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Risk-Return Convergence in CEE Stock Markets: Structural Breaks and Market Volatility*

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Abstract

We analyze the risk-return characteristics of nine European emerging stock market indices over the period from January 2000 to December 2013. We show that (i) the return distances declined and structural breaks in this characteristic are sparse; (ii) distances between standard deviations are more time-varying than return distances and several structural breaks have been identified through this risk metric; (iii) the mixed characteristic, i.e. risk-return distances declined over time and were subject to an occurrence of several breaks. The relationship between risk-return characteristics and market volatility is also examined. While the results clearly showed that this relationship is generally positive, the return, risk and risk-return distances increased during the more volatile periods. At the same time, for several CEE markets, this effect is mitigated during bearish market conditions. Overall, our results suggest that even in times of higher volatility, benefits for investors from international diversification to CEE emerging markets may still exist.

1. Introduction

Stock market co-movements have been studied extensively during the last few decades, as international diversification may provide investors significant gains compared with solely domestic asset allocation. An underlying idea stemming from a classic mean-variance portfolio framework is that low correlations between asset returns provide a decrease in the risk of the portfolio. Thus most of the empirical works have focused on examining correlations between equity indices all over the world (a short review of the recent studies will be provided in the next section).

Unfortunately for investors, international financial markets are now more integrated and, particularly in the case of equity markets, the overall evidence suggests that in the last decade, correlations between global stock market returns have increased, so the benefits of international diversification are gradually diminishing. The last "safety net" for equity investors are emerging markets, which are still considered to be a distinct and to an extent more independent asset class.

In this paper we will focus on the emerging stock markets of Central and Eastern Europe (CEE), namely those of Croatia, the Czech Republic, Estonia, Hungary, Latvia, Lithuania, Poland, Romania and Slovenia. The return, risk and risk-return characteristics are examined to verify whether these markets' characteristics converge to developed European equity markets, represented by the Euro Stoxx

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50 index. In general, we show evidence in favor of return, risk and risk-return convergence of CEE markets towards the developed European markets. The risk and, as a consequence, risk-return convergences are not stable, with several markets showing periods of divergence or non-convergence. Our results suggest that convergence depends on market conditions; more specifically, we find strong evidence that market volatility slows down the return, risk and risk-return convergence of CEE markets. Thus, contrary to other empirical studies, we show that CEE stock markets still offer diversification opportunities even in turbulent market conditions.

2. Stock Market Integration, Co-Movements and Convergence of CEE Markets

The area of stock market integration is not only crucial for policy makers, but more importantly also for individual and institutional investors. In general, a financially integrated market is a market for a given set of financial instruments and/or services where all potential market participants (1) face a single set of rules; (2) have equal access to the set of instruments/services; and (3) are treated equally when they are active in the market (Baele et al., 2004). Financial integration is closely linked to the so-called law of one price (assets with identical risk and returns should be priced equally on different markets), but the broader definition stated above does not necessarily induce full market integration under the law of one price. On one hand, financial integration is indeed beneficial (see, for example, Babecký et al., 2013 for details), but on the other hand, the major pitfall of market integration is that individual/institutional investors are exposed to the same structural shocks and so the risks of their portfolios may not be diversified as thoroughly as they had believed.

As correlations between markets are viewed as a manifestation of integration per se (because it is not a trivial matter to establish the degree of integration, see Bekaert and Harvey, 2002 and Bekaert et al., 2003 for further discussion), most of the empirical studies explore stock market integration using some form of correlation analysis. Such an approach is practical as well, as correlations are used to optimize investment portfolios.

The overall evidence suggests that there is a significant increase in the correlation of returns between emerging and developed markets. Among others, Lahrech and Sylwester (2011) examined cross-market linkages among the equity markets of Argentina, Brazil Chile, and Mexico with the US market on a sample covering the period from December 1988 to March 2004 using the standard dynamic conditional correlation approach (DCC). The maximum observed DCCs ranged from from 0.45 (Chile) to 0.63 (Mexico).

Kenourgios and Samitas (2011) also provide evidence of increasing correlations of Balkan emerging stock markets (Turkey, Romania, Bulgaria, Croatia and Serbia) with developed European markets (UK, Germany and Greece)[1] and the US market over the period from January 2000 to February 2009. Correlations of the Bulgarian stock market were rather low (from 0.15 to 0.19) as opposed to those of the Turkish stock market (around 0.4 in all cases), but all DCCs increased at the end of the sample, supporting the evidence for the herding behavior during the 2008 stock market crash period.

[1] Greece is still considered as developed market by the authors of this study. As of November 2013, MSCI classified Greece as an emerging market. In 2014 S&P and Dow Jones are considering the reclassification of Greece as an emerging market.

Syllignakis and Kouretas (2011) observed a significant increase in DCCs between emerging European stock markets (the Czech Republic, Poland, Hungary, Slovakia, Estonia, Romania and Slovenia) and the US, German and Russian stock markets during the financial crisis of 2007–2009 (the sample covers the period from October 1997 to February 2009). With the US and Germany, average correlations were highest for the CEE-3 (the Czech Republic, Poland and Hungary) stock markets (around 0.5). Estonia, Romania and Slovenia reached significantly lower average DCCs (around 0.2). European emerging markets also seemed to be more segmented from the Russian market, as the average correlations remained at about the same levels only in the case of Estonia and Romania (both 0.23), while all other average DCCs dropped. Not surprisingly, all correlations of the Slovak stock market, which is basically inefficient,[2] are basically zero.

Using the sample of CEE-3 stock markets and two developed markets (Germany and the US) over the period from January 1998 to March 2010, Baumöhl et al. (2011) showed that endogenously detected volatility breaks in weekly stock market returns are significantly associated with the estimated DCCs. Correlations ranged from 0.5 to 0.7 at the end of the examined sample with a sharp peak detected during the recent financial crisis. The same sample of CEE markets was examined by Gjika and Horváth (2013), who used daily data from December 2001 to October 2011 to estimate time-varying correlations with the Euro Stoxx 50 index. The DCCs increased significantly after accession of the CEE-3 countries to the European Union (May 2004) and remained at those high levels (approximately 0.6–0.7) during the recent financial crisis.

Horváth and Petrovski (2013) compared stock market co-movements between the CEE-3 and Southeastern Europe (Croatia, Macedonia, and Serbia) with Western Europe (Stoxx Europe 600) over the period from January 2006 to May 2011. Comparing these two groups of emerging European markets, the authors concluded that the degree of cross-market linkages is much higher in the CEE-3 countries (DCCs range from 0.6 to 0.8) as opposed to those of Southeastern Europe (the correlations of Serbia and Macedonia of around 0.2 with a few peaks up to 0.8 and correlations of Croatia evolve from nearly zero correlation at the beginning of the sample to values as high as those for the CEE-3).

Higher correlations of emerging markets during the last few years might not necessarily be a manifestation of strengthening relationships between stock markets. As these years were marked by the global financial crisis and European debt crisis, the rise in correlations may only be a product of contagion. Baumöhl and Lyócsa (2014) showed on a sample of 32 emerging and frontier markets (including those of the CEE region), that the relationship between conditional volatility and time-varying correlations is significant and positive. Such findings suggest that the benefits of international diversifications are weakened during more volatile periods, i.e. when investors need them the most.

From the perspective of investors seeking effective international diversification, it is important to notice that not only do correlations among markets evolve over time, but also as Babetskii et al. (2007) and Eun and Lee (2010) showed the risk-

[2] The Slovak stock market is often excluded from most empirical studies, primarily due to its small size, small number of actively traded stocks, low level of liquidity and near absence of initial public offerings.

return characteristics of stock markets change as well. On a sample covering the period from January 1995 to July 2006, Babetskii et al. (2007) found evidence of the β- and σ-convergence of returns between the Czech, Polish and Hungarian national markets and the Euro Stoxx Index. Eun and Lee (2010) covered a sample of 14 emerging markets[3] over the period from 1989 to 2007; they found evidence of convergence for return, risk and risk-return distances for most of the selected emerging markets. On a sample of 17 developed markets, the authors also confirmed that return distances increased with an increase in market volatility.[4] This result is quite surprising because, as we mentioned above, most of the empirical studies documented that higher volatility is associated with higher correlations.

