Are South East Europe stock markets integrated with regional and global stock markets?

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Abstract

This paper analyses whether stock markets of South East Europe (SEE) have become more integrated with regional and global stock markets during 2000s. Using a variety of co-integration methodologies we show that SEE stock markets have no long-run relationship with their mature counterparts. This means that SEE markets might be immunized to external shocks. We also model time varying correlations among these markets by using Multivariate Generalised Autoregressive Conditional Heteroschedastic (MGARCH) models as well as the Exponential Weighted Moving Average (EWMA) methodology. Results show that the correlations of UK and US equity markets with South East Europe market change over time. These changes in correlations between our benchmark markets and individual SEE market pairs are not uniform although evidence of increasing convergence among South East Europe and developed stock market is evident. Also examined in this paper whether the structure of correlations between returns of indices in different markets changed in different phases of the 2007-2009 global financial crisis. Overall our results show that diversification benefits are still possible for investors wishing to diversify their portfolio between developed and emerging SEE stock markets.

Keywords: South East Europe, Stock markets, Cointegration, Correlation.
JEL classifications: C32, G15.

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1. Introduction

During 2000s countries of South Eastern Europe (SEE) experienced strong economic growth and most of them liberalised their financial markets. In light of the recent accession of Bulgaria and Romania to the European Union (EU) and their future entry in the Euro area, it has become increasingly important to follow developments in SEE stock markets. This study provides a comprehensive overview on the state of financial integration of a group of SEE countries[1] with more advanced economies. The aim to this paper to shed further light about the relationship between SEE as well as Germany, UK and US equity markets is based on several reasons. Firstly, most of the SEE economies have gone through extensive reforms that have allowed them to go through robust economic growth patterns attracting also consistent FDI (table 1)[2]. FDI's flows in emerging stock markets are usually motivated by international investor expectations of higher returns and reduced portfolio risks (Divecha et al., 1992; Eaker et al., 2000; Middleton et al., 2008). The increase in net inflows to SEE emerging economies during 2000s is a clear sign of the attractive investment opportunities for international investors. Secondly SEE stock markets are quite modest compared to developed countries such as Germany, UK and USA as shown by both the number of listed companies and the ratio of market capitalization to GDP (table 2). It may be relevant to analyse whether lower capitalizations and domestically oriented SEE markets are in some way linked to higher capitalization markets. Thirdly, a typical feature of several SEE stock markets is low liquidity[3]: annual turnover ratio in SEE stock markets ranges from 6.3% in Croatia to 20.5% in Slovenia. This contrast with 142.4% and 179.4% in UK and USA respectively. So it is interesting to see whether markets with different level of liquidity tend to move together. Fourthly, during the recent US sub-prime financial crisis, market capitalization as percentage of GDP in SEE sock markets has fluctuated widely: these figures (table 2) ranged from 9.9% (Romania) to 38,6% (Croatia) in 2008. These figures suggest that probably the US crisis also hit these emerging stock markets[4]. Said that, a further goal of our study was to detect how quickly the US crisis spread through the SEE stock markets. Finally, our work aims to evaluate whether the integration of SEE stock markets is taking place more rapidly at regional level (by considering the German stock market as a leading European stock market) or at global level (by considering both the UK and US stock markets).

[1] We limit our analysis to the following SEE countries: Bulgaria, Croatia, Greece, Slovenia, Romania and Turkey. We excluded other countries belonging to that area due to data availability.

[2] Gilmore et al. (2005) argue those Eastern Europe countries which are expected to be full members of European Union (EU) and European Monetary Union (EMU) may have positive effects on both economies and equity markets.

[3] Also Korczak and Bohl (2005) find that Central and Eastern Europe (CEE) stock markets are small and illiquid. These characteristic can hinder efficient capital raising and valuation. Further small dimension of CEE stock markets make them very sensitive to shift of regional and worldwide portfolio adjustment of large international investors (Egert and Kocenda, 2007; Kasman et al., 2009).

[4] According to Bartram and Bodnar (2008), the recent financial crisis caused a drop of the global equity market capitalisation of more than 56% from October 2007 to February 2009.

Table 1 – Economic growth and FDI in SEE countries

	2000	2001	2002	2003	2004	2005	2006	2007	2008	Average
GDP growth (%)										
Bulgaria	5.40	4.10	4.50	5.01	6.64	6.25	6.75	6.17	6.01	5.64
Croatia	3.03	3.83	5.44	4.96	4.25	4.21	4.74	5.47	2.36	4.25
Greece	4.48	4.20	3.44	5.58	4.92	2.90	4.50	4.04	2.93	4.11
Romania	2.10	5.70	5.10	5.20	8.40	4.17	7.90	6.00	9.43	6.01
Slovenia	4.39	2.85	3.97	2.84	4.29	4.35	5.90	6.76	3.54	4.32
Turkey	6.77	-5.70	6.16	5.27	9.36	8.40	6.89	4.67	0.90	6.01
FDI, net inflows (% GDP)										
Bulgaria	7.95	5.98	5.80	10.49	10.80	15.86	24.51	29.60	18.45	14.38
Croatia	5.20	6.92	4.15	6.05	2.65	4.02	7.05	8.52	6.92	5.72
Greece	0.86	1.21	0.04	0.69	0.91	0.27	2.02	0.63	1.49	0.90
Romania	2.80	2.88	2.50	3.10	8.63	6.55	9.29	5.86	6.94	5.39
Slovenia	0.68	2.47	7.19	1.04	2.47	1.51	1.67	3.25	3.51	2.64
Turkey	0.37	1.71	0.49	0.57	0.71	2.07	3.81	3.40	2.49	1.73

Source: World Development Indicators.

Table 2 – Features of SEE and developed stock markets

	2000	2001	2002	2003	2004	2005	2006	2007	2008	Average
Listed companies										
Bulgaria	503	399	354	356	332	331	347	369	334	369
Croatia	64	62	66	66	145	145	183	353	376	162
Germany	1022	749	715	684	660	648	656	658	638	714
Greece	329	338	341	339	340	307	318	292	280	320
Romania	5555	5140	4870	4484	4030	3747	2478	2096	1824	3802
Slovenia	38	38	35	134	140	116	100	87	84	85
Turkey	315	310	288	284	296	302	314	319	284	301
UK	1904	1923	2405	2311	2486	2759	2913	2588	2415	2411
USA	7524	6355	5685	5295	5231	5143	5133	5130	5603	5677
CAP/GDP ratio										
Bulgaria	4.9	3.71	4.70	8.78	11.38	18.71	32.62	55.10	17.75	17.51
Croatia	12.85	14.50	15.01	18.08	26.92	29.07	59.15	11.67	38.64	25.09
Germany	66.85	56.68	34.27	44.18	43.51	43.78	56.24	63.49	30.36	48.81
Greece	88.28	66.04	46.64	55.23	54.27	59.00	77.87	84.84	25.40	61.95
Romania	2.89	5.29	9.95	9.38	15.61	20.81	26.73	26.54	9.96	14.12
Slovenia	12.81	13.93	19.97	24.55	28.69	22.13	39.03	61.39	21.55	27.11
Turkey	26.07	24.05	14.59	22.45	25.01	33.38	30.65	44.23	16.05	26.27
UK	174.41	147.17	115.64	132.20	128.11	134.12	155.78	137.63	69.26	132.7
USA	154.68	137.50	106.53	130.79	140.35	137.26	148.10	145.16	83.29	131.51
Stock/GDP										
Bulgaria	0.46	0.52	1.11	0.99	2.07	5.11	4.77	13.90	3.31	3.58
Croatia	0.88	0.51	0.55	0.70	1.21	1.8	3.72	6.98	4.96	2.36
Germany	56.26	75.07	61.14	46.97	51.22	63.20	85.38	101.42	84.77	48.81
Greece	75.75	28.52	16.87	19.95	18.84	26.55	40.18	48.52	29.68	33.87
Romania	0.64	0.64	0.88	0.74	1.25	3.44	3.47	4.78	1.84	2.21
Slovenia	2.34	3.89	4.35	2.52	3.47	2.21	2.62	5.75	2.58	3.30
Turkey	67.07	39.76	30.36	32.70	37.51	41.58	42.95	46.68	32.62	41.24
UK	124.21	126.53	118.46	118.85	168.66	182.75	174.16	368.28	242.49	180.48
USA	326.30	288.22	243.54	142.53	166.41	173.97	253.63	310.10	258.76	240.38
Turnover										
Bulgaria	9.24	12.90	13.85	16.27	22.82	35.20	19.58	34.20	10.77	19.42
Croatia	7.41	4.00	3.80	4.77	5.95	6.69	8.70	8.60	7.42	6.37
Germany										
Greece	63.69	39.10	25.99	43.96	37.47	48.30	60.84	64.00	59.18	49.17
Romania	23.06	15.70	22.96	8.76	11.59	21.00	15.96	20.80	11.33	16.79
Slovenia	20.67	30.50	Na	12.71	13.92	8.97	8.83	12.30	6.91	20.53
Turkey	206.19	161.50	163.43	192.39	182.32	154.91	140.53	134.70	118.52	138.39
UK	66.60	78.40	135.40	100.58	140.53	141.88	123.81	270.10	226.85	142.68
USA	200.80	201.30	202.51	122.81	126.54	129.10	182.81	216.50	232.36	179.41

Notes. Listed companies are the domestically companies listed on the country's stock exchange at the end of the year. CAP/GDP is the market capitalization of listed companies as percentage of GDP. Stock/GDP is the total values of shares traded as percentage of GDP. Turnover ratio is the total value of shares traded divided by the average market capitalization.
Source: World Development Indicators.

Relevant empirical literature dealing with the relationship between developed and SEE stock markets is almost totally absent although the high rate of economic growth of these economies in the last 10 years. Said that our paper aims to fill that gap. The rest of this paper is structured as follows. Section 2 review the relevant literature. Section 3 shows methodologies used in this study. Section 4 present data used in this study. Section 5 presents the empirical results. Section 6 concludes.

