STOCK MARKET CO-MOVEMENTS IN CENTRAL AND EASTERN EUROPE

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Abstract

We examine the co-movements of the Central and Eastern European emerging stock markets, namely those of Visegrad Group – the Czech Republic, Hungary, Poland, and Baltic States – Estonia, Latvia, Lithuania with developed markets (represented by the STOXX Global 1800 Index) over the period from January 2000 to December 2013. Mutual relationships are estimated in both standard and asymmetric DCC MV-GARCH models. Further on, time-varying correlations are used as a proxy of stock market integration and are explained by the smooth transition logistic trend model to examine, whether this process can be considered as gradual over time. We found that Visegrad stock markets exhibit in average higher correlations and the transition process is smoother in comparison to Baltic markets. Also positive relationship between deviations from the long-term logistic trend and market volatility has been confirmed. Thus, in more volatile periods correlations tend to be higher; providing decreasing diversification benefits for the international investors.

Key words: emerging stock markets, integration, dynamic conditional correlations, non-linear models

JEL Code: C32, G01, G15

Introduction

Many emerging markets implemented financial liberalization policies during the last few decades. In such liberalizing environment, one would expect an increase in market integration, but regulatory liberalizations might 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 & Harvey, 2002). Full-scale integration between markets is unlikely as structural differences between markets exist. To name few: different industry shares, size of companies, non-synchronous trading effects, cognitive differences among investors (e.g. home bias, see Lucey & Zhang, 2010). This means that even if markets are fully liberalized and there are no existing formal barriers, some natural barriers still occurs to slow down market integration.

In this paper we examine, whether the process of stock market integration in CEE region may be described as a smooth transition from a lower-state level to higher-state level integration. First, we compute dynamic conditional correlations as our proxy of integration with developed markets (represented by the STOXX Global 1800 Index). Second, smooth transition logistic trend model is fitted to estimated correlations to examine, whether the evolution of co-movements may be regarded as gradual process. Third, deviations from this long-term trend are explained by market volatility.

1 Brief literature overview

Our study is closely linked to the work of Chelley-Steeley (2004), who according to our knowledge was the first who applied the smooth transition trend (STR) model to estimated stock market correlations. 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 to January 2002. In her later study (Chelley-Steeley, 2005), she used the same methodology to analyze the process of integration of equity markets of the CEE countries (the Czech Republic, Hungary, Poland) and Russia with respect to the US, the UK, Germany, Japan, and France during the period from July 1994 to December 1999. In both works, co-movements were estimated as bivariate correlations, which have been calculated for each month using the daily returns within the corresponding month.

As such correlations may be distorted, dynamic conditional correlations (DCCs) were utilized by Lahrech & Sylwester (2011) to establish the degree of stock market integration between the US and Latin American stock markets in the period from December 1988 to March 2004. STR model was then fitted to the estimated DCCs. Same approach was applied by Durai & Bhaduri (2011) on a sample of markets from the US, UK, Germany, India, Malaysia, Indonesia, Singapore, South Korea, Japan, and Taiwan over the period from July 1997 to August 2006.

In comparison to above-stated studies, we allow the presence of asymmetry effects in conditional variance and in conditional correlations as well. Moreover, our contribution to existing empirical works is that the deviations from non-linear logistic trend are further explained by market volatility. This step of consequent analysis stemmed from the results of Syllignakis & Kouretas (2011), Gjika & Horvath (2013), and Baumöhl & Lyócsa (2014). All these works pointed to the fact that correlations are closely linked to market volatility. Since correlations tend to be higher when volatility increases, benefits from international diversification (even in emerging markets) are diminishing. Such result is of a particular interest for investors, because correlations and volatility serve as inputs for the computation of investment portfolio.

