



**SCHOOL OF ECONOMICS  
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# **Stock Market Integration of the European Emerging Markets: Rolling Window and Dynamic Conditional Correlation Approaches**

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## **Abstract**

This essay investigates the extent to which the four emerging Central Eastern European stock markets of the Czech Republic, Hungary, Poland and Ukraine have become integrated with the developed market of the European Union over the sample period from 1997 to 2010. Rolling-window correlation and a more advanced, dynamic conditional correlation approach with GARCH and EGARCH specifications are utilized to measure the level of integration. According to our estimates, the level of integration for new EU members has substantially increased over the last years, especially after these countries' admission to the European Union in 2004. For Ukraine, the correlation coefficient is lower and fluctuates less, which indicates that this country can still be considered for diversification purposes.

**Keywords:** market integration, equity correlations, DCC-GARCH, Central and Eastern European countries, stock markets, international diversification

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## 1. Introduction

At the beginning of 1990s after the USSR collapse, a number of Central and Eastern European countries (CEEC) started to transform their economies from centrally planned to a free market. One of the consequences was the establishment of stock markets, which showed substantial growth in size and level of sophistication, attracting attention of not only international investors, but academics as well.

The level of integration of international financial markets is a very important issue, since it influences portfolio management strategies of investors, who seek diversification possibilities. Policy-makers are also interested in financial integration, since it may affect financial stability of the country.<sup>1</sup> As a result economic integration, liberalization and international investment process, intensive international stock market integration with growing interdependencies was observed during the last decades, and this may in fact hinder the possibilities to diversify by investing in emerging financial markets.

The equity markets of Central and Eastern European (CEE) region are of crucial importance and specific interest mainly due to two reasons: new European Union (EU) members are actively looking for integration into the international (we focus on the EU area as an international one) capital markets; the investors are searching for new possible portfolio opportunities stemming from portfolio diversification to the CEE stock markets.

Most of the CEEC markets started to operate in the mid-1990s, so due to the short sample period and data problems the literature on them is not as extensive as on developed markets. Among the CEEC, those of the Poland, Hungary and the Czech Republic have attracted most of the attention of academics due to their economies' faster growth relative to their regional counterparts, such as Slovakia, Slovenia, Bulgaria, Croatia and Baltic countries, in addition to political stability and their prospects of joining the European Union, successfully realized. A wide range of methodologies has been used to empirically test the stock market integration. Most of the recent studies confirm that integration of the CEE countries with developed markets has increased over time (Gelos and Sahay, 2000; Lucey and Voronkova, 2005; Chelley-Steeley, 2005; Syriopoulos, 2004), and strengthened after their EU accession (Wang and Moore, 2008; Cappiello et al., 2005; Caporale and Spagnolo, 2010).

The purpose of this essay is to study how the integration of CEE markets with EU market evolved through time. We apply two methods of integration measurement: a rolling-window correlation and a more advanced, dynamic conditional correlation approach, using

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<sup>1</sup> Caporale and Spagnolo, 2010

GARCH(1,1) and EGARCH(1,1) model specifications for conditional variance. A low return correlation coefficient among markets is considered as a sign of potential diversification benefits, and an opportunity for portfolio risk reduction based on modern portfolio theory of Markowitz (1952) and others.

Our study contributes to the existing literature on integration of CEEC stock markets and developed markets in several ways. First, we employ the most recent data, which will allow us to study the effect of the financial crisis of 2008-2009 on the integration and volatility pattern of stock returns. Second, we employ both GARCH and EGARCH model specifications for conditional volatility to measure dynamic correlation, which, as far as we are concerned, has not been applied previously in one study. Third, we try to extend the previous analyses and include Ukraine into our study (the previous works focused mainly on Czech Republic, Hungary and Poland due to data availability) in order to investigate whether its stock market returns pattern differs substantially from those of other CEE countries.