2. Literature review

A number of existing contributions has dealt with linkages among emerging Eastern Europe and developed stock markets. Lucey and Voronkova (2008) investigate both long- and short-run relationships between the Russian and developed stock markets in the 1994-2004 period. The first relation is examined through the Johansen-Juselius cointegration test: no long run relationships between Russian and seven markets was found. DCC multivariate GARCH models were used to examine the short-run dynamics: bivariate conditional correlations between Russian and several developed markets (i.e. UK and US), show that correlations increased especially during the 1998 Russian crisis. Exploring the short and long-term relationships between the US stock markets and three Central European (CEE) markets (Czech Republic, Hungary, and Poland) during the 1995-2001 period, Gilmore and McManus (2002) found no evidence of both bilateral and multilateral relationships between the US and the three CEE markets either in the short- and long term period. Scheichher (2001) documented also that the interaction among these three CEE equity markets seems to be quite limited. Syriopoulos (2007) investigates the relationships between CEE stock markets (Czech Republic, Hungary, Poland, Slovakia) and developed stock markets (Germany, US) over the period 1997-2003. Results show a long-run relationship between the CEE and the developed stock markets, however in the short-period the US stock market exerts a stronger impact then the German market on the CEE stock markets. Voronkova (2004) explored the degree of integration among three emerging markets (Czech Republic, Hungary, Poland), three developed European markets (France, Germany and UK) and the US over 1993-2002 period. Using conventional cointegration tests (i.e. the Engle-Granger and the Johansen cointegration procedure) her analysis indicates that emerging countries share a long-run relation with developed stock markets, however bivariate cointegration indicate the existence of co-movements between the developed markets and just only the Polish market. Using the Gregory-Hansen cointegration test that allow for structural change in the cointegration relation, results reveal long-run linkages between the Czech and Hungarian markets with the developed markets. Long-run relationships among CEE countries and developed markets is not always confirmed since Gilmore et al. (2005) show that for German and US investors willing to diversify their portfolios can benefit from investing into Czech Republic, Hungary and Poland equity markets due the absence of any long run relationship among these stock markets and western stock markets. This mixed results suggest the hypothesis of time-varying nature of the long run relationship among equity markets indexes which may occurs over long periods. Recent studies which focused on the periods after the conclusion of liberalization processes in the CEE countries have find more stable results. For instance, Samitas et al. (2007) explore the issue of integration among several Balkan stock markets

(Bulgaria, Romania, Serbia, Turkey, Croatia, FYROM, Albania), three developed European stock markets (Greece, Germany, UK) and the US. Using both the Johansen cointegration test and Gregory-Hansen on a sample data which covers a period of six years (from 2000 to 2006), these authors found evidence of equity market integration among emerging Balkan and developed equity markets. Syriopoulos and Roumpis (2009) examined linkages and time-varying co-movements between emerging Balkans equity markets (Bulgaria, Croatia, Cyprus, Romania, Turkey) and two developed equity markets (US and Germany) during the period 1998-2007. They find the presence of cointegration between the sample equity markets. Gilmore et al. (2008) show clearly no evidence of cointegration between developed European Union equity markets and three CEE countries for the period 1995-2005 by using the Johansen and Juselius cointegration procedure. Results are different by using the Hansen and Johansen cointegration method: it is shown the episodic evidence of cointegration among these markets[5]. The review of the literature shows clearly that the relationship among developed and eastern Europe stock markets is not very clear. Several factors may affect the results such as the period of time considered, the methodology used and the sample of stock markets chosen. In the period of time we considered, all stock markets have taken important measure in order to liberalise their financial system. Some of them are completing their process in order to be either member of the EU or the Euro area. Until the second half of 2000s, these SEE recorded also high rate of economic growth. These reasons make these stock markets very interesting for international investors looking for diversify their portfolio in emerging stock markets.

3. Data

The data consists weekly price index values for the SEE and developed stock markets from 8th November 2000 to 19th May 2010. We use weekly prices for weeks running from Wednesday to Wednesday to minimize effects of cross-country differences in weekend market closures (Beirne et al. 2010), as well as to overcome the more general problem of non-synchronous data.[6] All stock prices were taken in local currency from *Thomson Reuters Datastream* (table 3). As pointed out by Syriopoulos and Roumpis (2009), taking stock market prices in local currency has two main advantages, firstly changes are due just only to stock prices movements secondly these changes are not biased by exchange rate devaluations. The reasons behind the chose of developed stock markets like UK and US is that these stock markets are the biggest in the world (Schotman and Zalewska, 2006). On the other side the German stock market was chosen for two reasons. Firstly the German economy is the largest within Europe. Secondly the share of German investment in SEE is one of the larger so we would expect that the German market is most integrated with SEE stock markets.

[5] These authors argue for example that during the period 1995-2000, the cointegration disappears in 1998 as a consequence of the Asian-Russian crises on the CEE equity markets.

[6] As pointed put in several studies (Lo and McKinlay, 1990; Burns and Engle, 1998; Abad et al., 2009).This problem takes place because of time difference among markets imply that some markets are closed while other markets are still opened.

Table 3 – Stock market indices

Country	Index name	Currency
Bulgaria	BSE SOFIX	Lev
Croatia	CROBEX	Kuna
Germany	DAX30	Euro
Greece	ATHEX MID 40	Euro
Romania	BET	Lei
Turkey	ISE 100	Lira
Slovenia	SBI	Euro
UK	FTSE100	Pound Sterling
USA	S&P100	Dollar

Descriptive statistics of returns for each index considered are provided in table 4. Stock market returns are are positive for almost all SEE stock markets as opposed to negative values for developed stock markets. For the time period under study the Turkey stock index is the most volatile, as indicated by the standard deviation of 5.5%, while the US stock index appears to be most stable with standard deviation being 2.5%. Overall the returns of SEE markets show higher volatility[7] than for the two developed stock markets: this is not surprising and it is consistent with other studies (Goetzmann and Jorion, 1999; Chelley-Steeley, 2004) where it has been found that high volatility phenomenon characterize emerging stock markets. Further the reported Jarque-Bera statistic reject the null hypothesis that returns are normally distributed for all stock market. The value of the skewness is negative for each index indicating that large positive stock returns are less common than large negative stock returns. Further kurtosis statistic is greater than 3 indicating that all returns series are leptokurtic having significantly fatter tails and higher peaks. Overall we found that the average daily return for our sample of emerging markets is 0.17% compared to -0.05% for developed stock markets. For volatility we found that the average daily standard deviation of returns is 3.94 for our sample of emerging market compared with 2.93 for the developed market sample. According to these statistics, emerging stock markets appear very attractive investment for international investors.

Table 4 – Summary statistics of the weekly stock market returns, 2000-2010

Index	N obs	Mean	Minimum	Maximum	Std Dev	Skewness	Kurtosis	Jarque-Bera Test	p-value
Bulgaria	497	0.257	-28.207	18.003	4.330	-0.917	12.024	1756.306	0.00
Croatia	497	0.171	-13.176	11.591	3.255	-0.427	5.292	123.991	0.00
Germany	497	-0.031	-15.224	17.154	3.574	-0.632	6.580	298.531	0.00
Greece	497	-0.171	-14.331	15.809	3.926	-0.373	4.660	68.632	0.00
Romania	497	0.362	-20.722	11.999	3.956	-0.789	5.760	209.374	0.00
Turkey	497	0.288	-32.836	23.343	5.598	-0.698	7.187	403.554	0.00
Slovenia	497	0.128	-18.064	11.001	2.626	-1.258	11.349	1574.932	0.00
UK	497	-0.045	-12.731	13.587	2.651	-0.329	6.810	309.698	0.00
USA	497	-0.076	-15.386	10.505	2.584	-0.447	7.338	406.411	0.00

Notes: Weekly returns are computed as $R_t = [ln(P_t/P_{t-1})] \times 100$, where P_t is the price of the index at instant *t*. The Jarque-Bera statistic tests the null hypothesis of a normal distribution and is distributes as a χ^2 with 2 degrees of freedom.

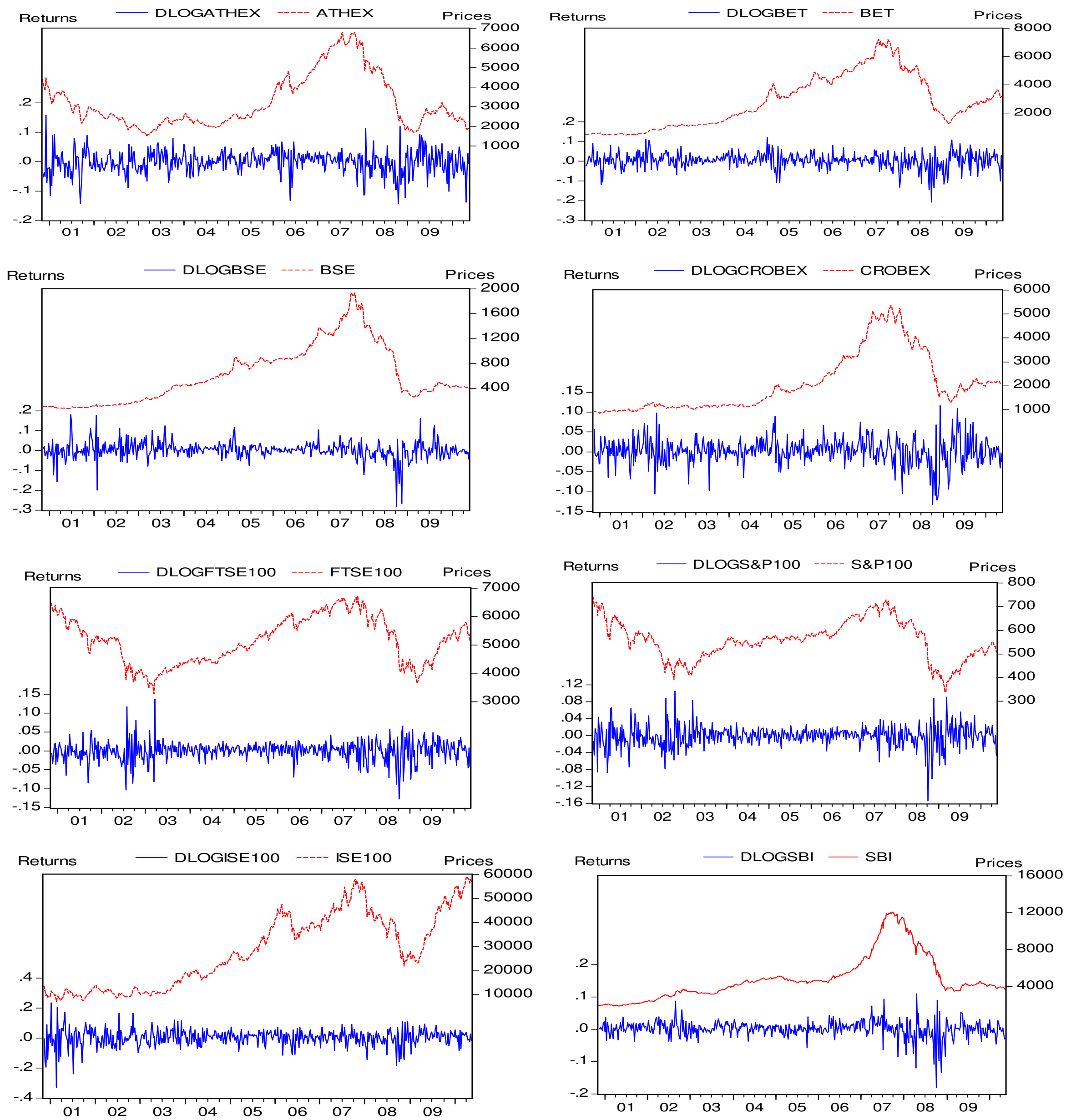
Figure 1 shows SEE development during the period considered. It can be seen from the figure that the stock indices saw a slow growth until the first half of the period considered, increase sharply between September 2005 and August 2008[8] and declined sharply up to the end of 2008. We also distinguish periods with moderate (positive and negative) returns (i.e low volatility) from periods with high (positive and negative)

[7] With the exception of the Slovenian stock market.

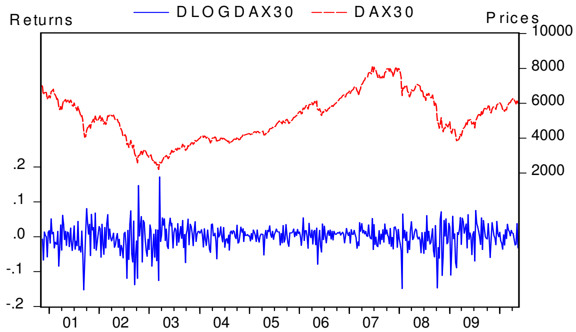
[8] As pointed out by Dvorak and Podpiera (2006), the announcements of the European Union (EU) enlargement may be considered one of the causes of the dramatic increases in stock prices of some candidate countries.

returns (i.e. high volatility). As pointed out by Bartram and Bodnar (2009), during the 2007 financial crisis SEE markets prices registered a steep decline as occurred in mature stock markets. However SEE markets returns experienced generally less volatility over the period than both UK and US stock markets[9] (fig. 1). As pointed out by Dvorak and Podpiera (2006), the constant rise in SEE stock returns up to the recent eurptin financial crisis, may be due to an increasing integration of these markets with global stock markets following the announcements of the EU enlargement to the South East Europe.