2 Data and methodology

Daily closing values of stock market indices for six CEE emerging markets, namely those of the Czech Republic, Hungary, Poland, Estonia, Latvia, and Lithuania, were obtained from Datastream. To overcome the non-synchronous trading effects, weekly returns were calculated by averaging daily closing values within the corresponding week. To provide a viewpoint of a US-based investor, all indices are denominated in US dollars. As a benchmark index of developed stock markets we used the STOXX Global 1800 Index. Our sample starts in January 2000 and ends in December 2013 (from 712 to 723 weekly observations).

To estimate the stock market co-movements we used the bivariate two-step DCC model of Engle & Sheppard (2001), as well as asymmetric version proposed by Cappiello et al. (2006). In the first step, ARMA-GARCH models were fitted to obtain the standardized residuals (ten various GARCH-class models has been considered). In our procedure, we allow up to 5 lags in mean equation and 2 lags in variance equation to capture autocorrelation and ARCH effects. Skewed generalized error distribution is considered instead of the usually assumed normal distribution. The selection of the best model was based on the Peña & Rodríguez (2006) test of no-autocorrelation and no-ARCH effects in standardized residuals[1]. From the final set of suitable model specifications, we selected the one which fits the data best according to the Bayesian information criterion (BIC)[2].

In the second step, the resulting standardized residuals were used to estimate the following DCC(1,1) model:

$$\mathbf{H}_t = \mathbf{D}_t \mathbf{R}_t \mathbf{D}_t \tag{1}$$

[1] Test was performed for up to *int*[0.05*T*] lags with critical values obtained via Monte Carlo simulations (Lin & McLeod, 2006)

[2] ARMA-GARCH specifications are available upon request.

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

$$\mathbf{Q}_t = (1-\alpha-\beta)\overline{\mathbf{Q}} + \alpha\boldsymbol{\varepsilon}_{t-1}\boldsymbol{\varepsilon}_{t-1}^T + \beta\mathbf{Q}_{t-1} \tag{3}$$

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

where $\mathbf{H}_t$ is variance-covariance matrix, $\mathbf{D}_t$ is a diagonal matrix of time-varying conditional standard deviations from univariate GARCH models, $\mathbf{R}_t$ is the time-varying correlation matrix, $\overline{\mathbf{Q}}$ is the unconditional correlation matrix in the dynamic correlation structure $\mathbf{Q}_t$ (estimated as $T^{-1}\sum_{t=1}^{T}\hat{\boldsymbol{\varepsilon}}_t\hat{\boldsymbol{\varepsilon}}_t^{\mathrm{T}}$), and $\boldsymbol{\varepsilon}_t$ is a vector of standardized residuals. The standard restrictions were imposed: $\alpha, \beta \geq 0$, and $\alpha + \beta < 1$. A typical element of $\mathbf{R}_t$ takes the form of $\rho_{ij,t}$, which are the estimated DCCs. We have also considered the asymmetric DCC version proposed by Cappiello et al. (2006), however, no significant asymmetry in correlations was found. Thus, in further analysis we utilized correlations from the standard DCC model.

In the next step, we verify whether the evolution of stock market co-movements can be considered as a gradual process. The non-linear STR logistic model of Granger & Teräsvirta (1993) is thus fitted to obtain DCCs. The model takes the following form:

$$\rho_{ij,t} = \alpha_{ij} + \beta_{ij}S_t(\gamma_{ij}, \tau_{ij}) + \upsilon_{ij,t} \tag{5}$$

$$S_t(\gamma_{ij}, \tau_{ij}) = (1 + \exp(-\gamma_{ij}(t - \tau_{ij}T)))^{-1}, \gamma_{ij} > 0 \tag{6}$$

where $\rho_{ij,t}$ are the estimated DCCs, α, β are regression parameters and υ_t is the error term. The logistic function $S_t(\gamma, \tau)$ is defined in (6), 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 process to from the first regime α to $\alpha + \beta$ to be slow and gradual. For larger values of γ, the shift between the two regimes of correlations is more faster. If the parameter $\beta < 0$, the co-movements between the two markets declined in the second regime, i.e., after the endogenously detected break in correlations (at date τT).