3. Data Description and Methodology

3.1 Data

Stock market convergence was studied for nine CEE countries—Croatia (HRV), the Czech Republic (CZE), Estonia (EST), Hungary (HUN), Latvia (LVA), Lithuania (LTU), Poland (POL), Romania (ROU) and Slovenia (SVN)—during the period from January 2000 to December 2013. Our sample covers not only the period of the CEE countries' accession to the European Union, but also the financial crisis and the sovereign debt crisis in Europe.

Daily closing prices of stock market indices for the CEE countries were obtained from Thomson Reuters Datastream. We used the following market indices:[5] CROBEX [CTCROBE], PX [CZPXIDX], OMXT [ESTALES], BUX [BUXINDX], OMXR [RIGSEIN], OMXV [LNVILSE], WIG20 [POLWG20], BET [RMBETRL] and Slovenia-DS [TOTMKSJ]. Prices on the developed European markets were proxied with the Euro Stoxx 50 index.[6] We perform our analysis based on local currency returns as well as euro returns, which allows us to observe possible changes in return convergence induced by exchange rates. Daily exchange rates were obtained from Datastream.

Our analysis was performed using monthly average returns or the standard deviation of daily returns, calculated from synchronized consecutive daily returns. First, for each month and each pair of markets prices were synchronized. Next, daily consecutive returns were calculated (see Baumöhl and Výrost, 2010 for details of this synchronization process). Finally, monthly averages or standard deviations were used in our analysis. We prefer using monthly returns, as calculating the standard deviation of returns from four or five returns (four or five trading days a week for the weekly data frequency) might be imprecise because it is subject to large swings, as one

[3] No CEE markets were included in their sample.

[4] No evidence was provided for emerging markets. Our study fills this gap.

[5] Datastream mnemonics are in brackets. The referees pointed out that the comparison of stock indices among different markets is problematic, as the underlying structure (industry structure, size of firms) differs so greatly, particularly for emerging markets. It might be that an initial public offering of a financial institution and its subsequent introduction into a national stock market index might lead to the increasing similarity of returns between markets, as financial institutions tend to be more interconnected. However, in this study we are not interested in why the similarity of returns increases and therefore this is of no particular concern. Note that structural differences between markets should, *ceteris paribus*, only influence the equilibrium (defined by a certain level of return, risk and risk-return distances) to which markets are converging.

[6] Data was obtained from www.stoxx.com.

outlying observation might considerably influence the resulting estimate of market volatility. This in turn influences risk distances (distances between standard deviations) and consequently also risk-return distances. Furthermore we are interested in the long-term trends of distances rather than short-term dynamics. On a related note, Eun and Lee (2010) used a data frequency of six months. The entire analysis is conducted using the R software.

3.2 Distances

Stock market convergence was tested using return, risk and risk-return distances, as in Eun and Lee (2010). The idea introduced in Eun and Lee (2010) was to measure the co-movement of two markets by measuring the degree of similarity of the first two moments of the two market returns' distributions. The similarity of mean returns between market i and j is defined in terms of Euclidean distance, simply as $DR_{ijt} = |r_{it} - r_{jt}|$, $t = 1,2,\ldots,T$, where r_t is the mean return in month t. Risk distance is defined similarly, as the Euclidean distance between the standard deviation of returns, $DS_{ijt} = |sd_{it} - sd_{jt}|$, where sd_t is the standard deviation of returns for the given month t.

Suppose that returns on two markets are +1% and +3%, or –1% and –3%, or –1% and +1%. All three cases describe a different situation on the markets, but from the viewpoint of similarity it is the same ($DR_{ijt} = 2$ for all three cases). If the last case seems odd, consider a case where the first market now declines –0.5% and the other increases by 0.5%. Compared to the previous situation, the markets are more alike (in terms of returns) as the distance is lower ($DR_{ijt} = 1$) even though the first market declined and the second increased. Further, suppose that returns on the two markets increase by 10% and 12%, respectively. Now, the return distance is again 2, but clearly with such extreme (monthly) returns it seems intuitive to consider this situation to be an indication of higher co-movement of returns than the previous case with +1% and +3%. This is an obvious disadvantage of the methodology,[7] though from a practical point of view, it might be at least mitigated with the introduction of the risk-return distance (to be defined latter).

The risk-return distance is defined as the Euclidean distance between two points, one with coordinates (DRw_{ijt}, DSw_{ijt}) and the origin (0, 0), where DRw_{ijt} and DSw_{ijt} are weighted return and risk distances. The weighting is necessary, as variables do not have the same variance and thus the distance between (DR_{ijt}, DS_{ijt}) and the origin (0, 0) could be influenced more by one variable compared to another. We use the following weighting:[8]

$$W\left(DR_{ij}\right) = \sqrt{\sum_{t=1}^{T} DR_{ijt}^2 \Big/ \left(\sum_{t=1}^{T} DR_{ijt}^2 + \sum_{t=1}^{T} DS_{ijt}^2\right)} \tag{1}$$

$$W\left(DS_{ij}\right) = \sqrt{\sum_{t=1}^{T} DS_{ijt}^2 \Big/ \left(\sum_{t=1}^{T} DR_{ijt}^2 + \sum_{t=1}^{T} DS_{ijt}^2\right)} \tag{2}$$

[7] We would like to thank the reviewers, Benoît Sévi, and discussants at the 12th INFINITI Conference on International Finance in Prato in 2014 for pointing out this aspect of return distances.

[8] This weighting is slightly different from Eun and Lee (2010), as most of our analysis was based on distances between pairs of markets, see equations 4 and 5 in Eun and Lee (2010).

The normalized risk-return distances (which we will refer to simply as risk-return distances) are calculated as:

$$RR_{ijt} = \sqrt{\left(DR_{ijt}/W\left(DR_{ij}\right)\right)^2 + \left(DS_{ijt}/W\left(DS_{ij}\right)\right)^2} \tag{3}$$

where $DR_{ijt}/W(DR_{ij})$ and $DS_{ijt}/W(DS_{ij})$ are the aforementioned weighted return and risk distances, DRw_{ijt} and DSw_{ijt}. This normalization only multiplies observations by a constant so that: (i) the variables have comparable scale and (ii) it preserves the dispersion structure of the resulting series, which is necessary, as we are concerned with a long-term trend (convergence) of risk-return distances.[9]

In our analysis, we will also study the evolution of cross-market averages of distances. If i denotes CEE markets, and j the developed market, then $CEE\left(DR_t\right) = 1/n\sum_i DR_{ijt}$ denotes the average distance of CEE market returns to the developed European market returns at time t. As CEE markets differ significantly in size (e.g. in 2012 the market in Poland had larger market capitalization than the rest of the CEE markets combined), we have also used a weighted cross-market average $CEEw\left(DR_t\right) = \sum_i w_i DR_{ijt}$, where w_i denotes the relative share of ith market's capitalization to the overall market capitalization of CEE markets, i.e. $\sum_i w_i = 1$. Weights were changed annually based on data from the World Bank's World Development Indicators.[10] Risk (CEE(DS_t), CEEw(DS_t)) and risk-return (CEE(RR_t), CEEw(RR_t)) distances were defined in a similar manner.

3.3 Convergence Hypothesis

Our tests for convergence will be based on the following model:

$$D_{ijt} = \eta\left(t\right)_{ij} + \sum_{k=1}^{K} \beta_{kij} x_{kijt} + u_{ijt} \tag{4}$$

where D_{ijt} is the distance, $\eta(t)_{ij}$ is a trend function, and x_{kijt} is a set of explanatory variables. Similarly to Eun and Lee (2010), we will assume that $\eta(t)_{ij}$ is a linear trend function and we will assume that $K = 0$ (unconditional convergence) or $K > 0$ (conditional convergence). In general, we will estimate regression models of the following form:

$$D_{ijt} = \alpha_{ij} + \beta_{ij} t + \sum_{k=1}^{K} \gamma_{kij} x_{kijt} + u_{ijt} \tag{5}$$

The convergence hypothesis is tested via the estimate of the β_{ij} coefficient. Evidence of $\beta_{ij} < 0$ is interpreted as convergence between the two series as this suggests that, in general, the absolute difference between two series is decreasing in time. Therefore the coefficient $\beta_{ij} < 0$ may be interpreted as the parameter describing the speed of convergence.