Figure 1 – Time series of weekly returns and prices from 2000 to 2010



[9] As pointed out by Christie (1982) when stock market prices move downward , the coefficient of the debt/equity ratio rises. The main consequence is an increasing riskiness (volatility) of the stock market.



Correlations among market returns (table 5) averaged between 2% and 77% during the whole period. Correlation coefficients between the SEE and the developed stock markets are found relatively low suggesting possible diversification benefits in Eastern Europe emerging markets. However, the correlations for the whole period can hide the progress towards integration that has been made by a number of countries. As we can see from table 3 there is an evident increase in the size of correlations among stock market returns in the two sub-periods. For example, during 2000-2005 the correlations coefficients between the returns of S&P100 and BET had been 1.3%, but increased to 47.7% during 2005-2010. The correlation coefficient between UK and Romania rose (and changed sign) from -1.2% to 51,5%. Similar patterns can be observed between other stock markets. More in general the average correlation between emerging and developed market returns over the period is 36.4%, 20% and 51% in the first- and second- sub period respectively. These results suggest that correlations between emerging and developed markets have increased over time. Further we computed the average weekly returns for our sample market at aggregate level, our findings show that average returns for our sample of developed markets are 0.013% whilst for emerging -0.283%. These results do not support the traditional point of view of practitioner circles about higher returns for emerging rather than developed markets[10]

Table 5 – Correlation coefficients of weekly stock market returns

Panel A: 2000-2010	ATHEX	BET	BSE	CROBEX	DAX30	FTSE100	ISE 100	SBI	S&P500
ATHEX	1.00								
BET	0.366	1.0							
BSE	0.168	0.339	1.00						
CROBEX	0.353	0.345	0.298	1.00					
DAX30	0.576	0.261	0.183	0.349	1.00				
FTSE100	0.518	0.282	0.183	0.354	0.830	1.00			
ISE 100	0.369	0.284	0.2	0.281	0.380	0.397	1.00		
SBI	0.305	0.394	0.322	0.417	0.298	0.306	0.301	1.00	
S&P100	0.422	0.264	0.192	0.294	0.772	0.77	0.389	0.298	1.00

Panel B: 2000-2005[a]	ATHEX	BET	BSE	CROBEX	DAX30	FTSE100	ISE 100	SBI	S&P500
ATHEX	1.00								
BET	0.1	1.00							
BSE	-0.011	0.057	1.00						
CROBEX	0.169	0.121	0.077	1.00					
DAX30	0.504	-0.013	0.005	0.219	1.00				
FTSE100	0.427	-0.012	-0.03	0.251	0.812	1.00			
ISE 100	0.239	0.101	0.073	0.147	0.214	0.215	1.00		
SBI	0.089	0.153	0.03	0.182	0.182	0.219	0.203	1.00	
S&P100	0.402	0.013	0.015	0.168	0.789	0.717	0.262	0.2	1.00

[10] Also Bilson et al. (2002) come to the same conclusions by comparing the monthly returns of 17 and 19 emerging and developed stock markets during the period 1984-1997.

Panel C: 2005-2010[b]	ATHEX	BET	BSE	CROBEX		FTSE100	ISE 100	SBI	S&P500
ATHEX	1.00								
BET	0.555	1.00							
BSE	0.325	0.546	1.00						
CROBEX	0.475	0.44	0.459	1.00					
DAX30	0.667	0.547	0.408	0.488	1.00				
FTSE100	0.595	0.515	0.391	0.434	0.863	1.00			
ISE 100	0.537	0.498	0.371	0.46	0.646	0.639	1.00		
SBI	0.418	0.497	0.481	0.512	0.418	0.373	0.423	1.00	
S&P100	0.441	0.477	0.372	0.396	0.756	0.821	0.567	0.375	1.00

Notes.[a] From November 8th, 2000 to August 14th, 2005. [b] From August 15th 2005 to May 25th 2010.

4. Methodology

When two or more variables are co integrated, that is, if there exists a particular linear combination of these nonstationary variables which is stationary, in such cases a long-run relationship between these variables exists. When more than two variables are involved, cointegration analysis can be carried out through multivariate cointegration tests. In this study we use the Johansen cointegration test (1988). In order to carry out that test, we first formulate the following VAR model:

$$y_t = \Gamma_1 y_{t-1} + \Gamma_2 y_{t-2} + \ldots + \Gamma_p y_{t-p} + \varepsilon_t \quad (1)$$

where y_t is a $n \times 1$ vector of variables and ε_t is an $n \times 1$ vector of innovations. Assuming that y_t is a vector of I(1) variables, while *r* linear combinations of y_t are stationary, we can write:

$$\Pi = \gamma\beta' \quad (2)$$

where γ and β are vector of dimension $k \times r$. Again β denotes the matrix of cointegrating vectors, while γ represents the matrix of weights with which each cointegrating vector enters each of the y_t equations. The Johansen approach involves testing hypotheses about the cointegrating rank *r* of the long-run matrix Π. Two different likelihood ratio tests can be used. The first one is the trace test (λ_{trace}) which tests the null hypothesis of *r* cointegrating vectors against the alternative hypothesis of *n* cointegrating vectors. The second one is the maximum eigenvalue test ($\lambda_{\max}$) where the null hypothesis of *r* cointegrating vectors against the alternative of $r+1$ co-integrating vectors is tested. These tests can be calculated as follows:

$$\lambda_{trace} = -T \sum_{j=r+1}^{k} \log(1 - \hat{\lambda}_j) \quad (3)$$

$$\lambda_{\max} = -T \log(1 - \hat{\lambda}_{j+1}) \quad (4)$$

If the test statistic value exceeds the critical values then we reject the null hypothesis and accept the alternative.

We also perform Engle and Granger (1987) cointegration test which is based on the following model estimated by OLS:

$$y_t = \alpha + \beta x_t + \varepsilon_t \tag{5}$$

where y_t and x_t are stock returns of two market indices. Estimated residual ε_t from the above equation are considered to be temporary deviation from long-run equilibrium. The ADF unit root tests are then conducted on the estimated residual ε_t through the following linear equation:

$$\Delta\varepsilon_t = \alpha\varepsilon_{t-1} + \sum_{i=1}^{m} \beta_i \Delta\varepsilon_{t-i} + \omega_t \tag{6}$$

If the residuals are found to be stationary the null hypothesis of no equilibrium relationship between stock returns of two markets is rejected (i.e. no long run relationship exists between stock market returns).

Gregory and Hansen (1996) argue that standard tests for cointegration are appropriate for testing the hypothesis of no cointegration against the alternative of cointegration given that these tests assume that the cointegration relationship among variable of interest is time-invariant. However if we are interested to evaluate whether the long run relationship change at a single unknown time during the sample period, then our null hypothesis (no cointegration) is the same, while the alternative is different than the conventional cointegration test. In other words, Gregory and Hansen (1996) test allow for a regime shift in either the intercept alone or the entire coefficient vectors. This regime shift is called structural break and is the alternative hypothesis of the Gregory-Hansen cointegration test. Gregory and Hansen (1996) argues that there are several forms of structural change, however they discuss and model only three forms. These forms can be modelled through three different models each of on one allowing structural change in the cointegrating relationship. The first one is called Model C (level shift model), that is:

$$y_{1t} = \mu_1 + \mu_2\varphi_{t\tau} + \alpha y_{2t} + e_t \tag{7}$$

where $y = \lfloor y_{1y}, y_{2t} \rfloor$ is a vector of variable we are interested to study the long run relationship, whilst μ_1 represents the intercept before the shift, and μ_2 represents the change in the intercept at the time of the shift. If we introduce a time trend into the level shift model, then we get the Level shift model with trend (C/T) which is specified as follows:

$$y_{1t} = \mu_1 + \mu_2\varphi_{t\tau} + \beta t + \alpha^T y_{2t} + e_t \tag{8}$$

Another possible structural change allows the slope vector to shift as well. This further model is called *regime shift* model (C/S) which is specified as follows:

$$y_{1t} = \mu_1 + \mu_2\varphi_{t\tau} + \alpha_1^T y_{2t} + \alpha_2^T y_{2t}\varphi_{t\tau} + e_t \tag{9}$$

In the C/S model μ_1 and μ_2 are defined as in the level shift model, α_1 denotes the cointegrating slopes coefficients before the regime shift, and α_1 denotes the changes in the slope coefficients

All models above permits structural change through the dummy variable δ_t which is defined as:

$$\varphi_{t\tau} = \begin{cases} 1 & if \quad t > [n\tau] \\ 0 & if \quad t \le [n\tau] \end{cases} \tag{10}$$

where the unknown parameter $\tau \in (0,1)$ denotes the timing of the chage point, and $[n\,\tau]$ denotes integer part. For all modes (C, C/T, C/S), the augmented Dickey-Fuller (ADF) statistic is calculated by regressing $\Delta\hat{e}_{t-1\tau}$ and $\Delta\hat{e}_{t-1\tau},\ldots,\Delta\hat{e}_{t-k\tau}$ for some suitably chosen lag truncation K. Following Gregory and Hansen (1996) the ADF statistic is just the t-statistic for the regressor $\hat{e}_{t-1\tau}$ and is denoted as $ADF(\tau) = tstat(\hat{e}_{t-1\tau})$

.

Unbiased estimates of unconditional correlation can be calculated by a weighted moving average. This methodology can involve either equal (EW) or exponential weighting moving average (EWMA). The last is preferred to the EWMA because puts more weight on the more recent observations. These means that extreme returns in the past become less important in the average. One of the advantages of using exponential rather than equal weighting is that shocks to correlation die out exponentially, at a rate determined by the smoothing constant. Following Alexander (2008), suppose we are considering two stock returns, in order to calculate EWMA estimates of variance $(\hat{\sigma}_t^2)$ and covariance $(\hat{\sigma}_{12,t}^2)$ of the two returns, we use the following formulae:

$$\hat{\sigma}_t^2 = (1-\lambda)\sum_{i=1}^{\infty}\lambda^{i-1} r_{t-1}^2 \tag{11}$$

and

$$\hat{\sigma}_{12,t}^2 = (1-\lambda)\sum_{i=1}^{\infty}\lambda^{i-1} r_{1,t-i}^2 r_{2,t-i}^2 \tag{12}$$

As pointed out by Alexander (2008), equations can rewritten in the form of recursions as follows:

$$\hat{\sigma}_t^2 = (1-\lambda) r_{t-1}^2 + \lambda \hat{\sigma}_{t-1}^2 \tag{13}$$

and

$$\hat{\sigma}_{12,t} = (1-\lambda) r_{1,t-1} r_{2,t-1} + \lambda \hat{\sigma}_{12,t-1}^2 \tag{14}$$

An alternative notation used for both eq.13 and 14 is $V_\lambda(r_t)$ for $\hat{\sigma}_t^2$ and $COV_\lambda(r_{1,t}, r_{2,t})$ for $\hat{\sigma}_{12,t}^2$. Further in order to calculate EWMA correlation the covariance is divided by the square root of the product of the two EWMA variance estimates (Alexander, 2008). That is:

$$\rho_{12,t} = \frac{COV_\lambda(r_{1,t}, r_{2,t})}{\sqrt{V_\lambda(r_{1,t}) V_\lambda(r_{2,t})}} \tag{15}$$

The main question with EWMA is which value of λ should be used? There is no one best method for optimising the value of λ. the optimal λ used by Riskmetrics has been 0.94 for daily data thus in our work we took that value.