Finally, we also examined the short-term deviations from the long-term logistic trend by estimating two simple regression models:

Model 1: domestic volatility included

$$\hat{\upsilon}_{ij,t} = \eta_{ij} + \phi_{ij}\hat{\upsilon}_{ij,t-1} + \pi_{ij}\sigma_{i,t-1} + \varepsilon_{ij,t} \tag{7}$$

Model 2: foreign volatility included

$$\hat{\upsilon}_{ij,t} = \eta'_{ij} + \phi'_{ij}\hat{\upsilon}_{ij,t-1} + \pi'_{ij}\sigma_{j,t-1} + \varepsilon'_{ij,t} \tag{8}$$

where $\hat{\upsilon}$ are the residuals from fitted STR model, η is the constant term, ϕ the autoregressive coefficient, and π the parameter for domestic (*i*-th CEE country) or foreign market volatility (*j*). Lagged dependent variable was added because of high autocorrelation of residuals which might lead to high size distortions. Two alternative specifications are estimated due to multicollinearity problem, which occurs as the volatilities are highly correlated. The volatility of market returns was estimated using the range-based estimator (see, Molnár, 2012):

$$\sigma_t = 0.5(h_t - l_t)^2 - (2\ln 2 - 1)c_t^2 + j_t^2 \tag{9}$$

where $c_t = ln(C_t) - ln(O_t)$, $h_t = ln(H_t) - ln(O_t)$, $l_t = ln(L_t) - ln(O_t)$, $j_t = ln(O_t) - ln(C_{t-1})$, and O_t, H_t, L_t, C_t are open, high, low, and closing prices, respectively, in a given week. As a sensitivity analysis, we also considered to estimate volatility simply as squared demeaned returns and also as a standard deviation of daily returns in a given week.

3 Empirical results

Basic descriptive statistics of the estimated time-varying correlations are presented in Tab. 1. It is apparent that the minimal correlations are reported in the beginning of our sample and the highest one at the end. In average, stock markets from the Visegrad Group showed higher degree of co-movements than Baltic markets. The evolution of DCCs is captured in Fig. 1.

Tab. 1: Descriptive statistics of the estimated DCCs

	Czech	Hungary	Poland	Estonia	Latvia	Lithuania
Min	-0.0167	0.2593	0.3005	-0.0669	-0.1599	-0.1968
(date)	17.05.2002	30.08.2002	23.08.2002	02.08.2002	13.06.2003	18.04.2003
Max	0.8302	0.7904	0.8100	0.6871	0.5947	0.7492
(date)	04.11.2011	04.06.2010	04.11.2011	14.10.2011	17.05.2013	04.11.2011
Average	0.5737	0.5633	0.6207	0.3913	0.2986	0.3310

Source: own calculations

After the estimation of DCCs we may proceed to our next step, which is fitting the STR model to time-varying correlations. These results are presented in Tab. 2. The highest correlations in the first regime are reported for Poland (0.52), while the lowest are for Latvia (0.11). Again, the Visegrad markets showed higher co-movements in the first regime, as opposed to the Baltic stock markets. In the second regime all correlations increased significantly, while specifically in the case of Lithuania this increase in correlations was quite tremendous (0.41). With regard to the speed of transition (parameter γ), we may conclude that the co-movements of the Visegrad markets tend to more gradual than those of the Baltic markets. From visual inspection of the estimated DCCs and fitted values from non-linear trend model in Fig. 1 we can also see, that correlations of the Baltic markets are much more volatile. Transition midpoints are set almost equally for the Visegrad markets (within the year 2006), while for Estonia and Latvia it is the year of 2004 and for Lithuania up until 2009.