This idea is straightforward and certainly not new; some roots of empirical studies using this idea may be found in the growth theory. For example, Lichtenberg

[9] The correlation between normalized risk-return distances and non-normalized risk-return distances (hypotenuse without weighting of return and risk distances) ranged from 0.903 to 0.978 for returns in local currency and from 0.898 to 0.979 for returns in euros.

[10] Because data for 2013 were not available, we used the same weights as in 2012.

(1994) defined convergence between two series as $d(\mathrm{V}[(r_{it}, r_{jt})])/dt < 0$ (dubbed as σ-convergence), wherein the necessary but not sufficient condition for convergence is $d(\mathrm{E}[D_{ijt}])/dt < 0$. The latter is explicitly tested here and it corresponds to what is dubbed as β-convergence. Lichtenberg (1994) suggested that in an empirical framework, both conditions can be tested using a simple regression with a linear trend. This approach has some attractive features: (i) it is basically model free (Eun and Lee, 2010), (ii) except for the trend model, it does not require any prior economic assumptions, and (iii) it preserves simplicity, which is often sought by investors and policymakers.

We deviate from Eun and Lee (2010) in several subtle ways. For example, the insufficiency of $d(\mathrm{E}[D_{ijt}])/dt < 0$ for convergence implies that the residuals from (5) have to be tested as well. For example, if $\beta_{ij} < 0$ but $d(\mathrm{V}[u_{ijt}])/dt > 0$, then the convergence is in question, as the variance from the declining differences is actually increasing. Such a situation might be dubbed as "spurious convergence."

3.4 Structural Breaks in Stock Market Convergence: Convergence Regimes

As reported in numerous studies, stock market co-movements are time-varying (see Section 2). Accession to the European Union (EU) or, more likely, the negotiations prior to the entry of CEE countries into the EU might have promoted the inflow of foreign capital to CEE markets. Additionally, in the course of the periods before, during and after the recent financial crisis, the co-movements between stock markets might have changed considerably as real economies were affected by the global economic slowdown and international investors were rebalancing their portfolios.

To allow for time-varying convergence, we allowed for different convergence regimes. A simple linear time trend model was estimated with one or two breaks in both constant and trend. The dating of breaks was performed via minimization of the residual sum of squares (RSS) using the algorithm of Bai and Perron (2003). The trimming parameter was set to int$\{0.2T\}$ observations. The convergence was assessed by estimating the following model:

$$D_{ijt} = \alpha_{0ij} + \beta_{0ij} t + \sum_{b=1}^{B} \alpha_{bij} DU_{bijt} + \sum_{b=1}^{B} \beta_{bij} DT_{bijt} + u_{ijt} \tag{6}$$

where B denotes the number of structural changes in coefficients or, differently, $m = B + 1$ is the number of convergence regimes; if $t > T_{b1}$: $DU_{1ijt} = 1$ and $DT_{1ijt} =$ $= t - T_{b1}$, 0 otherwise, if $t > T_{b2}$, $DU_{2ijt} = 1$ and $DT_{2ijt} = t - T_{b2}$, 0 otherwise. $T_{b1} < T_{b2}$ denote the dates of structural breaks.

We estimated models with zero, one and two structural breaks, but we also show the preferred number of breaks as suggested by the modified HQ information criterion as proposed in Hall et al. (2013), i.e.:

$$MHQ = \ln\left(RSS\right) + \frac{2\ln\left(\ln\left(T\right)\right)}{T}\left(p\left(B+1\right)+3B\right) \tag{7}$$

where p is the number of estimated coefficients. As shown in Hall et al. (2013), in many instances this choice of information criterion had similar statistical properties as the HAC test of Bai and Perron (1998, 2003).

Residuals from estimated models (5) and (6) were tested for the presence of autocorrelation using the test proposed by Peña and Rodríguez (2006), where the critical values were obtained via the Monte Carlo simulation. The autocorrelation was tested up to the first int$\{0.05T\}$ lags. If the null of no-autocorrelation was rejected, standard errors of coefficient estimates were obtained using the Newey-West standard errors with the automatic bandwidth selection procedure (Newey and West, 1994) with the quadratic spectral weighting scheme. If no autocorrelation was indicated, we tested for the presence of heteroskedasticity using the nonparametric unweighted bootstrap version of the White (1980) test as used in Cribari-Neto and Zarkos (1999). If the null of homoskedasticity is rejected, standard errors were derived from the HC-3 matrix as proposed in MacKinnon and White (1985). Otherwise, standard errors were estimated under the assumption of homoskedastic errors with no autocorrelation.

Monthly returns, standard deviation and residuals from regression models were tested for the presence of a unit root using the KPSS test procedure as proposed in Sul et al. (2005). Finally, to test for the presence of spurious convergence, residuals from each model were tested for the presence of structural changes in unconditional volatility using the κ_2 test of Sansó et al. (2004) and the ICSS algorithm of Inclán and Tiao (1994).[11]

4. Empirical Findings

4.1 Descriptive Evidence of Risk-Return Convergence

From 2000 to the end of 2013, the smallest average return distance was measured for the three Visegrad group countries, i.e. the Czech Republic, Hungary and Poland (see *Table 1*). Considering the relative market size (compared to other CEE markets), political stability during the transition and early EU accession negotiations to the EU, these markets may have attracted more foreign investors and thus achieved a higher return co-movement.

Risk distances have slightly different patterns, with the Czech Republic, Estonia, Croatia and Poland having the smallest risk distances, while Latvia, Romania and Hungary had the largest risk distances. Risk-return distances reflect the co-movement of both returns and risk. As suggested from previous calculations, our analysis confirms that the smallest risk-return distances are measured for the Czech Republic and Poland, but small risk-return distances have also been estimated for Estonia.

By comparing only returns and risk we can already see that the similarity between Estonian returns and developed European stock market returns is greater than the similarity between Hungarian and developed European stock market returns. Clearly, when risk distances are taken into account, larger risk distances for Hungary manifest into a larger risk-return distance.[12] Our findings for the Estonian stock

[11] The κ_2 test might be also regarded as a heteroskedasticity test; therefore this test complemented the White (1980) test, and if structural breaks in volatility were identified, we used the HC-3 matrix as described in the testing procedure described above. The code for this test, written in the *R* software, is available upon request.

[12] According to the data from the World Bank, in 2012 the market capitalization in Hungary was about nine times larger (in US dollars) compared to the capitalization in Estonia while the turnover ratio was still six times larger in Hungary.

Table 1 Average Return, Risk and Risk-Return Distances

	Return distances	Risk distances	Risk-return distances
Croatia	0.0030	0.0043	0.0085
Czech	0.0022	0.0035	0.0067
Estonia	0.0028	0.0042	0.0079
Hungary	0.0024	0.0048	0.0084
Latvia	0.0032	0.0053	0.0103
Lithuania	0.0032	0.0046	0.0090
Poland	0.0022	0.0044	0.0076
Romania	0.0035	0.0053	0.0101
Slovenia	0.0026	0.0046	0.0084
CEE Group	0.0028	0.0046	0.0085
CEE Group (weighted)	0.0024	0.0044	0.0079

market are surprising due to the smaller Estonian market capitalization and turnover ratio.

The decline in the values of the return, risk and risk-return distances over the sample period may be regarded as evidence of return convergence and the size of this decline as a measure of the speed of convergence. Although it is difficult to compare the speed of convergence between individual markets, as the initial conditions may have been widely different, looking at the average values across the CEE markets may shed light on the overall trends in the region. Comparing the final observations taken in December 2013 with the initial observations in January 2000, the return distance among the CEE markets declined by 66.79%, risk distances declined by 60.96% and risk-return distances declined by 64.13%. The picture is similar when comparing average distances weighted by the relative market capitalization of the CEE markets (58.90%, 59.43% and 57.68% declines in return, risk and risk-return distances, respectively).