A further way of capturing interactions between the volatility of *N* different financial markets returns is to estimate a multivariate GARCH model for the time series $y_t = (y_{1t}, y_{2t}, \dots, y_{Nt})'$. The label "multivariate GARCH" refers to a model for a multivariate time series y_t in which the conditional variances of the individual series are estimated simultaneously (by maximum likelihood). The seminal paper on multivariate GARCH is by Engle et al. (1984), which introduced the bivariate ARCH model. A rigorous analysis of the theoretical properties of multivariate GARCH models, however, did not appear until Engle and Kroner (1995), which was based on the earlier working paper by Baba et al. (1990). There are numerous different representations of the multivariate GARCH models proposed by Engle and Kroner (1995). In multivariate GARCH models, since y_t is a vector of dimension $(N \times 1)$, the conditional mean of y_t is an $(N \times 1)$ vector μ_t and the conditional variance of y_t is an $(N \times N)$ matrix H_t. The main representation are the VECH, diagonal, BEKK and constant correlation representations. The BEKK representation of the multivariate GARCH improves on both the VECH and diagonal representations, since H_t is almost guaranteed to be positive-definite. The BEKK representation assumes the following model for H_t:

$$H_t = A_0 + \sum_{t-1}^{q} A_I^* \varepsilon_{t-I} \varepsilon_{t-i}' A_i^{*'} + \sum_{i=1}^{p} B_i^* H_{t-i} B_i^{*'} \tag{16}$$

Where ε_t are the error terms associated with the conditional mean equations for each stock market, A_0 is a $(N \times N)$ positive definite matrix of parameters and A_i^* and B_i^* are $(N \times N)$ matrices of parameters. After estimating a BEKK model for each pair of mature and emerging stock markets we calculate the conditional correlation $\rho_{ji,t}$ as follows:

$$\rho_{ji,t} = \frac{h_{ji,t}^2}{h_{j,t}h_{i,t}} \tag{17}$$

Where $h_{j,t}$ $(h_{i,t})$ is the standard deviation for the return $r_{j,t}(r_{j,t})$ on a *j-esimo* (*i-esimo*) mature (emerging SEE) stock market $r_{j,t}(r_{j,t})$, and $h_{ji,t}^2$ is the covariance among each pair of mature and emerging markets returns. One disadvantage of the BEKK models is that the parameters cannot be easily interpreted, that's why we decided to following Li and Majerowska (2008), by using the estimated BEKK conditional covariance to measure the extent of market linkages in terms of volatility.

Engle (2000) argues that a valid alternative to multivariate GARCH models is given by Dynamic Conditional Correlations (DCC) models. The main advantage is that this models have the flexibility of the univariate GARCH and are less complex to estimate respect to the multivariate GARCH models. DCC models can be used to parameterize the conditional correlation directly (Engle, 1999). Following Engle and Sheppard (2001) and Engle (2002) , we consider a multivariate GARCH model where returns r_t conditional to a set of information Ω_{t-1}, have mean zero and variance covariance matrix H_t, that is $r_t \mid \Omega_{t-1} \sim N(0, H_t)$, where $H_t \equiv D_r R_t D_t$, D_r is a $(n \times n)$ diagonal matrix of time varying deviations from univariate GARCH models with $\sqrt{h_{i,t}}$ on the ith diagonal, and R_t is the time varying correlations matrix. The DCC-GARCH model estimates conditional volatilities and correlations in two steps. In the first step the mean equation of each asset in the sample, nested in a univariate GARCH model of its conditional variance is estimated. Hence we suppose the conditional variance of each asset follows a univariate GARCH (p,q) process, given by the following expression:

$$h_{it} = \omega_i + \sum_{p=1}^{P_i} \alpha_{ip} r_{it-p}^2 + \sum_{q=1}^{Q_i} \beta_{iq} h_{it-q} \tag{18}$$

These univariate variance estimates are then used to standardise the zero-mean return innovations for each asset. In the second step we use the following dynamic correlation structure:

$$R_t = diag(Q_t)^{-1} Q_t diag(Q_t)^{-1} \tag{19}$$

where $Q_t = (1-\alpha-\beta)\overline{Q} + \alpha\mu_{t-1}\mu_{t-1}' + \beta Q_{t-1}$ refers to a $(k \times k)$ symmetric positive definite matrix with $\mu_{it} = \varepsilon_{it} / \sqrt{h_{iit}}$, $\overline{Q}$ is the $(k \times k)$ unconditional variance matrix of μ_t, and α and β are non-negative scalar parameters satisfying $\alpha + \beta < 1$. Finally, the conditional correlation coefficient ρ_{ij} between two assets *i* and *j* can be computed by the following equation:

$$\rho_{ij} = \frac{(1-\alpha-\beta)\overline{q}_{ij} + \alpha\mu_{i,t-1}\mu_{j,t-1} + \beta q_{ij,t-1}}{\left[(1-\alpha-\beta)\overline{q}_{ij} + \alpha\mu_{i,t-1}^{2} + \beta q_{ij,t-1}\right]^{1/2}\left[(1-\alpha-\beta)\overline{q}_{jj} + \alpha\mu_{j,t-1}^{2} + \beta q_{jj,t-1}\right]^{1/2}} \tag{20}$$

5. Results

The first step is to test whether the series are not stationary. The classical regression model requires that the dependent and independent variable in a regression be stationary. In the presence of non-stationary variables there might be what is called spurious regression. Hence, before fitting any reasonable model, we have to examine the time series properties that are used in the models. This can be done by using several unit root tests like Augmented Dickey Fuller (ADF) and Phillip-Perron (PP) tests. Results (table 6) shows that all variables are integrated of order one, i.e I(1).

Table 6 – Unit root tests for daily stock market indices in log form

	ADF test			
	Index in log level		Index in first log difference	
	Constant	Trend	Constant	Trend
ATHEX	-1.159	-1.132	-19.498	-19.498
	(0.693)	(0.921)	(0.00)	(0.00)
BET	-1.789	-0.999	-8.971	-9.103
	(0.385)	(0.941)	(0.00)	(0.00)
BSE	-1.554	0.103	-9.871	-19.654
	(0.504)	(0.997)	(0.00)	(0.00)
CROBEX	-1.294	-0.720	-18.644	-18.679
	(0.633)	(0.970)	(0.00)	(0.00)
DAX30	-1.641	-2.328	-24.193	-24.235
	(0.460)	(0.416)	(0.00)	(0.00)
FTSE100	-2.128	-2.319	-24.129	-24.133
	(0.233)	(0.421)	(0.00)	(0.00)
ISE100	0.706	-2.466	-25.535	-23.521
	(0.842)	(0.344)	(0.00)	(0.00)
SBI	-1.720	-0.450	-8.901	-9.165
	(0.420)	(0.985)	(0.00)	(0.00)
S&P100	-2.351	-2.289	-23.285	-23.280
	(0.156)	(0.438)	(0.00)	(0.00)
	PP test			
	Index in log level		Index in first log difference	
	Constant	Trend	Constant	Trend
ATHEX	-1.378	-1.393	-19.865	-19.849
	(0.593)	(0.862)	(0.00)	(0.00)
BET	-1.678	-0.794	-20.454	-20.424
	(0.441)	(0.964)	(0.00)	(0.00)
BSE	-1.547	-0.228	-20.345	-20.423
	(0.00)	(0.992)	(0.00)	(0.00)
CROBEX	-1.424	-0.890	-19.054	-19.024
	(0.571)	(0.955)	(0.00)	(0.00)
DAX30	-1.630	-2.315	-24.124	-24.168
	(0.466)	(0.424)	(0.00)	(0.00)
FTSE100	-2.043	-2.244	-24.144	-24.149
	(0.268)	(0.463)	(0.00)	(0.00)
ISE100	-0.714	-2.526	-23.499	-23.486
	(0.840)	(0.314)	(0.00)	(0.00)
SBI	-1.747	-0.414	-22.744	-22.653
	(0.406)	(0.986)	(0.00)	(0.00)
S&P100	-2.360	-2.294	-23.267	-23.262
	(0.153)	(0.435)	(0.00)	(0.00)

Notes. The lag length has been chosen using the Schwarz information criterion with, Maxlag=17 (Automatic based on SIC). MacKinnon (1996) one-sided p-value among parentheses. For the ADF and PP tests the null hypothesis is the presence of a unit root.

After checking the order of integration we proceed to determine whether there exists a long-run relationship among SEE and mature stock markets by estimating VAR models. The first step involves to determine choosing the optimal number of lags (q) to apply the VAR. AIC and SC were used to determine the optimal number of lags. Relatively to the SEE and UK equity markets, AIC selected 5 lags while the SC selected 1 lags: in order to estimates the more parsimonious model, we chose to follow SC indication, so a VAR with 1 lags was chosen. Relatively to the SEE and the UK equity markets both AIC and SC selected VAR different number of lags: we decided to choose the more parsimonious model VAR with just 2 lags as indicated by SC. Finally for the SEE and German stock markets, we follow SC results by estimating a VAR with 1 lag. After selecting VAR with optimal number of lags, Johansen cointegration test were performed by using both the trace statistic (i.e. λ_{trace}) and the maximum value statistic (i.e. λ_{max}). The empirical findings (tab. 7) do not support the presence of a cointegration relationship among the UK and the SEE markets. Also considering the US and SEE as well as Germany and SEE stock markets we do not find evidence of cointegration relationship. Because of λ_{trace} and λ_{max} do not find any cointegration equations, the main conclusion is that SEE market are not integrated with mature stock markets, in other words no long-term relationship between these markets took place during the period considered in this study. These results are quite surprising given the leading role of the German stock market in Europe and the role of both the UK and US stock markets worldwide. Our results differ from those of Syriopoulos and Roumpis (2009) who found that leading stock markets (namely the German and US) are cointegrated with Balkan equity markets[11]. However these authors performed the cointegration test taking into consideration all countries while it would have been useful to check the existence of the cointegration by running the test twice: firstly considering the German and Balkan stock markets, then considering the US and Balkan equity markets. In other words running a cointegration test among mature and emerging stock markets could show likely to at least a long run relationship which could be just that among developed stock markets rather than the relationship among developed and emerging stock markets. We tested that hypothesis and we found that λ_{trace} indicate two cointegration equations at 5% level whilst λ_{max} indicates no cointegration[12]

Table 7 – Tests for the number of Cointegrating vectors

SEE and UK stock markets				
	λ_{trace}	Critical value 5%	λ_{max}	Critical value 5%
r = 0	108.270	125.6	32.250	46.231
r ≤ 1	76.019	95.75	22.697	40.077
r ≤ 2	53.321	69.81	18.804	33.876
r ≤ 3	34.517	47.85	17.175	27.584
r ≤ 4	17.341	29.79	11.528	21.131
r ≤ 5	5.812	15.49	5.803	14.264
r ≤ 6	0.009	3.841	0.009	3.841
SEE and US stock markets				
	λ_{trace}	Critical value 5%	λ_{max}	Critical value 5%
r = 0	103.58	125.6	32.559	46.231
r ≤ 1	71.02	95.75	23.206	40.077
r ≤ 2	47.813	69.81	18.251	33.876
r ≤ 3	29.562	47.85	14.583	27.584
r ≤ 4	14.979	29.79	8.862	21.131

[11] That is Bulgaria, Croatia, Cyprus, Greece, and Romania stock markets.
[12] Results are available upon request.

	λ_{trace}	Critical value 5%	λ_{max}	Critical value 5%
r ≤ 5	6.116	15.49	6.112	14.264
r ≤ 6	0.004	3.841	0.004	3.841

SEE and Germany stock markets

	λ_{trace}	Critical value 5%	λ_{max}	Critical value 5%
r = 0	116.27	125.6	37.04	46.231
r ≤ 1	79.23	95.75	26.09	40.077
r ≤ 2	53.14	69.81	19.34	33.876
r ≤ 3	33.79	47.85	17.23	27.584
r ≤ 4	16.55	29.79	10.55	21.131
r ≤ 5	5.99	15.49	5.95	14.264
r ≤ 6	0.041	3.84	0.041	3.841

Notes: The 5% critical values provided by MacKinnon et al. (1999) indicate no cointegration.