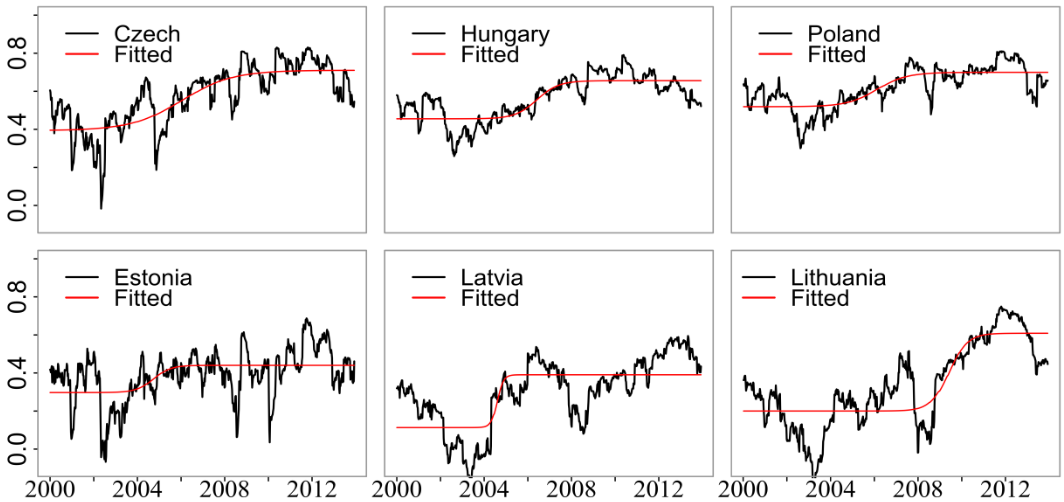
Tab. 2: Results from smooth transition model

	α	β	γ	τ	R^{2*}	Transition midpoint
Czech	0.3936 ***	0.3167 ***	0.0172 **	0.4317 ***	0.6271	27.01.2006
	(0.0392)	(0.0501)	(0.0082)	(0.0384)		
Hungary	0.4553 ***	0.2004 ***	0.0382 ***	0.4617 ***	0.6608	16.06.2006
	(0.0200)	(0.0252)	(0.0117)	(0.0153)		
Poland	0.5189 ***	0.1807 ***	0.0287 **	0.4372 ***	0.5854	10.02.2006
	(0.0223)	(0.0279)	(0.0120)	(0.0246)		
Estonia	0.2972 ***	0.1430 ***	0.0496	0.3424 ***	0.2272	15.10.2004
	(0.0384)	(0.0443)	(0.0439)	(0.0326)		
Latvia	0.1131 ***	0.2774 ***	0.1374	0.3322 ***	0.5060	27.08.2004
	(0.0394)	(0.0448)	(0.0980)	(0.0076)		
Lithuania	0.2002 ***	0.4085 ***	0.0475 **	0.6805 ***	0.6721	03.07.2009
	(0.0256)	(0.0418)	(0.0209)	(0.0115)		

Source: own calculations

Notes: *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. R^{2*} denotes squared correlation coefficient between the observed and fitted values. The standard errors in parentheses were calculated using a variance-covariance matrix with a quadratic spectral weighting scheme and an automatic bandwidth selection procedure, as in Newey & West (1994). Note, that we are not interested in the significances in this model. The STR models exhibit high levels of autocorrelations which cannot be successfully addressed by simply using HAC robust standard errors (first order autocorrelation $\rho(1) > 0.90$). We report standard errors and critical values to facilitate comparison with previous studies (Lahrech & Sylwester, 2011; Durai & Bhaduri, 2011).

Fig. 1: DCCs and fitted values from smooth transition model



Source: own calculations

In the final step of our analysis we estimated simple regression models, to verify, whether deviations from long-term non-linear trend can be explained by volatility of market returns. Results are presented in Tab. 3.