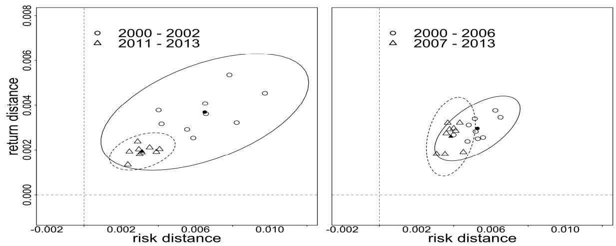
Comparing the initial and final observations might be sensitive to the rather volatile monthly distances (see the small *adj.* R^2 in *Tables 2–4* in the next section). We have therefore calculated average distances over the first 24 months after 2000 with market distances averaged over the last 24 months prior to 2013 (see the chart at left in *Figure 1*). To take into account the possible effect of the financial crisis on the convergence of returns and risks, we have also compared the average distances of the CEE markets over the first half of the sample period with the second half (see the chart at right in *Figure 1*).

Regardless of the period observed, *Figure 1* suggests convergence of return and risk distances. Both return and risk distances declined, but when larger periods are taken into account the convergence is less obvious. This may be attributed to the financial crisis in the second half of our dataset, as increases in distances are visible in our data from 2007 to roughly 2010.

4.2 Convergence Hypothesis and Structural Breaks

Evidence from the previous section suggests that the CEE markets as a group and individual CEE markets have converged in returns and distances towards

Figure 1 The Risk and Return Distances among Nine CEE Stock Markets



the developed European markets. We test these findings formally, by estimating model (5) with $K = 0$, i.e. a simple linear time trend model, and by estimating model (6) with $B = 1, 2$, i.e. a linear time trend model with one or two structural breaks in coefficients.

4.2.1 Return Distances

Results from testing the convergence of returns are reported in *Table 2*. Estimating a simple linear time trend model resulted in negative and significant coefficients for all CEE markets except for Estonia (positive, but not significant) and Slovenia (negative, but not significant). On average, the cross-market average return distances in the CEE markets declined, and this decline was statistically significant. It should be noted that the very low adjusted coefficient of determination is of little concern here as at this stage because we are interested only in the general trend of these distances.[13]

One could argue that convergence is time-varying, or at least that there are different convergence regimes. In several instances, an allowance for two convergence regimes resulted in a break dated around the recent financial crisis for most sample markets (Croatia, the Czech Republic, Estonia, Latvia, Lithuania, Romania and Slovenia). The results for the cross-average return distances (*CEE*, *CEEw*) are particularly interesting as the break in return distances was dated to October 2007, i.e. when the first signs of the impending crisis emerged. In these instances (except for Slovenia and the Czech Republic), the break resulted in a sudden shift (increase) in return distances followed by an increase of the speed of convergence (negative coefficient). Although the speed of convergence increased, so did (at least temporarily) the return distances. This finding is in contrast with studies showing higher co-movements during turbulent periods (e.g., Baumöhl et al., 2011; Kenourgios and Samitas, 2011).

According to the information criterion, a two-regime model specification was preferred only for the unweighted average of return distances. Further on, the results from models allowing three convergence regimes do not seem to have a clear pattern. This might be the consequence of the fact that, according to the information criterion, a two-break model specification is preferred only for Romania, where one break occurred before the crisis (March 2007) and ended after the crisis (April 2009), during which the return distances increased and even diverged, which shows that the Romanian equity market was unique at the time of the financial crisis.

[13] Apparently, compared to the long-term trend, the variability of return, risk and risk-return distances is large.

Table 2 Unconditional Convergence of Return Distances with Structural Breaks

	HRV	CZE	EST	HUN	LVA	LTU	POL	ROU	SVN	CEE	CEEw
α_0	**0.004**^{a}	**0.003**^{a}	**0.003**^{a}	**0.003**^{a}	**0.004**^{a}	**0.004**^{a}	**0.003**^{a}	**0.005**^{a}	**0.003**^{a}	**0.004**^{a}	**0.003**^{a}
β_0	**-0.009**^{b}	**-0.014**^{a}	0.002	**-0.010**^{a}	**-0.013**^{a}	**-0.009**^{b}	**-0.008**^{b}	**-0.018**^{a}	-0.004	**-0.009**^{a}	**-0.009**^{a}
adj. R^2	1.8%	7.4%	-0.5%	5.3%	4.2%	2.2%	3.5%	6.9%	0.1%	8.0%	9.0%
α_0	**0.004**^{a}	**0.004**^{a}	**0.002**^{a}	**0.003**^{a}	**0.005**^{a}	**0.004**^{a}	**0.002**^{c}	**0.006**^{a}	**0.004**^{a}	**0.004**^{a}	**0.004**^{a}
β_0	**-0.017**^{b}	**-0.039**^{a}	**0.023**^{a}	**-0.015**^{a}	**-0.036**^{a}	**-0.017**^{c}	0.095	**-0.055**^{a}	**-0.026**^{a}	**-0.022**^{a}	**-0.019**^{a}
break	VIII.08	X.07	IV.10	VII.11	X.07	I.08	I.02	V.07	XII.06	X.07	X.07
α_1	**0.003**^{b}	**0.003**^{a}	**-0.002**^{c}	**0.002**^{b}	**0.003**^{a}	**0.003**^{a}	**-0.003**^{c}	**0.005**^{a}	**0.002**^{a}	**0.002**^{a}	**0.001**^{a}
β_1	**-0.049**^{c}	0.007	-0.049	**-0.082**^{b}	-0.006	**-0.046**^{b}	-0.096	-0.012	0.008	-0.014	-0.005
$\beta_0+\beta_1$	**-0.066**^{b}	**-0.032**^{b}	-0.026	**-0.096**^{b}	**-0.042**^{a}	**-0.063**^{a}	-0.002	**-0.067**^{a}	**-0.018**^{c}	**-0.036**^{a}	**-0.023**^{a}
adj. R^2	7.5%	13.6%	7.5%	8.1%	9.7%	9.6%	9.3%	19.7%	4.4%	18.3%	12.6%
α_0	**0.004**^{a}	**0.004**^{a}	**0.002**^{a}	**0.004**^{a}	**0.003**^{b}	**0.004**^{a}	**0.002**^{c}	**0.006**^{a}	**0.004**^{a}	**0.004**^{a}	**0.004**^{a}
β_0	**-0.021**^{c}	**-0.030**^{a}	0.007	**-0.039**^{b}	0.154	-0.013	0.095	**-0.057**^{a}	-0.018	**-0.015**^{a}	**-0.018**^{a}
break	IV.07	VIII.08	IX.05	IX.04	I.02	V.08	I.02	III.07	VIII.04	VIII.08	IV.07
α_1	-0.001	**0.005**^{a}	**-0.002**^{c}	**0.001**^{b}	-0.003	**0.004**^{a}	**-0.003**^{b}	0.001	**-0.002**^{a}	**0.003**^{a}	-0.001
β_1	**0.243**^{b}	**-0.203**^{a}	**0.091**^{b}	0.016	-0.178	**-0.116**^{a}	-0.074	**0.337**^{a}	**0.083**^{a}	**-0.107**^{a}	**0.135**^{a}
$\beta_0+\beta_1$	**0.222**^{c}	**-0.233**^{a}	**0.099**^{b}	**-0.023**^{a}	**-0.024**^{b}	**-0.129**^{a}	0.021	**0.280**^{a}	**0.065**^{a}	**-0.122**^{a}	**0.117**^{a}
break	VI.09	XI.10	II.10	VII.11	X.07	VII.11	III.07	IV.09	IV.09	VII.11	V.09
α_2	**-0.005**^{b}	**0.001**^{c}	**-0.003**^{b}	**0.002**^{a}	**0.003**^{a}	**0.002**^{c}	**-0.001**^{b}	**-0.007**^{a}	**-0.003**^{a}	**0.002**^{a}	**-0.003**^{a}
β_2	**-0.235**^{b}	**0.252**^{a}	**-0.131**^{a}	**-0.074**^{c}	-0.018	0.027	-0.020	**-0.302**^{a}	**-0.054**^{b}	**0.075**^{b}	**-0.119**^{a}
$\beta_0+\beta_1+\beta_2$	-0.013	0.019	-0.032	**-0.096**^{b}	**-0.042**^{a}	**-0.102**^{c}	0.001	**-0.022**^{c}	0.011	-0.047	-0.002
adj. R^2	10.6%	19.2%	12.4%	9.2%	13.2%	10.5%	10.3%	29.5%	7.8%	22.1%	17.9%
MHQ	0	0	0	0	0	0	0	2	0	1	0

Notes: Superscripts *a*, *b* and *c* denote significance at the 1%, 5% and 10% levels, respectively. The trend coefficient is multiplied by 1000. MHQ denotes the preferred number of breaks according to the modified HQ criterion of Hall et al. (2013). The KPSS test did not reject the null of no unit root in residuals for all estimated models. According to the Sansó et al. (2004) test, breaks in unconditional volatility of residuals were present for some series, but the break was always associated with a decline in volatility, thus no evidence of spurious convergence was found.