Huang et al. (2000) and Egert and Kocenda (2007) argue that in the absence of long-term equilibrium relations between stock markets, an analysis of short-term interactions might provide further information about the relationships among stock markets by investigating whether a causal relationship among markets exists through the Granger Causality method (Granger, 1969). The Granger method seeks to determine how much of a current variable, y, can be explained by past values of y and whether adding lagged values of another variable x can improve the explanation. The variable y is then said to be "Granger-caused" by the variable x if the last helps predict y, that is, if the coefficients on the lagged x's are statistically significant, as measured by an *F-Test*. In our study the Granger-causality test was applied to analyse the direction of causality among returns of mature stock markets and SEE stock markets. Results are shown in table 8. We do reject the hypothesis that UK does not cause Croatian, Romanian and Turkish stock markets. German does cause the same markets as the UK stock index, but also causes the Greek stock market. On the other side the US stock market is found to lead all SEE markets. It is not unexpected that the US stock market has an impact on a major number of SEE stock markets respect to the UK stock index given the global role of the US market[13]. This may be also explained by favourable trade balances the SEE countries enjoy with the US (Huang et al. 2000). On the other hand there is no reverse causation from emerging to developed stock markets, since the *F-values* are statistically insignificant. Overall results suggest that on the one side, the direction of causality is from mature to SEE emerging stock markets, on the other side stock prices of some mature stock markets can be used to predict stock price changes in several SEE stock markets.

Table 8 – Granger-causality test of the relationship among UK, US and SEE stock markets

Panel A : UK and SEE	F-statistic	Probability
FTSE100 does not cause BSE market	1.291	0.275
BSE does not cause FTSE100 market	1.789	0.168
FTSE100 does not cause CROBEX market	9.372**	0.0001
CROBEX does not cause UK market	0.059	0.942
FTSE100 does not cause ATHEX market	1.317	0.268
ATHEX market does not cause UK market	1.566	0.209
FTSE100does not cause BET market	4.724**	0.009
Romanian market does not cause UK market	0.179	0.835
FTSE100does not cause ISE market	4.425**	0.012
ISE market does not cause UK market	0.004	0.995
FTSE100 does not cause SBI market	1.863	0.156

[13] Investigating relations among Eastern Europe and western stock markets also Syriopoulos (2007) found that the direction of causality run from US to Eastern Europe markets, showing the leading role of the US market.

Slovenian market does not cause SBI market	0.522	0.593
Panel B : US and SEE		
SP100 does not cause BSE market	2.673**	0.059
Bulgarian does not cause US market	2.850**	0.058
SP100 does not cause Croatian market	11.0411**	2.0e-05
Croatian does not cause US market	0.018	0.981
SP does not cause Greek market	3.140**	0.044
Greek market does not cause US market	0.286	0.751
US does not cause Romanian market	7.543**	0.00
Romanian market does not cause US market	3.77	0.023
US does not cause Turkish market	9.021**	0.00
Turkish market does not cause US market	0.231	0..793
US does not cause Slovenian market	2.875**	0.057
Slovenian market does not cause US market	0.254	0.775
Panel C : Germany and SEE		
German does not cause Bulgarian market	1.33	0.265
Bulgarian does not cause German market	1.163	0.313
German does not cause Croatian market	7.023**	0.00
Croatian does not cause German market	0.836	0.433
German does not cause Greek market	0.510	0.6
Greek market does not cause German market	2.525*	0.081
German does not cause Romanian market	3.462**	0.03
Romanian market does not cause German market	1.064	0.345
German does not cause Turkish market	6.138**	0.002
Turkish market does not cause German market	0.265	0.766
German does not cause Slovenian market	3.841	0.022
Slovenian market does not cause German market	1.682	0.186

The traditional approach to cointegration assumes that cointegration vectors are time invariant. However the power of cointegration tests is substantially reduced when applied to cointegrated series which experience a change in their cointegrating relationship. In order to overcome that problem Gregory and Hansen (1996) extend the Engle-Granger cointegration test in order to explicitly allow for breaks at an unknown time in their long-run relationship. These authors argue that the rejection of cointegration may be due to a shift in the cointegration vector during the sample period and develop a test that assumes the null hypothesis of no cointegration against the alternative hypothesis of cointegration with one structural break. The Gregory-Hansen test (GH hereafter) accounts for one structural change that occurs at an unknown time and can be implemented by using three different models. The results for GH cointegration test are given in table 9. Because of the 5% critical value is lower that the GH test statistic in all models, we do not reject the null hypothesis of no cointegration in all cases with the exception of Germany and SEE markets using the GH test with constant. Figures 2, 3 and 4 evidence that clearly there is a well-defined single minimum for all models although in every case, with the exception above mentioned, the structural break is not statistically significant.

Table 9 - Gregory and Hansen (1996) cointegration test

Model specification	Breakpoint	GH Test statistic	5% Critical Value	Reject Ho of No Cointegration
Panel A : UK and SEE markets				
Fullbreak (C/S)	2004:12:22	-6.660	-6.41	No
Trend (C/T)	2002:07:03	-5.966	-5.83	No
Constant (C)	2002:07:03	-6.007	-5.56	No
Panel B: US and SEE markets				
Fullbreak (C/S)	2005:07:13	-7.899	-6.41	No
Trend (C/T)	2002:05:22	-5.303	-5.83	No
Constant (C)	2005:09:07	-5.212	-5.56	No
Panel C: German and SEE markets				
Fullbreak (C/S)	2003:09:24	-7.768	-6.41	No
Trend (C/T)	2002:06:26	-5.975	-5.83	No
Constant (C)	2002:06.26	-5.358	-5.56	Yes

The critical values for the Gregory-Hansen tests are drawn from Gregory and Hansen (1996).

Figure 2 – UK and SEE stock indexes: Gregory and Hansen cointegration test

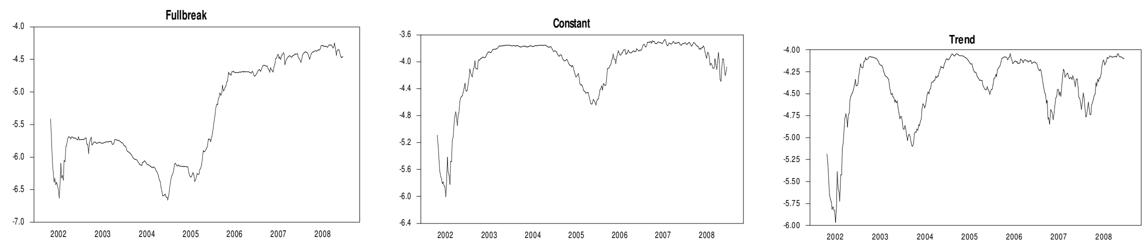


Figure 3 – US and SEE stock indexes: Gregory and Hansen cointegration test

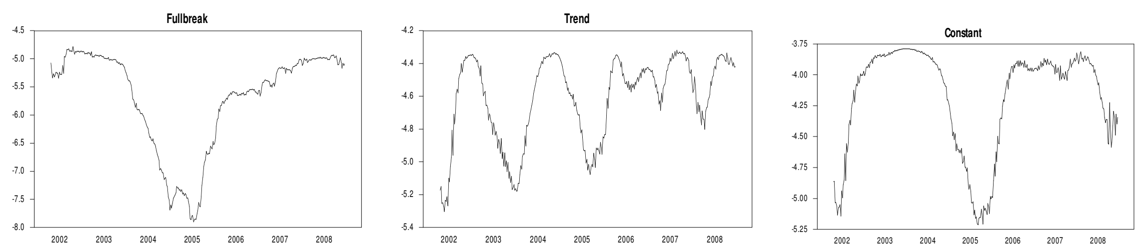
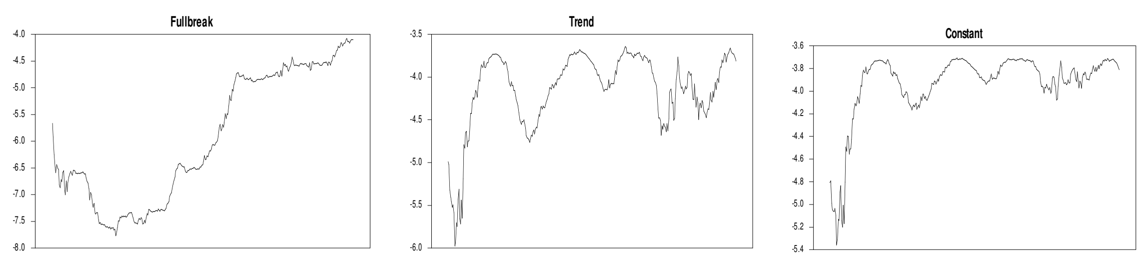


Figure 4 – Germany and SEE stock indexes: Gregory and Hansen cointegration test



Cointegration results show that generally SEE market have no long run relationship with both regional and global financial markets. Gilmore et al. (2008) argue that the lack of cointegration among stock markets make possible to use a vector autoregression model in first difference in order to detect further comovements among stock market indices. The main aim of using that methodology is to obtain the variance decomposition of forecast errors resulting from the VAR model in order to obtain information of the proportions of the variance in returns into domestic and foreign factors. In other words if a stock market is not affected by other stock markets, then the variance of its returns should be due exclusively by domestic factors (Gilmore et al., 2008). Table 10 shows the variance decomposition result over a 3-week period for 3 VAR models[14]. The first one was estimated including Germany and the SEE stock markets[15], the second one including UK and SEE equity markets[16], and the last one including USA and SEE stock markets[17]. The Bulgarian and Romanian equity markets are less influenced by developed stock markets than the other SEE markets. Results suggest that 1.514 % of the error in the forecast of the Bulgarian equity returns 3 weeks out is due to shock coming from Germany. More in general SEE markets appear to be affected by both the UK and US markets, however the origin of the variation in SEE stock market returns is mainly due to domestic factors. Analysing Central and Eastern Europe equity markets, also Chelley-Steeley (2005) came the conclusion that in those emerging stock markets seems that domestic factors are more important in explaining returns variance rather than shock coming from mature stock markets.

Table 10 –Forecast error variance decomposition of returns

Week	Bulgaria			Croatia			Greece		
	Germany	UK	USA	Germany	UK	USA	Germany	UK	USA
1	1.442	3.406	3.309	5.318	15.185	9.718	0.000	27.836	18.716
2	1.501	3.322	3.489	5.617	18.360	13.135	0.069	28.289	20.012
3	1.514	3.539	5.162	5.598	18.349	14.872	0.074	28.729	20.042
	Romania			Slovenia			Turkey		
	Germany	UK	USA	Germany	UK	USA	Germany	UK	USA
1	0.688	8.731	8.082	3.193	9.932	9.04	5.284	16.439	16.122
2	0.659	9.981	10.591	3.119	10.227	9.55	6.076	16.847	16.733
3	0.676	9.901	11.642	3.135	10.247	9.88	6.185	16.878	17.320

Notes. The first column under each SEE country heading reports the forecast error variance decomposition of a VAR model including Germany and the SEE markets, while the second and third column include the UK and USA.

