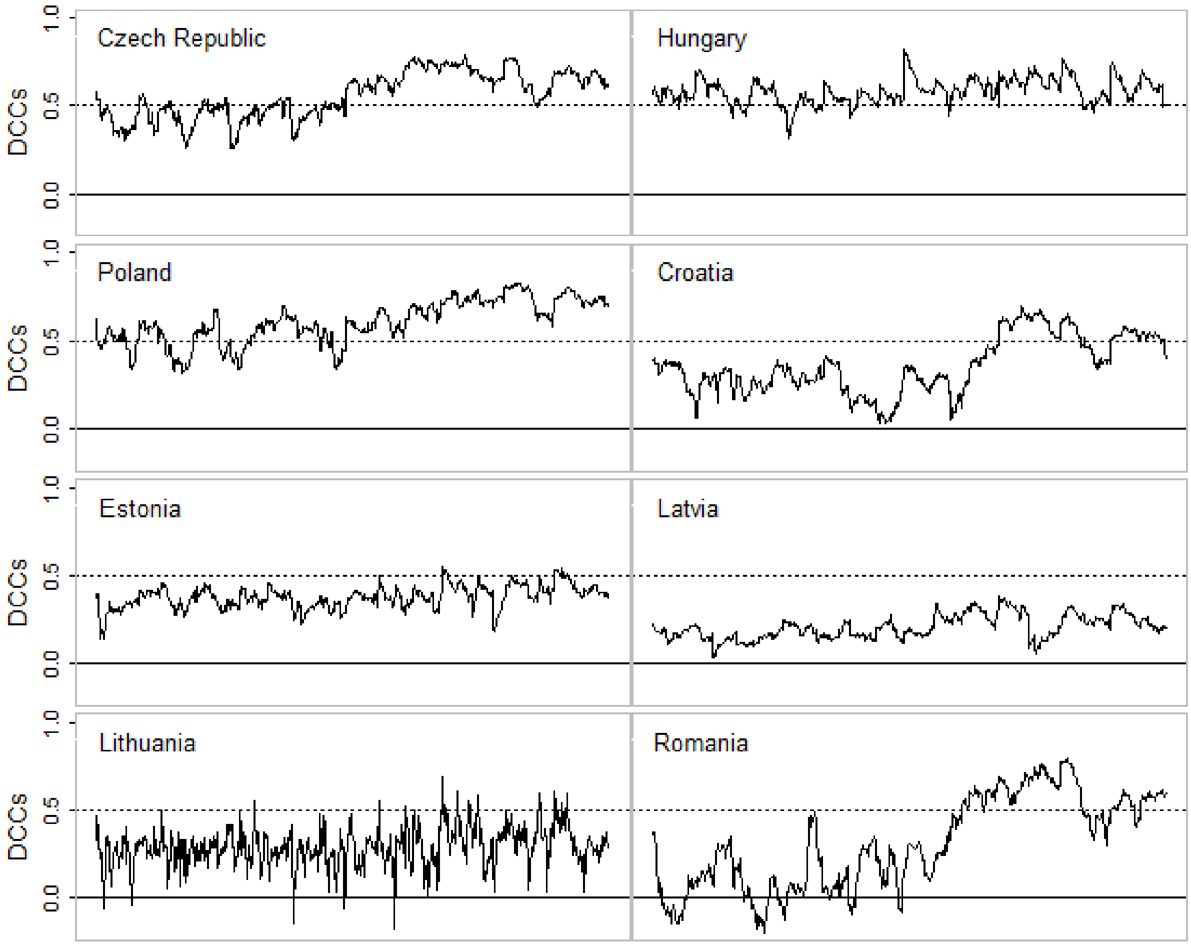

Figure 1 Estimated dynamic conditional correlations.