Table 3 Unconditional Convergence of Risk Distances with Structural Breaks

	HRV	CZE	EST	HUN	LVA	LTU	POL	ROU	SVN	CEE	CEEw
α_0	**0.006**[a]	**0.004**[a]	**0.006**[a]	**0.005**[a]	**0.008**[a]	**0.006**[a]	**0.006**[a]	**0.008**[a]	**0.007**[a]	**0.006**[a]	**0.006**[a]
β_0	-0.017	-0.010	**-0.018**[b]	0.000	**-0.036**[b]	-0.014	**-0.018**[a]	**-0.028**[a]	**-0.033**[a]	**-0.019**[a]	**-0.015**[b]
adj. R^2	2.3%	1.1%	4.5%	-0.6%	6.1%	1.4%	5.3%	5.7%	15.4%	10.6%	6.5%
α_0	0.002	0.001	**0.003**[b]	**0.005**[a]	0.004	0.002	**0.005**[a]	**0.009**[a]	**0.007**[a]	**0.003**[a]	**0.003**[a]
β_0	**0.215**[b]	**0.208**[b]	**0.195**[a]	0.002	**0.349**[b]	**0.273**[a]	-0.006	**-0.113**[b]	0.077	**0.173**[a]	**0.130**[a]
break	VIII.03	III.03	III.03	IX.08	X.02	III.03	II.10	XII.04	VII.03	III.03	III.03
α_1	**-0.009**[a]	**-0.005**[c]	**-0.006**[a]	**0.004**[b]	**-0.011**[b]	**-0.009**[a]	**-0.004**[a]	**0.006**[b]	**-0.007**[a]	**-0.006**[a]	**-0.004**[b]
β_1	**-0.205**[b]	**-0.217**[b]	**-0.199**[a]	**-0.106**[a]	**-0.358**[b]	**-0.265**[a]	**0.070**[b]	0.057	-0.071	**-0.178**[a]	**-0.141**[a]
$\beta_0+\beta_1$	0.010	-0.009	-0.004	**-0.104**[a]	-0.009	0.007	**0.064**[b]	**-0.056**[b]	0.005	-0.005	-0.011
adj. R^2	18.0%	10.1%	16.7%	9.7%	16.6%	15.3%	8.9%	10.6%	34.6%	30.5%	14.7%
α_0	**0.005**[b]	0.001	**0.005**[a]	**0.004**[a]	**0.006**[b]	**0.006**[a]	**0.005**[a]	**0.010**[a]	**0.007**[a]	**0.005**[a]	**0.005**[a]
β_0	-0.069	**0.189**[a]	**-0.042**[c]	0.029	**0.206**[b]	-0.101	0.010	-0.231	**0.077**[c]	0.031	-0.024
break	III.02	V.03	V.02	VIII.05	IV.03	V.02	II.04	II.02	VII.03	VI.02	VI.02
α_1	**0.016**[a]	**-0.007**[a]	**0.009**[a]	**0.004**[a]	**-0.011**[a]	**0.016**[a]	**-0.005**[a]	**0.009**[a]	**-0.008**[a]	**0.007**[a]	**0.007**[a]
β_1	**-0.656**[a]	**-0.141**[a]	**-0.385**[a]	**-0.287**[a]	**-0.190**[c]	**-0.750**[a]	**0.184**[a]	-0.171	**-0.084**[c]	**-0.517**[a]	**-0.351**[a]
$\beta_0+\beta_1$	**-0.726**[a]	**0.048**[b]	**-0.427**[a]	**-0.258**[a]	0.016	**-0.851**[a]	**0.193**[a]	**-0.402**[a]	-0.008	**-0.486**[a]	**-0.374**[a]
break	VII.04	IX.09	XI.04	IX.08	VII.09	VI.04	II.07	XII.04	IV.07	IX.04	IX.04
α_2	**0.005**[a]	**-0.004**[a]	**0.004**[a]	**0.008**[a]	**0.005**[b]	**0.006**[a]	**-0.005**[a]	**0.009**[a]	**0.003**[a]	**0.005**[a]	**0.005**[a]
β_2	**0.728**[a]	-0.038	**0.420**[a]	**0.154**[a]	**-0.174**[a]	**0.855**[a]	**-0.202**[a]	**0.346**[a]	-0.026	**0.472**[a]	**0.352**[a]
$\beta_0+\beta_1+\beta_2$	0.002	0.011	-0.007	**-0.104**[a]	**-0.158**[a]	0.005	-0.009	**-0.056**[b]	**-0.034**[a]	**-0.013**[b]	**-0.022**[a]
adj. R^2	34.0%	15.3%	22.5%	23.5%	19.9%	29.3%	12.4%	17.6%	37.4%	38.1%	24.1%
MHQ	2	1	1	2	1	2	0	0	1	2	2

Note: Same as under *Table 2*.

4.2.2 Risk Distances

The decrease in risk distances may be interpreted as evidence of increased influence of common risk factor(s) on the evolution of market returns. All else being equal, such a development would provide evidence in favor of increased integration between markets.

Test results for the convergence of risk distances are presented in *Table 3*. The evolution of similarity between the standard deviations of the CEE and developed European markets seems to be very different from the results found for return distances. Within our sample period, unconditional convergence in standard deviations occurred for Estonia (which did not witness return convergence), Latvia, Poland, Romania and Slovenia. However, in many cases (except Poland and Romania, which converged under no break specification), the preferred specifications suggested one or two breaks in the process of risk convergence.

One-break models were preferred for the Czech Republic, Estonia, Latvia and Slovenia, where after the break the risk distances suddenly decreased and the convergence even accelerated. Breaks for these countries occurred between 2002 and 2004, i.e. around the announcement of these countries' impending membership in the EU (December 2002) and subsequent formal accession (May 2004). Considering one-break models, similar patterns were also visible when studying the results for the whole group of CEE countries, i.e. (i) a break in 2003, (ii) followed by a decrease in risk distances and (iii) an increase in convergence.

A two-break model was suggested for Hungary, Croatia, Lithuania and the cross-market averages of the CEE markets. For Hungary, the breaks in August 2005 and September 2008 resulted in a temporal increase in risk distances. Other two-break model specifications had similar patterns: a break in the first half of 2002 characterized by a small increase in risk distances and an increase in the speed of convergence, followed by a second break in 2004, when the risk convergence decreased. These results offer support for the hypothesis that, in general, the exposure of CEE markets to common factors has been increasing during the past 14 years, but since 2004 this exposition to common factors has slowed (not decreased). Of course, this is certainly not true for all countries, but it seems to be supported by our results for the CEE group.

The *adj.* R^2 of the estimated models is generally higher than for models estimated for return distances. Together with the fact that the information criterion suggests more regimes for risk distance, one could assume that the similarity between the standard deviations of market returns is more time-varying than the similarity between return distances.

4.2.3 Risk-Return Distances

For the risk-return distances, we reject the hypothesis of no convergence for all markets and cross-market averages as the trend coefficients in the no-break model are all negative and statistically significant at least at the 10% significance level (this applies only for Estonia). Considering the suggestion by the information criterion, the no-break model specification is preferred for Estonia, Hungary, Lithuania, Poland and the weighted cross-market averages of all CEE markets. In these instances, one could assert that since 2000 the similarity between returns and risks has steadily increased, i.e. risk-return distances have decreased.