A further point we want to analyse the existence of time varying correlations between developed and SEE emerging markets. With that goal we use EWMA, BEKK and DCC methodologies. The reason for using more than one methodology is testing robustness of our results, in other words we want to find out whether results are indifferent to the method of analysing time varying correlation between stock markets. The EWMA methodology was the first one used and results are shown in Fig 5, 6 and 7. Overall EWMA correlations of each SEE market with Germany, UK and US vary within the range 0-83% in 2000-2010[18]. Figure 5, 6 and 7 clearly show that there is evidence of a general positive correlation among the markets although short

[14] As pointed out by Gilmore et al. (2008), the decomposition procedure is sensitive to different orderings of the variables used in the VAR model. In each of the VAR model estimated, we decided to order the stock markets considering the capitalization/GDP ratio (see tab. 2) and ordering markets from higher to lowest values of that ratio.
[15] The optimal lag indicated by the AIC was 3, while the SC selected 1 lag. We decide to estimate the more parsimonious model as indicated by the SC.
[16] The AIC selected a VAR of order 3, whilst the SC selected a VAR with 1 lag. We chose the last one as the more parsimonious.
[17] Both AIC and SC indicated an optimal lag equal to 3.
[18] The low values of correlation during the first two years (fig. 6) are due to the fact that EWMA methodology gives more weight to the recent data than older included in the data set. However as pointed out by Roh (2007), placing much value only on the recent data, may lead to measurement errors in evaluating the relationship between variables.

periods of negative correlation also exist. It is also evident that correlations between developed and SEE stock markets have increase up to the first half of 2008. There might be several factors which can be considered responsible for increasing correlation. Some of SEE countries become members of the European Union only in the first part of 2000s, while other are candidates for the accession[19]. The process of European unification might have increased the degree of financial integration of these countries with leading financial markets[20]. On the other side, the correlations among these markets seem to be decreasing during the recent financial crisis. Most likely, the decline in correlation might be due to the 2007-2009 global financial crisis triggered by the US subprime crisis. One of the reasons of that decline could be the fact that during period of financial crisis, investors tend to become more risk averse and thereby prompting shifts of funds out of the stock market into safer assets classes, such as bonds. However, in order to take into consideration the exceptional circumstances of that crisis, we further discuss in Section 5 the behaviour of correlations among stock markets during different phases of the 2007-09 financial crisis.

Figure 5 – EWMA correlations of Germany and SEE stock markets

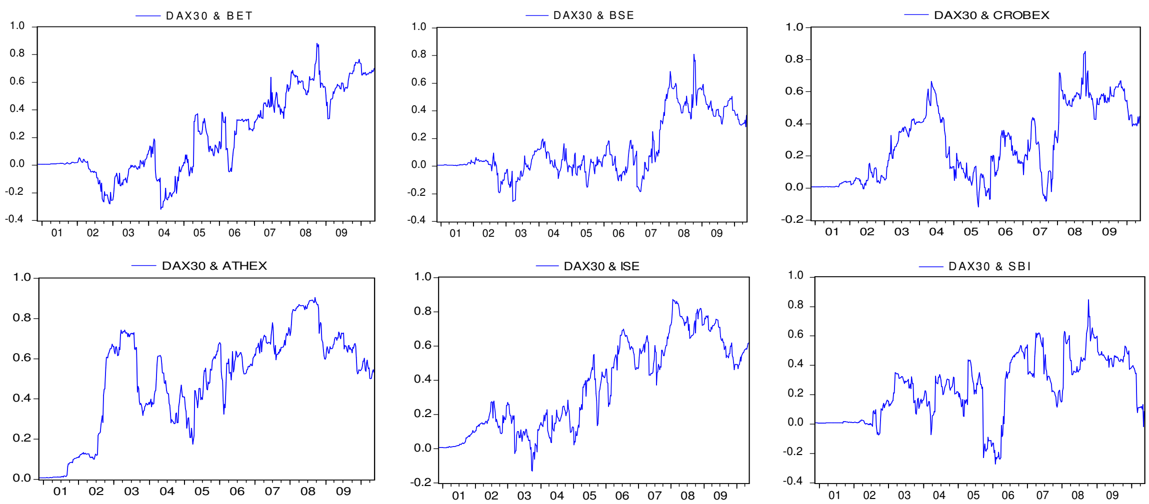
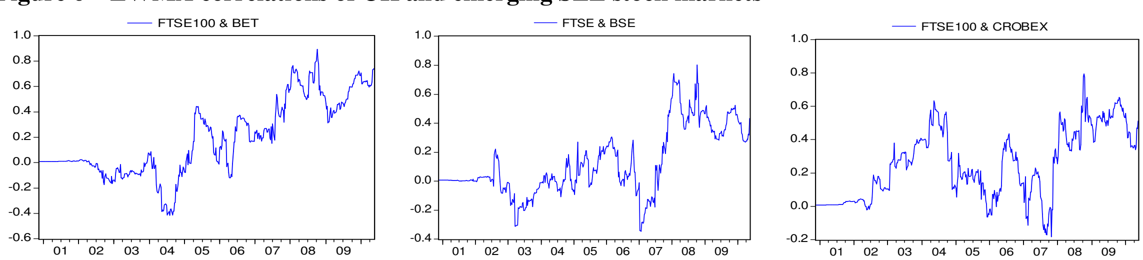


Figure 6 – EWMA correlations of UK and emerging SEE stock markets



[19] Slovenia joined the EU on 1 May 2004, Romania and Bulgaria on 1 January 2007. While Croatia and Turkey are both official candidate States to join the EU.

[20] As pointed out by several authors (Ng, 2000; Bekaert and Harvey, 2005) an increasing financial integration among stock markets may due to the removal of barriers to capital flow. However some authors (Longin and Solnik, 1995; Bodart and Reding, 1999) argue that the process of integration seems to be characterised by time variation. High level of integration seem to characterise the relation among stock markets during period of economic downturn.

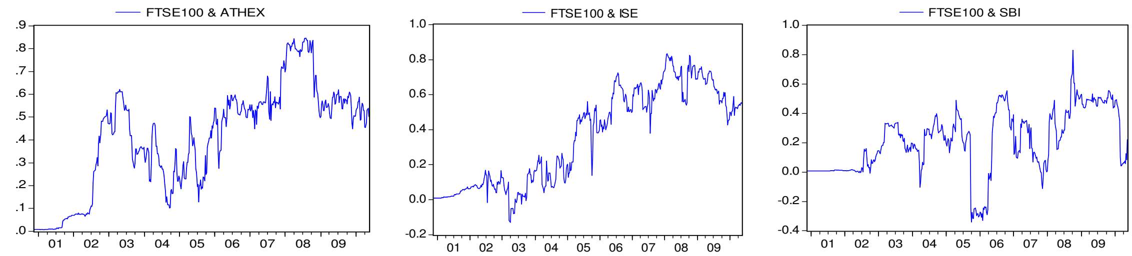
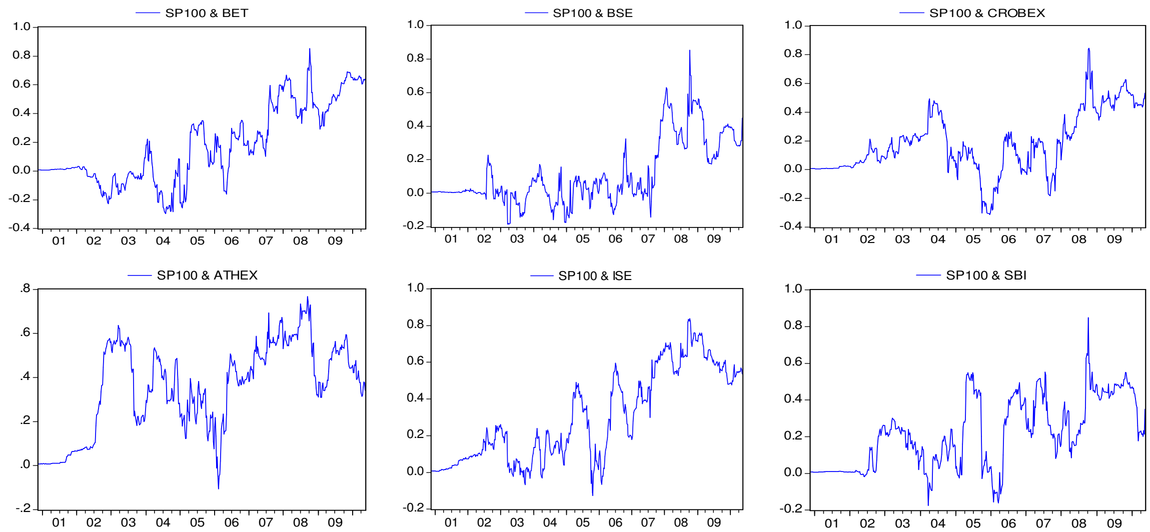


Figure 7 – EWMA correlations of USA and emerging SEE stock markets



The time-varying correlations estimated by BEKK models are presented in Fig. 8, 9 and 10. Results suggest limited interactions between the SEE stock markets and the others mature stock markets in the first half of 2000s. However SEE markets seem to have a more robust pattern of increasing correlation with the US stock market although the sharp decline following the sub-prime financial crisis. Overall our results are consistent with the observations in Scheicher (2001) and Li and Majerowska (2008). Both these authors find that the co-movement between global stock markets and emerging markets are weak.

Figure 8 – BEKK Estimated conditional correlations between Germany and SEE stock markets

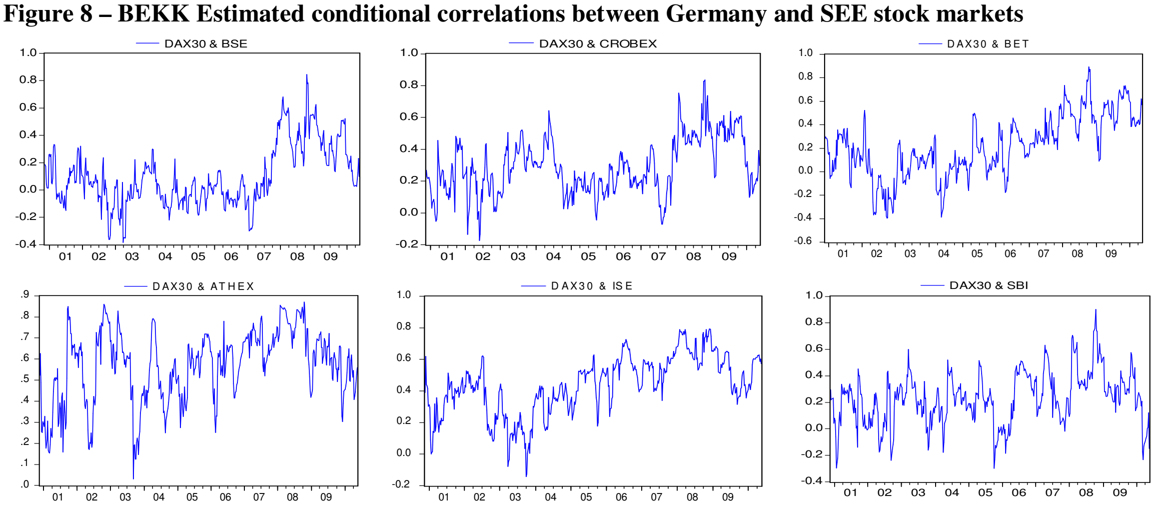


Figure 9 – BEKK Estimated conditional correlations between UK and SEE stock markets