Tab. 3: Short-term deviations from long-term trend

		Model 1: domestic volatility			Model 2: foreign volatility		
		Estimate	Std. Error		Estimate	Std. Error	
Czech	Intercept	-0.0045	0.0019	**	-0.0058	0.0021	***
	Lagged	0.9384	0.0146	***	0.9358	0.0151	***
	Volatility	0.1639	0.0693	**	0.3464	0.1211	***
Hungary	Intercept	-0.0033	0.0017	**	-0.0038	0.0017	**
	Lagged	0.9606	0.0110	***	0.9627	0.0104	***
	Volatility	0.1046	0.0647		0.2270	0.1240	*
Poland	Intercept	-0.0038	0.0016	**	-0.0017	0.0014	
	Lagged	0.9512	0.0159	***	0.9536	0.0159	***
	Volatility	0.1182	0.0528	**	0.0944	0.0917	
Estonia	Intercept	-0.0046	0.0025	*	-0.0069	0.0028	**
	Lagged	0.9364	0.0143	***	0.9364	0.0142	***
	Volatility	0.2223	0.1262	*	0.4467	0.1832	**
Latvia	Intercept	-0.0028	0.0013	**	-0.0027	0.0014	**
	Lagged	0.9792	0.0071	***	0.9805	0.0072	***
	Volatility	0.1210	0.0485	**	0.1577	0.0666	**
Lithuania	Intercept	-0.0038	0.0017	**	-0.0031	0.0018	*
	Lagged	0.9779	0.0087	***	0.9786	0.0087	***
	Volatility	0.1828	0.0897	**	0.1701	0.1184	

Source: own calculations
Notes: *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. "Lagged" corresponds to the regression parameter (ϕ_1) of lagged dependent variable.

All volatility coefficients are positive, meaning that during the more volatile periods, deviations from non-linear time trend are prone to be higher. This result is not surprising as it is in the line with previous research (see, Syllignakis & Kouretas, 2011; Gjika & Horvath, 2013; Baumöhl & Lyócsa, 2014), which proved the positive relationship among correlations and market volatility. At least one volatility coefficients (domestic or foreign) is statistically significant in all cases, where in the case of Hungarian stock market foreign volatility seems to be more relevant from the view of co-movements with developed markets, and for Poland and Lithuania conversely, foreign volatility is not significant.

When squared demeaned returns or standard deviations are considered as a proxy of market volatility, these results are even more convincing (in terms of statistical significance of the regression parameters)[3]. Finally, we have also performed the analysis within a LSTAR framework, i.e. estimating the following model:

$$\rho_{ij,t} = \alpha_{ij} + \phi_{ij}\rho_{ij,t-1} + \pi_{ij}\sigma_{i,t-1} + \beta_{ij}S_t\left(\gamma_{ij},\tau_{ij}\right) + \upsilon_{ij,t} \qquad (10)$$

[3] We do not present results for different proxies of volatility here; however, they are available upon the request.

This specification mitigates the problem of autocorrelated residuals ($\rho(1) \approx 0.05$). The model was estimated with range-based volatility estimator and most of our conclusions regarding the effect of market remained. For example, all volatility coefficients were positive and for all but Estonia at least one volatility coefficient was also significant.

Conclusion

We examined the integration process of CEE emerging stock markets and verified a hypothesis that this process has been gradual over time. Our proxy of stock market integration was dynamic conditional correlations among these European markets and the STOXX Global 1800 Index, which represented developed stock markets. We found that correlations of Visegrad markets are in average higher than those of Baltic stock markets and the transition process is also more gradual in Visegrad markets.

Further on, we also verified whether the deviations from non-linear time trend can be attributed to the market volatility. It appears those in more turbulent times, whether on local or foreign markets, the stock market co-movements tend to be higher, as we found positive relationship between deviations from long-term trend and market volatility. This finding is in the line with previous research in stock market integration area and has implications for international portfolio theory. It seems that the benefits of diversification into emerging stock markets are slightly diminishing over time.

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