Table 4 Unconditional Convergence of Risk-Return Distances with Structural Breaks

	HRV	CZE	EST	HUN	LVA	LTU	POL	ROU	SVN	CEE	CEEw
α_0	**0.011**[a]	**0.009**[a]	**0.009**[a]	**0.010**[a]	**0.015**[a]	**0.011**[a]	**0.010**[a]	**0.015**[a]	**0.011**[a]	**0.011**[a]	**0.011**[a]
β_0	**-0.032**[a]	**-0.033**[a]	**-0.017**[c]	**-0.019**[b]	**-0.058**[b]	**-0.028**[b]	**-0.030**[a]	**-0.054**[a]	**-0.034**[a]	**-0.034**[a]	**-0.030**[a]
adj. R^2	4.7%	7.4%	1.5%	3.4%	9.7%	3.6%	9.1%	11.0%	9.4%	16.3%	14.3%
α_0	**0.008**[a]	**0.010**[a]	**0.005**[a]	**0.011**[a]	**0.008**[b]	**0.008**[a]	**0.012**[a]	**0.015**[a]	**0.011**[a]	**0.010**[a]	**0.009**[a]
β_0	**0.225**[b]	**-0.057**[a]	**0.247**[a]	**-0.035**[b]	0.790	**0.232**[a]	**-0.086**[a]	**-0.086**[a]	0.080	**0.127**[a]	**0.072**[b]
break	III.03	VIII.08	III.03	IX.08	I.02	IV.03	IX.05	IV.08	VI.03	III.03	III.03
α_1	**-0.009**[a]	**0.006**[c]	**-0.007**[a]	**0.005**[b]	-0.016	**-0.008**[a]	**0.004**[a]	**0.010**[a]	**-0.008**[a]	**-0.006**[a]	**-0.004**[a]
β_1	**-0.230**[b]	-0.075	**-0.251**[a]	**-0.073**[b]	-0.823	**-0.241**[a]	0.041	**-0.145**[b]	-0.071	**-0.139**[a]	**-0.091**[b]
$\beta_0+\beta_1$	-0.005	**-0.132**[c]	-0.004	**-0.109**[a]	**-0.033**[c]	-0.009	**-0.045**[a]	**-0.231**[a]	0.008	-0.012	**-0.019**[b]
adj. R^2	12.0%	12.8%	8.5%	8.7%	19.9%	9.6%	11.5%	21.3%	22.6%	27.0%	17.8%
α_0	**0.011**[a]	**0.010**[a]	**0.005**[a]	**0.010**[a]	0.008	**0.012**[a]	**0.011**[a]	**0.016**[a]	**0.012**[a]	**0.010**[a]	**0.009**[a]
β_0	-0.131	**-0.057**[a]	**0.229**[a]	-0.040	0.790	-0.171	-0.039	**-0.108**[a]	0.041	**0.114**[a]	0.062
break	III.02	VIII.08	IV.03	I.05	I.02	V.02	II.04	II.07	IX.03	IV.03	IV.03
α_1	**0.017**[a]	**0.013**[a]	**-0.010**[a]	**0.006**[a]	-0.013	**0.017**[a]	**-0.005**[a]	**-0.003**[c]	**-0.010**[a]	**-0.008**[a]	**-0.006**[a]
β_1	**-0.780**[a]	**-0.568**[a]	**-0.145**[c]	**-0.188**[a]	-0.946	**-0.663**[a]	**0.265**[a]	**0.863**[a]	0.070	**-0.099**[b]	-0.017
$\beta_0+\beta_1$	**-0.910**[a]	**-0.625**[a]	**0.085**[a]	**-0.227**[a]	**-0.156**[a]	**-0.834**[a]	**0.225**[a]	**0.755**[a]	**0.111**[a]	0.015	**0.045**[b]
break	VII.04	XII.10	IV.10	IX.08	VI.07	VIII.04	III.07	V.09	IV.09	VIII.08	IX.09
α_2	**0.009**[a]	**0.005**[a]	**-0.005**[a]	**0.008**[a]	**0.009**[a]	**0.008**[a]	**-0.006**[a]	**-0.015**[a]	**-0.004**[b]	**0.004**[a]	**-0.005**[a]
β_2	**0.893**[a]	**0.638**[a]	**-0.110**[c]	**0.119**[b]	0.055	**0.811**[a]	**-0.235**[a]	**-0.848**[a]	**-0.114**[b]	**-0.135**[a]	-0.032
$\beta_0+\beta_1+\beta_2$	-0.018	0.013	-0.026	**-0.109**[a]	**-0.100**[a]	-0.023	-0.010	**-0.093**[a]	-0.003	**-0.121**[a]	0.013
adj. R^2	22.9%	21.9%	16.9%	15.8%	24.5%	18.3%	15.3%	30.1%	27.9%	37.5%	26.0%
MHQ	2	2	0	0	1	0	0	2	1	2	0

Note: Same as under *Table 2*.

The one-break model was suggested for Latvia and Slovenia. Under the preferred specification, the risk-return distances have not converged for Slovenia. The trend coefficient in the first regime (β_0) is positive but insignificant, as is the sum of the trend coefficients ($\beta_0 + \beta_1$) after the break. However, a sudden decrease in the risk-return distances occurred in June 2003. This is also the reason why the no-break model suggested convergence for Slovenia. The increase in similarity between risk-return distances for Latvia is more in line with the general observation for the CEE markets. The break is dated to January 2002 and is accompanied by a sudden decline of risk-return distances and reversion to convergence ($\beta_0 + \beta_1$ is negative in the second regime and significant).

Two-break models have been preferred for Croatia, the Czech Republic and Romania, as well as for the unweighted cross-market average of the CEE markets. Breaks for Romania and the Czech Republic might be attributed to the recent financial crisis. The first regime switch for Romania occurred in February 2007 and was followed by a divergence of risk-return distances, which ended with the regime change in April 2009, accompanied by convergence (although insignificant) of risk-return distances. The first regime switch for the Czech Republic occurred in August 2008 and, although it was followed by an increase in convergence, it was also accompanied by a sudden increase in risk-return distances. The overall effect suggests an increase in risk-return distances during the crisis since the sudden increase of risk-return distances is offset by an increase in the speed of convergence only after 20 months following the first break. This regime ended in December 2010 and led to another sudden increase in risk-return distances but also to non-convergence (insignificant sum of trend coefficients).

When using the unweighted cross-market averages of the CEE markets, we found that the two-break model is preferred, i.e. the results on risk-return convergence are sensitive to the choice of weighting. The second break occurred in August 2008 and, similar to the case of the Czech Republic, it was followed by an increase in risk-return distances but also by an increase in convergence.

4.3 Convergence Hypothesis and Changing Market Conditions

The results from Section 4.2 are interesting as they not only suggest that the similarity between returns increased, but also indicate that this process was not stable over time. In this section we will explore this time-variance of return, risk and risk-return distances in more detail. As numerous breaks occurred during the financial crisis, we assumed that changing market conditions may have explanatory power toward distance measures. We used market volatility as a proxy for changes in the market.

We first estimated the following model:

$$D_{ijt} = \alpha_{0ij} + \beta_{0ij}t + \gamma_{1ij}sd_{it} + \gamma_{2ij}sd_{jt} + u_{ijt} \tag{8}$$

Market volatility was calculated using the standard deviation (sd) of daily consecutive returns in a given month for a given market (i or j). A significant coefficient of a given standard deviation would imply that as conditions in a given market changed, so did the distances. More specifically, when the coefficient of a standard deviation of returns on the developed European markets is significant, it suggests that distances change with movements in the developed European markets.

When the sign of this coefficient is positive, shocks to the developed European markets are not transmitted (or at least not as much) to the CEE markets, as distances increase. A significant and positive coefficient for a standard deviation of returns on a CEE market implies that local factors still play a significant role, as local shocks increase the dissimilarity between returns, thus making the evolution of returns on the local market more distinct.