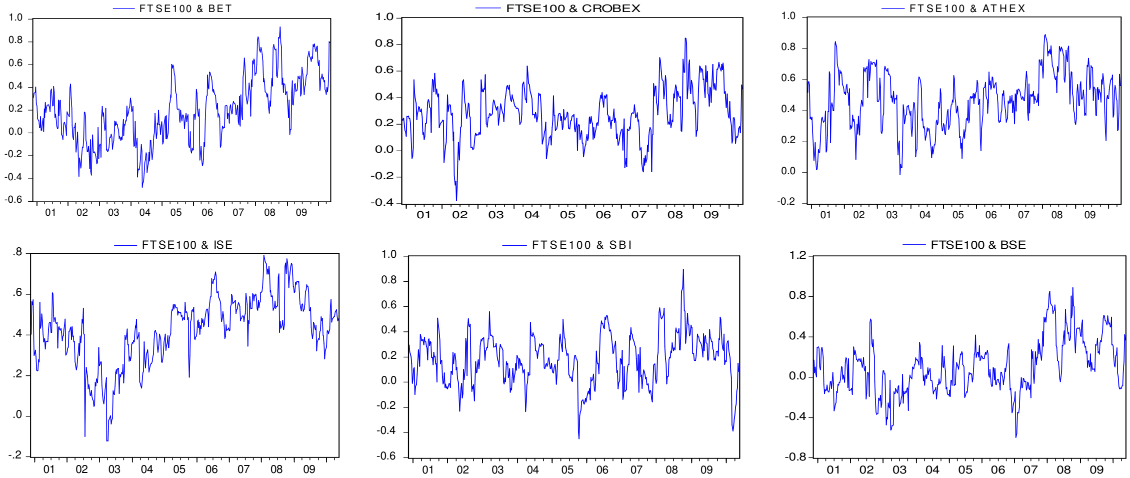
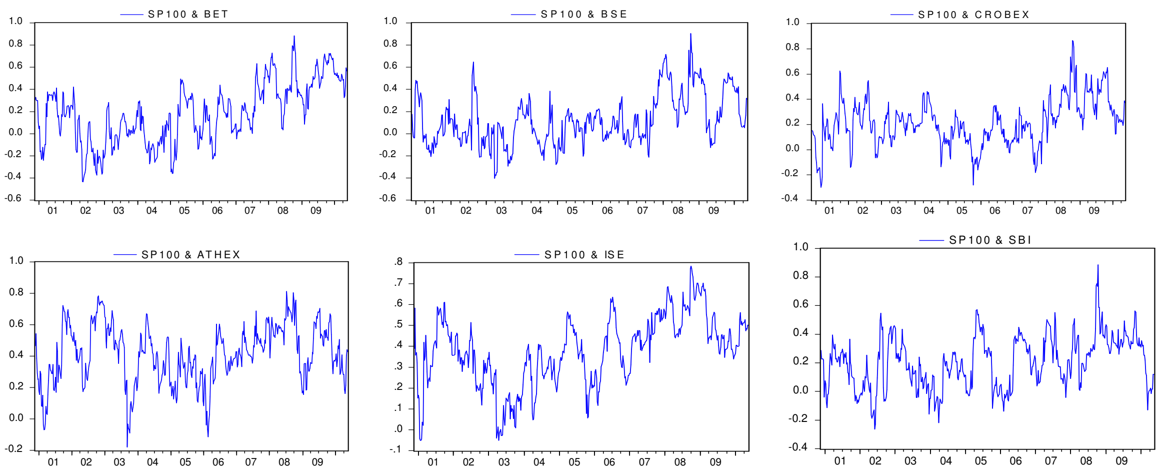


Figure 10 – BEKK estimated conditional correlations between USA and SEE stock markets.



DCC-GARCH(1,1) model results show a change in the pattern of conditional correlations in the second half of 2000s. As emerge from Figures 11, 12 and 13 the conditional correlation is relatively low between the UK and CROBEX stock markets for most of the sample period considered. What is evident is the change in the pattern of conditional correlations from 2007. For instance, after accessing to the EU, the correlations between the CROBEX and the UK equity markets, raised dramatically. The same trends seem to characterize correlations among the FTSE and the BET stock market returns , while UK equity returns with BSE fluctuate over the period with no apparent trend. For each correlation among developed and SEE stock markets we also note an abrupt jump in the correlation evident during the 2007-2009 global financial crisis. Several studies (King and Wadhwani, 1990; Collins and Biepke, 2003) used the correlations among stock markets as a measure of contagion during period of financial turmoil. In these studies have been showed that an increase in the correlations during period of financial crisis in an evident sign of contagion across stock markets. Our results suggest that despite no evidence of long run relationship, SEE stock markets were hit by shocks originating from mature Western stock markets: in other words we may suppose that some forms of contagion took place during the 2007-2009 financial crisis.

Figure 11 – Time varying correlations for UK vs SEE emerging market

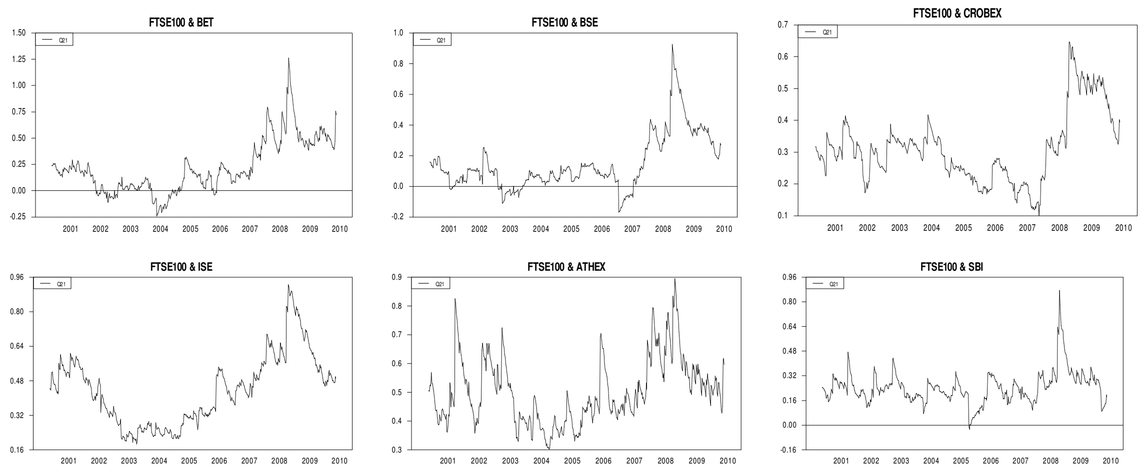


Figure 12 – Time varying correlations for US vs SEE emerging markets

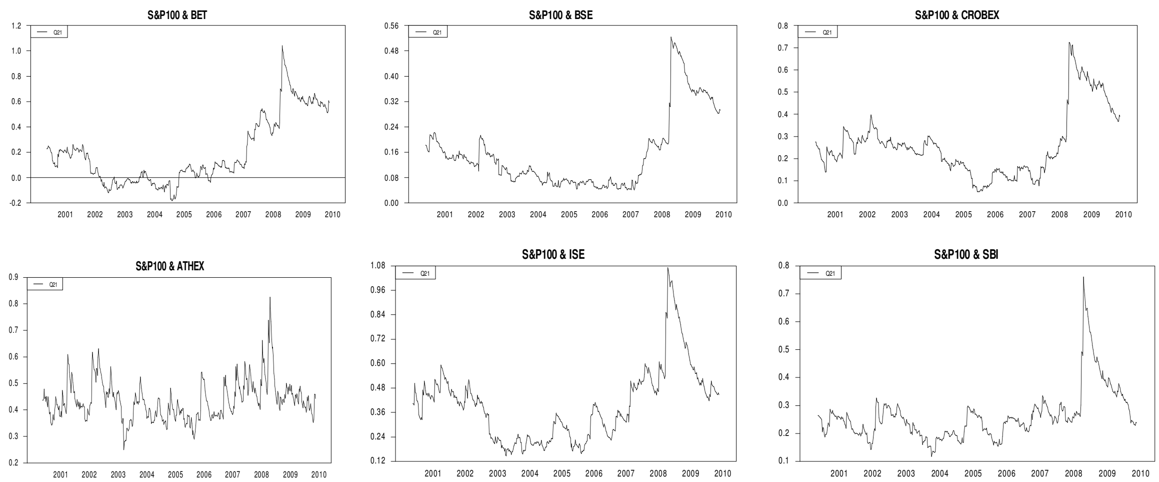
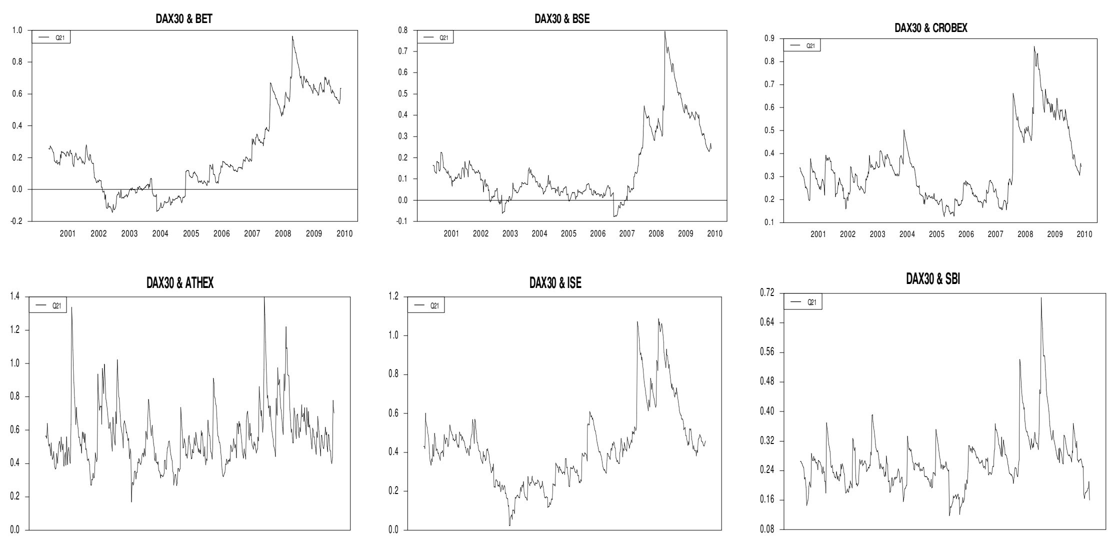


Figure 13 - Time varying correlation for Germany vs SEE emerging markets



Statistical analysis of correlation coefficients in different phases of the 2007-2009 financial crisis

In this section we analyse the dynamic of correlation coefficients movements by strictly adopting the methodology used in Chiang et al. (2007). The previous analysis show clearly that the pair-wise conditional-correlation coefficients between stock returns of developed and emerging SEE markets increased quickly in the period following the 2007 financial crisis[21] which took place with the collapse of two Bear Stearns hedge funds in July 2007 (Kenc and Dibooglu, 2010) and spread from US to other international stock markets. However the crisis hit with some lag the SEE emerging stock markets. In order to take into consideration the lag we use the following model which allow to carry out a statistical analysis of correlation coefficients[22] in different phases of the financial crisis:

$$\rho_{it} = \sum_{p=1}^{P_i} \phi_p \rho_{ij,t-p} + \sum_{K=1}^{3} \alpha_k DM_{k,t} + e_{ij,t} \quad (20)$$

where $\rho_{ij,t}$ is the pairwise correlation coefficient between the stock returns of developed and SEE emerging markets such that i = Germany, UK and USA whereas j = Bulgaria, Croatia, Greece, Romania, Turkey, Slovenia. The lag length in the above equation is determined by AIC criterion and each dummy variable $DM_{k,t}$ (k = 1,2,3) corresponds to different phase of the financial crisis. $DM_{1,t}$ is the dummy variable for the first phase of the crisis period (18/7/2007 – 1/10/2008); $DM_{1,t}$ is the dummy variable for the second phase of the Financial crisis (8/10/2008 – 22/04/2009); $DM_{3,t}$ is the dummy variable for the post crisis period (23/04/2009 – 19/05/2010)[23]. The conditional variance equation is assumed to follow a GARCH (1,1) specification including also the three dummy variables described previously:

$$h_{ij,t} = A_0 + A_1 h_{ij,t-1} + B_1 \varepsilon^2_{ij,t-1} + \sum_{k=1}^{P_i} \phi_p \rho_{ij,t-p} + \sum_{K=1}^{3} d_k DM_{k,t} \quad (21)$$

As pointed out by Chang et al. (2007), if the estimated coefficients of the dummy variables are statistically significant then this means that a structural changes in the magnitude of mean or/and variance occurred. Results reported in table 11 show that generally none of the mean equation Dummy variables are statistically significant in the GARCH models for UK and SEE correlations as well as for US and SEE. On the other

[21] Our results are consistent with the study of Rigobon (2003). That author shows that during several recent financial crisis (Mexico 1994, Asia 1997 and Russia 1998), correlations coefficients among stock markets around the world are observed to be higher than during period of stability.