Estimating model (8) resulted in significant and positive coefficients for the standard deviations of returns on local markets (results available upon request). However, as noted in several previous studies (e.g. Baumöhl and Lyócsa, 2014), colinearity might be an issue with specifications using both volatility regressors. We have therefore decided to use different specifications:

$$D_{ijt} = \alpha_{0ij} + \beta_{0ij} t + \gamma_{1ij} sd_{it} + u_{ijt} \tag{9}$$

$$D_{ijt} = \alpha_{0ij} + \beta_{0ij} t + \gamma_{1ij} sd_{jt} + u_{ijt} \tag{10}$$

$$D_{ijt} = \alpha_{0ij} + \beta_{0ij} t + \gamma_{1ij} sd_{it} + \gamma_{2ij} ae_{jt} + \gamma_{3ij} aev_{jt} + u_{ijt} \tag{11}$$

$$D_{ijt} = \alpha_{0ij} + \beta_{0ij} t + \gamma_{1ij} sd_{jt} + \gamma_{2ij} ad_{jt} + \gamma_{3ij} adv_{jt} + u_{ijt} \tag{12}$$

In all of these specifications, we have used standard deviations of returns for one market only (i – denoting the CEE market, j – developed European market), thus overcoming the possible colinearity problem. The specifications of models (11) and (12) is similar to that of Eun and Lee (2010). Several prior studies have suggested that co-movements between returns may be asymmetric, with higher co-movements during periods of market declines (see Baumöhl et al., 2011). Further on, if one assumes the standpoint of an international investor, it is of particular interest to know whether and how distances change during turbulent periods and decline when diversification is most needed. Variables *ae* and *ad* are dummy variables equal to 1 when the average return in a given month t, in a given market (*ae* = CEE market, *ad* = = developed European market) was negative. Asymmetric effects may also be expected for market volatility and are captured with the variables *aev* and *adv* ($aev = ae \times sd_i$, $adv = ad \times sd_j$). As conclusions regarding the market volatility coefficients drawn from models (9) and (10) are similar to those from (11) and (12), we report only results from the latter models (results from models (9) and (10) are available as supplementary material).

Based on the results presented in panel A of *Table 5*, evidence supporting the convergence hypothesis of return distances is slightly weakened. Most of the trend coefficients are still negative and at least one significant trend coefficient is found for models (11) and (12) for all markets except Croatia, Estonia, Lithuania and Slovenia. At the same time, time trend coefficients for cross-market averages are still negative and with specification (12) significant at the 1% significance level.

Coefficients for the standard deviation of individual CEE and developed European market returns are positive in all cases and also significant for at least one of the models. More specifically, except for one case each for Poland and Slovenia, volatility coefficients are significant at the 5% significance level. It seems that during turbulent periods, the return distances actually increase. Asymmetric effects were rather rare, country specific and with alternating signs.

Table 5 Distance Convergence under Different Market Conditions

	Model 11 (volatility of emerging market)						Model 12 (volatility of developed market)					
	c	*t*	sd_i	*ae*	*aev*	adj.R^2	*c*	*t*	sd_j	*ad*	*adv*	adj.R^2
Panel A: Return distances												
HRV	0.001	-0.001	**0.195**^{a}	0.087	0.031	0.224	**0.002**^{a}	-0.006	**0.128**^{a}	-0.070	0.021	0.075
CZE	**0.001**^{a}	**-0.014**^{a}	**0.143**^{a}	0.061	0.020	0.256	0.001	**-0.010**^{b}	**0.198**^{a}	0.162	-0.121	0.264
EST	**0.002**^{a}	-0.002	**0.293**^{a}	**-1.266**^{c}	-0.249	0.225	**0.002**^{b}	0.004	**0.078**^{b}	-2.278	0.060	0.008
HUN	**0.002**^{a}	**-0.009**^{b}	**0.104**^{a}	0.045	-0.087	0.120	**0.002**^{a}	**-0.008**^{b}	**0.074**^{b}	0.185	-0.060	0.097
LVA	0.001	-0.002	**0.097**^{b}	**0.413**^{b}	0.164	0.171	**0.002**^{a}	**-0.009**^{b}	**0.145**^{a}	**1.032**^{a}	-0.125	0.178
LTU	**0.001**^{b}	-0.006	**0.131**^{b}	0.312	**0.198**^{c}	0.141	**0.002**^{a}	-0.006	**0.139**^{a}	-0.146	0.132	0.104
POL	**0.001**^{a}	0.000	**0.095**^{a}	0.115	**-0.152**^{c}	0.086	**0.003**^{a}	**-0.007**^{b}	0.017	0.152	-0.031	0.031
ROU	**0.002**^{c}	**-0.010**^{c}	**0.167**^{a}	0.138	-0.040	0.241	**0.003**^{a}	**-0.012**^{b}	**0.132**^{b}	**0.517**^{c}	0.074	0.181
SVN	**0.002**^{b}	-0.007	**0.073**^{c}	-0.289	0.182	0.052	**0.001**^{a}	0.000	**0.108**^{a}	0.829	**-0.272**^{b}	0.092
CEE	**0.001**^{a}	-0.002	**0.120**^{a}	**0.568**^{a}	**-0.100**^{c}	0.372	**0.002**^{a}	**-0.007**^{a}	**0.112**^{a}	**0.434**^{c}	-0.090	0.276
CEEw	**0.001**^{a}	**-0.006**^{b}	**0.115**^{a}	0.204	-0.112	0.290	**0.002**^{a}	**-0.007**^{a}	**0.095**^{a}	0.186	-0.077	0.231
Panel B: Risk distances												
HRV	0.003	0.000	**0.387**^{a}	**0.739**^{c}	**-0.715**^{a}	0.280	0.002	-0.011	**0.264**^{b}	0.228	-0.261	0.109
CZE	0.001	-0.007	**0.362**^{a}	0.293	**-0.312**^{c}	0.363	0.000	-0.003	**0.357**^{a}	0.316	-0.160	0.268
EST	**0.003**^{a}	-0.010	**0.257**^{a}	1.988	**-0.188**^{c}	0.161	**0.002**^{c}	**-0.010**^{c}	**0.313**^{a}	**6.917**^{c}	-0.147	0.282
HUN	0.001	0.005	**0.375**^{a}	-0.028	**-0.243**^{c}	0.309	**0.003**^{b}	0.003	0.138	0.225	-0.223	0.032
LVA	0.003	-0.011	**0.579**^{a}	-0.326	**-0.549**^{a}	0.543	**0.004**^{b}	**-0.028**^{b}	**0.320**^{a}	1.262	-0.059	0.139
LTU	0.005	-0.015	0.231	-0.385	-0.213	0.060	0.001	-0.005	**0.394**^{b}	0.106	-0.064	0.226
POL	0.001	0.003	**0.379**^{a}	0.088	**-0.373**^{a}	0.278	**0.005**^{a}	**-0.015**^{b}	0.095	-0.192	0.039	0.063