[22] Our analysis was conducted using correlation coefficients generated by the DCC models in section 4. The main reason of using DCC correlations rather than EWMA or BEKK correlation is that also Chang et al. (2007) used DCC correlations results in the model we estimated in section 5.

[23] We choose arbitrarily that period by using the values of returns and standard deviation of the US stock market. During the first phase of the crisis, the mean returns for the US was -0.4% whilst standard deviation was 2%. In the second phase of the crisis those values were respectively -1.1% and 5%. During the last period average return of S&P100 index was 0.4% and standard deviation 2%. During the overall period of our analysis (i.e., 2000-2010) average return was -0.7% and standard deviation just 2.5%.

hand DM_{1t} and DM_{2t} are statistically significant in GARCH mean equation used to model German and SEE stock returns. This results can be justified with the stronger commercial ties among German and SEE economies, while the same ties between UK and SEE are less important (see table 11) . Overall our results show that the correlations among SEE and developed stock markets changed during the first two phases of the sub-prime crisis. However changes are not permanent, given that $DM_{3,t}$ is generally not statistically significant in any variance equation estimated. On the other side, all of the estimates of the shock-squared terms (ϵ_{t-1}^2) and lagged variance (h_{t-1}) are significant, displaying a clustering phenomenon.

Table 11 – tests of changes in dynamic correlations between market returns during 2007-2009 financial crisis

Panel A : UK and SEE markets

	Bulgaria	Croatia	Greece	Romania	Turkey	Slovenia
Mean equation						
Constant	0.001	0.011**	0.033***	0.003*	0.007**	0.019***
	(1.195)	(2.543)	(2.904)	(1.657)	(2.161)	(4.879)
$\rho_{,t-1}$	0.960***	0.956***	0.929***	0.952***	0.977***	0.903***
	(58.917)	(65.74)	(41.726)	(86.807)	(116.08)	(65.139)
$DM_{1,t}$	0.017	0.003	0.012	0.025	0.006**	0.008
	(1.248)	(0.422)	(1.194)	(1.626)	(1.855)	(0.713)
$DM_{1,t}$	0.004	0.010	-0.0001	0.012	0.0002	0.005
	(0.602)	(1.621)	(-0.019)	(1.321)	(0.045)	(0.842)
$DM_{1,t}$	0.01*	0.006	0.006	0.022*	0.0009	0.005
	(1.715)	(1.424)	(0.890)	(1.794)	(0.325)	(1.126)
Variance equation						
Constant	0.0003***	3.02E-05***	8.91E-05***	0.0006	4.30E-06***	7.52e-05***
	(23.912)	(7.266)	(4.291)	(1.251)	(38.592)	(6.225)
ε_{t-1}^2	0.436***	-0.014***	-0.011***	-0.032***	-0.017***	-0.013***
	(9.508)	(-7.404)	(-4.744)	(-4.099)	(-279.99)	(-9.001)
h_{t-1}	0.306***	0.913***	0.939***	0.458	1.006***	0.938***
	(13.756)	(57.668)	(56.472)	(1.020)	(416.44)	(75.501)
$DM_{1,t}$	0.0014***	0.0001***	0.0001***	0.002	3.01e-05***	0.0001***
	(4.53)	(4.386)	(2.793)	(1.193)	(18.653)	(4.294)
$DM_{1,t}$	-0.001**	1.32E-05	-7.52E-05***	6.09e-05	-2.28e-05***	-6.26E-05
	(-2.474)	(1.119)	(-4.161)	(0.337)	(-5.885)	(-5.516)
$DM_{1,t}$	-4.35E-05	4.43E-07	8.02	0.001	2.52e-07	2.27E-05***
	(-0.733)	(0.075)	(0.582)	(1.147)	(0.167)	(1.846)
Q (4)	4.165	0.622	7.564	4.795	2.065	0.013
	(0.384)	(0.960)	(0.109)	(0.309)	(0.724)	(0.907)
LM ARCH (4)	0.515	0.553	0.181	0.216	1.143	0.025
	(0.724)	(0.696)	(0.947)	(0.929)	(0.335)	(0.876)

Panel B : US and SEE markets

	Bulgaria	Croatia	Greece	Romania	Turkey	Slovenia
Mean equation						
Constant	0.002**	0.005***	0.047***	0.0019	0.007***	0.007**
	(2.232)	(2.931)	(4.322)	(1.319)	(2.782)	(2.072)
$\rho_{,t-1}$	0.979***	0.971***	0.888***	0.950***	0.970***	0.965***
	(140.84)	(107.15)	(34.731)	(120.14)	(104.08)	(59.561)
$DM_{1,t}$	0.005***	-0.0008	0.012	0.026***	0.010	-0.0007
	(3.323)	(-0.220)	(1.499)	(3.269)	(2.203)	(-0.237)
$DM_{1,t}$	0.003	0.008	0.0013	0.021***	0.0017	-0.001
	(1.07)	(1.276)	(0.212)	(3.315)	(0.263)	(-0.187)
$DM_{1,t}$	0.003**	0.005	0.001	0.025***	0.0017	0.001
	(2.042)	(1.485)	(0.420)	(4.501)	(0.481)	(0.542)
Variance equation						
Constant	2.92E-05***	6.85E-05***	4.98E-05***	2.38E-05***	7.35E-06***	7.20E-05***
	(15.744)	(9.921)	(3.568)	(15.752)	(47.889)	(10.493)
ε_{t-1}^2	0.484***	0.3***	-0.018***	-0.026***	-0.03***	0.325***
	(13.858)	(8.020)	(-4.191)	(-20.701)	(-16.307)	(7.148)
h_{t-1}	0.428***	0.527***	0.955***	0.982***	1.007***	0.489***
	(23.339)	(14.829)	(60.019)	(399.32)	(449.77)	(14.994)
$DM_{1,t}$	8.41E-05**	0.0001***	0.0001***	0.0001***	8.12E-05***	7.07E-05***
	(2.130)	(5.514)	(2.849)	(11.968)	(28.402)	(2.857)
$DM_{1,t}$	5.74E-06	-3.73E-06	-5.20E-05***	-4.24E-06	-1.72E-05***	-4.74E-05***
	(0.638)	(-0.062)	(-4.190)	(-0.853)	(-3.001)	(-4.794)

$DM_{1,t}$	-1.99E-05***	-3.14E-06	-1.38E-05***	-3.35E-06	1.39E-06	-1.73E-05
	(-6.217)	(-0.143)	(-2.002)	(-0.983)	(1.287)	(-1.025)
Q(4)	4.053	3.329	2.746	13.873	4.785	5.650
	[0.399]	[0.504]	[0.601]	[0.008]	[0.310]	[0.227]
LM ARCH (4)	4.598	1.942	1.191	2.386	1.733	2.907
	[0.001]	[0.102]	[0.313]	[0.05]	[0.141]	[0.021]
Panel C: German and SEE markets						
	Bulgaria	Croatia	Greece	Romania	Turkey	Slovenia
Mean equation						
Constant	0.001	0.0124**	0.083***	0.0018	0.046***	0.045***
	(0.946)	(2.463)	(6.664)	(1.011)	(14.933)	(5.563)
$\rho_{,t-1}$	0.965***	0.950***	0.836***	0.973***	0.909***	0.803***
	(66.970)	(56.279)	(40.655)	(74.25)	(105.245)	(27.556)
$DM_{1,t}$	0.011*	0.008	0.023	0.019*	0.026**	0.045***
	(1.729)	(0.643)	(0.951)	(1.755)	(2.199)	(8.045)
$DM_{1,t}$	0.034**	0.017*	0.025	0.018	0.055***	0.062***
	(1.962)	(1.727)	(1.269)	(0.801)	(5.097)	(5.730)
$DM_{1,t}$	0.007	0.006	0.013	0.013	-0.005	0.004
	(1.517)	(1.328)	(0.899)	(1.520)	(-1.599)	(1.199)
Variance equation						
Constant	0.0003***	5.44E-05***	0.005***	0.0005	0.0006***	0.0006
	(14.015)	(6.876)	(18.674)	(1.573)	(18.340)	(1.372)
ε^2_{t-1}	0.247***	-0.014***	0.322***	-0.026***	0.304***	-0.029***
	(4.098)	(-11.460)	(8.851)	(-18.586)	(6.950)	(-164.21)
h_{t-1}	-0.095**	0.912***	-0.025	0.07	-0.0625***	0.357
	(-2.125)	(53.482)	(-0.903)	(0.118)	(-4.235)	(0.752)
$DM_{1,t}$	0.0005***	0.0002***	0.004**	0.0007	0.019***	0.0003
	(5.073)	(4.704)	(1.974)	(1.390)	(15.193)	(1.410)
$DM_{1,t}$	0.002***	3.16E-05***	0.001	0.001	0.020***	0.0009**
	(10.474)	(0.867)	(0.573)	(1.616)	(20.212)	(1.936)
$DM_{1,t}$	-0.0001***	-1.99E-05***	0.0001	-0.0001	-0.0001***	-0.0002
	(-2.996)	(-2.241)	(0.145)	(-1.204)	(-2.368)	(-1.352)
Q(4)	2.751	0.544	2.715	2.191	13.060	26.922
	[0.6]	[0.969]	[0.607]	[0.701]	[0.011]	[0.00]
LM ARCH (4)	2.525	0.239	0.183	0.777	1.157	0.198
	[0.04]	[0.916]	[0.946]	[0.540]	[0.328]	[0.939]

Notes. Three/two/one stars represent statistical significance at the 1%, 5%, and 10% levels, respectively. Numbers in (...) are Z-statistics. Q(4) is the Ljung-Box Q-statistics, testing the serial correlation of the residuals. ARCH(4) is the ARCH LM Test, testing the heteroskedasticity of the residuals. Numbers in [...] are p-values.

6. Conclusions

Cointegration results indicate that SEE equity markets does not show a long term relationship with our benchmark markets (Germany, UK and USA) The results have important implications for mature stock markets investors. For instance, because of the SEE markets do not share a common long run trend with both mature markets diversification benefits take place for German, UK and US investors in terms of portfolio diversification. In other words there is an attractive opportunity to developed stock markets investors to diversify their portfolios in SEE stock markets. We also find that bi-variate Granger causality tests revealed significant causality running from the US to SEE markets, showing the leading role of the US stock market. This paper also analysed the changing correlation between the equity returns of developed and SEE emerging market pairs. EWMA correlation results evidence positive correlation of SEE market with developed markets, although there are also short period of negative correlation. We also used a DCC GARCH model for estimating time varying correlations. We find that the correlations of UK and US equity markets with SEE market change over time, however changes in correlations between our benchmark markets and individual SEE market pairs is not uniform. Because of the correlation among some developed stock markets and emerging markets is increasing over time, we found that these SEE markets cannot longer to be considered emerging market but just stock markets moving toward developed markets. Our results might be very useful for international investors who are interested to diversify their portfolio internationally across markets characterised by different stages of financial development.

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