ROU	0.001	-0.006	**0.468**[a]	0.121	-0.266	0.445	**0.006**[a]	**-0.023**[b]	0.152	-0.097	0.306	0.084
SVN	**0.005**[a]	**-0.029**[a]	**0.174**[b]	0.887	0.142	0.210	0.002	**-0.024**[a]	**0.402**[a]	-1.005	-0.011	0.503
CEE	**0.003**[b]	-0.009	**0.265**[a]	0.302	**-0.273**[b]	0.259	**0.003**[a]	**-0.013**[a]	**0.280**[a]	-0.146	-0.151	0.420
CEEw	**0.003**[b]	-0.005	**0.272**[a]	0.208	**-0.296**[b]	0.250	**0.003**[a]	**-0.010**[b]	**0.197**[a]	-0.105	-0.056	0.217
Panel C: Risk-return distances												
HRV	**0.005**[a]	-0.004	**0.643**[a]	0.671	**-0.602**[a]	0.389	**0.005**[a]	**-0.021**[b]	**0.460**[a]	-0.055	-0.046	0.190
CZE	**0.004**[a]	**-0.030**[a]	**0.510**[a]	0.370	-0.263	0.436	0.002	**-0.020**[b]	**0.596**[a]	0.469	-0.294	0.407
EST	**0.006**[a]	-0.012	**0.613**[a]	1.251	**-0.526**[c]	0.268	**0.004**[a]	-0.007	**0.423**[a]	7.632	-0.027	0.198
HUN	**0.005**[a]	**-0.013**[b]	**0.489**[a]	0.036	**-0.351**[a]	0.350	**0.007**[a]	**-0.013**[c]	**0.251**[a]	0.429	-0.237	0.129
LVA	**0.004**[c]	-0.015	**0.690**[a]	0.417	-0.254	0.532	**0.008**[a]	**-0.044**[b]	**0.533**[a]	**2.595**[c]	-0.337	0.252
LTU	**0.007**[c]	-0.026	**0.422**[b]	0.018	0.104	0.155	**0.004**[a]	-0.014	**0.570**[a]	-0.091	0.047	0.277
POL	**0.004**[a]	0.000	**0.469**[a]	0.246	**-0.570**[a]	0.292	**0.009**[a]	**-0.027**[a]	**0.127**[c]	0.154	-0.065	0.101
ROU	**0.003**[c]	**-0.023**[b]	**0.662**[a]	**0.352**[c]	-0.249	0.553	**0.010**[a]	**-0.041**[a]	**0.334**[a]	**0.694**[c]	0.306	0.203
SVN	**0.007**[a]	**-0.036**[a]	**0.286**[a]	0.404	0.330	0.175	**0.005**[a]	**-0.021**[b]	**0.521**[a]	0.232	**-0.407**[b]	0.420
CEE	**0.005**[a]	**-0.013**[c]	**0.416**[a]	**1.208**[a]	**-0.442**[a]	0.470	**0.006**[a]	**-0.024**[a]	**0.433**[a]	0.464	-0.261	0.552
CEEw	**0.005**[a]	**-0.015**[b]	**0.416**[a]	**0.537**[b]	**-0.484**[a]	0.431	**0.006**[a]	**-0.022**[a]	**0.328**[a]	0.211	-0.169	0.382

Notes: Superscripts *a*, *b* and *c* denote significance at the 1%, 5% and 10% levels, respectively. The trend coefficient is multiplied by 1000. The KPSS test did not reject the null of no unit root in residuals for all estimated models. According to the Sansó et al. (2004) test, breaks in unconditional volatility of residuals were present for some series, but the break was always associated with a decline in volatility, thus no evidence of spurious convergence was found.

Evidence of conditional risk convergence under changing market conditions is rather weak. In (11) only one coefficient was negative and statistically significant (Slovenia). However, most time trend coefficients were still negative. It seems that a substantial amount of the variation in risk distances is captured by market volatilities. This effect is mitigated when the volatility of the local CEE market is coupled with a decline in the CEE market, as in specification (11) the coefficients related to the asymmetry in volatility are negative and in most cases significant. As volatility coupled with bearish market conditions in the CEE markets decrease the risk distances, it seems plausible to assume that these are reactions to the developments in the developed European markets,[14] i.e. spillovers of negative news seem to cause increased similarity between market volatilities.

Finally, it seems that there is evidence of risk-return convergence during our sample period for most of the CEE countries. The time trend coefficient is negative for all markets and all specifications (except for Poland in (11)). Furthermore, at least one of the trend coefficients is also significant for seven out of nine markets (Estonia and Lithuania being the only exceptions). These results are also confirmed when looking at the cross-market averages.

In general, the similarity between risk and returns decreased during more turbulent times, but for some markets it is mitigated when increased volatility is coupled with market declines. Thus we found some evidence for asymmetric volatility effects. An increase in volatility during bullish market conditions increases risk-return distances while having little impact during bearish market conditions (in most cases the sizes of the coefficients are negated). Although almost none of the *ae* or *ad* coefficients were significant, all were positive, thus suggesting that, in general, market declines (regardless of the market) increase risk-return distances.

These findings have some significant implications for international investors. First, regardless of whether one takes the position of the European or local investor, the effects are similar, i.e. coefficients have similar signs. An increase in volatility associated with bullish market conditions increases return distances, while bearish conditions in the respective markets coupled with increased volatility mitigated increases in distances in so far that for some instances the return distances even decrease. This indicates that during a crisis risk-return similarity might not increase.

4.4 Sensitivity to the Euro Currency

All evidence presented to this point is based on an analysis from the perspective of a local investor, i.e. the returns were calculated in local currencies and compared with returns of the developed European market in euros. The importance of the interaction between exchange rates and stock prices is recognized in the empirical literature (see flow-oriented and portfolio balance models, e.g. Dornbusch and Fischer, 1980; Gavin, 1989). It seems plausible to assume that a relationship between exchange rates and stock market co-movements should exist. As the local currency appreciates (regardless of the reasons), local markets attract foreign investors and demand for local assets increases. As domestic assets increase their share in international asset portfolios, the links between markets may increase.[15]

[14] The other way around seems less likely, i.e. developed European markets decrease when the CEE markets decrease.

Conversion of local currencies into euros had an impact on the analysis of unconditional convergence, particularly with regard to the risk distances. However, overall findings related to the evolution of the returns in the CEE market were not changed much by a conversion of local currency returns into euros (all results are available as supplementary material).[16] The results from estimated models (11) and (12) using the euro changed even less. Asymmetric effects were rare and volatility coefficients were in all specifications positive and in almost all cases statistically significant.

Finally, we have also considered a slightly different model specification of (9)–(10) with lagged volatility coefficients. Of the over 66 volatility coefficients, three were negative (and insignificant), while 44 were positive and statistically significant at least at the 10% significance level. This shows that our main finding that the similarity between returns tends to decrease during times of higher market volatility is very robust.

5. Concluding Remarks

In this paper we have analyzed the time-varying structure of risk-return characteristics of nine CEE stock markets. Our main results may be summarized as follows:

(1) Return distances declined over the sample period, as the time trend coefficients in a simple regression model were negative and significant in almost all countries (except Estonia and Slovenia). The same results are found for the CEE as a group (cross-market average return distances).

(2) The similarity between standard deviations of market returns is more time-varying than the similarity between return distances. Convergence in standard deviations occurred in the case of Estonia (where return convergence was not observed), Latvia, Poland, Romania and Slovenia. In most instances the information criteria suggested models with one or two breaks in coefficients as opposed to returns convergence where breaks were rather sparse.

(3) For the risk-return distances, we reject the hypothesis of no convergence for all examined markets and both cross-market averages, as the trend coefficients in the no-break model were all negative and statistically significant. Several structural breaks in risk-return distances have been identified as well.

(4) With regard to convergence under the different market conditions, our results clearly show that the similarity between risk and returns decreased during the more volatile periods, but for some markets it is mitigated when increased volatility is coupled with market declines.

[15] An additional source of risk contributing to the increase of market integration is the decrease of exchange rate volatility; see, for example, Fratzscher (2002).

[16] Based on the suggestion of the reviewers, we have also checked whether the effect of market volatility on return, risk and risk-return distances remains robust if we split the sample into two groups, i.e. before and after the recent financial crisis. The first sample ended at the end of 2007. The effect of market volatility on risk and risk-return distances was unchanged, but the effect of market volatility on return distances was weaker (though most of the coefficients remained positive), which might be due to the reduced sample size.

The last result is perhaps the most interesting one. It had been shown earlier (see Baumöhl and Lyócsa, 2014) that there is a positive relationship between correlations and volatility, i.e. correlations tend to be higher at times of higher volatility. In examining three risk-return characteristics, it is apparent that the same relationship to volatility holds for return, risk and risk-return distances. However, in this case this implies that during more volatile periods the risk-return characteristics tend to be more different—i.e. they diverge. Speaking in terms of stock market co-movements, the CEE markets behave in a more segmented manner when market uncertainty increases (at least when measured using return and risk distances). This finding appears to be in contrast to most of the empirical studies examining cross-market correlations but is in line with the findings of Eun and Lee (2010) for developed markets. As the concept of risk-return distances is similar to but distinct from return correlation, our results suggest that even at times of higher correlations, benefits for investors gained from international diversification to CEE emerging markets may still exist.

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