The limitations of our essay are that we only focus on four CEE countries: Ukraine and three countries, which entered EU - the Czech Republic, Hungary and Poland. We also use only one type of integration measurement – the correlation coefficient, while some academics employ vector autoregressive models to measure cointegration or use capital asset pricing model (the idea behind this method is that expected local returns in a fully integrated market depend only on non-diversifiable international factors).

Our results suggest that the level of integration for new EU members has substantially increased over the last years, especially after these countries' admission to the European Union in 2004. However, the level of integration of Ukraine remains almost the same. The results we obtained have important implications for the strategies of portfolio management: institutional investors and hedge funds should be more cautious while considering CEEC equity markets for the purposes of diversification. Since EU accession has increased the level of integration, it has also reduced the benefits of portfolio diversification. However, those CEE countries which have not entered the EU yet, such as Ukraine, can still display significantly lower levels of correlation with developed markets, therefore, they can still be attractive for investors for portfolio diversification purposes.

The rest of the paper is organized as follows: sections 2 and 3 introduce the historical and theoretical frameworks respectively, section 4 discusses methodology, data is presented in section 5, section 6 contains the empirical results obtained, section 7 concludes.

## **2. Historical framework**

This section presents the short historical background of the CEE equity markets: legal and political conditions for their establishment, such as privatization law, corporate restructuring etc; stages of financial development - dynamics of listed companies, transactions volume, capitalization etc; and their peculiar features: for instance, formation of stock exchange indices, trading in foreign securities, trading systems etc.

The CEE stock markets have a rather brief history compared to the mature markets of Europe, but they have already made significant progress in integration into the world economy:

- restructure of corporate and banking systems;
- reforms of legal and regulatory frameworks, especially in a property rights domain;
- transparency in accounting and transactions of shares.

These steps were made in the 1990s after collapse of the communism in a period of CEE transition to market economy and integration into the European economic society. The CEE market reconstruction involved a massive privatization, when the state-owned enterprises were reorganized into the public companies. For example, Hungarian transformation began when the government adopted a series of laws to establish an institutional framework for transfer of ownership from state to private subjects in the late 1980s.

At the earlier stage, the stage of establishment, CEE stock markets experienced the lack of adequate regulatory framework, dominance of a small number of firms, less incentives for firms to list (due to the requirement of disclosure and the high cost of raising funds through the equity market) and negative return on stock market investments (on a risk adjusted basis).<sup>2</sup>

Nevertheless, at present level of development the CEE stock exchanges have an organization comparable to the developed European exchanges and they are full members of The Federation of European Stock Exchange (FESE).

### **2.1 The Budapest Stock Exchange (the BSE).**

Foundation of this stock exchange has its roots in December of 1987, when Hungarian banks concluded an agreement about controlled stock exchange trading. However, the Securities Act, a legal framework for the BSE establishment, entered into force only in March

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<sup>2</sup> Wang and Moore, 2008

1990. The first BSE trading session took place on 21 June 1990 – the shares of one company only were offered. By the end of the year 1990 six companies were listed with a total capitalization of US\$ 0,26 bn. BUX, the BSE market index, was introduced on the second of January 1991 and lost about 16% of its value during twelve months of 1991.

The first few years of market operation were very cumbersome: although shares of more and more companies were traded, the number of transactions did not increase significantly. For instance, by the end of 1992 twenty three companies were listed with the average of 27 number of transactions per day, and in 1994, on average, 229 transactions per day were recorded for 40 listed companies. The BSE was at its peak in 1999: 66 listed companies, the total capitalization of 36,6% of the Hungarian GDP (or US 16,4 bn), and 5846 average daily transactions. After 2000 a mild decline in many statistics of the Exchange was observed. Several changes followed the next year. In March 2001 trading on the unregulated market system began, which allowed trading in foreign securities. Restructure of the BSE category system took place in April of the same year 2001: the shares were classified into the categories “A” and “B” based on a modified set of criteria, additionally, a “T” segment for equities with large growth potential was created. In November of 2005 the BSE started commodity trading.

The FESE accepted the BSE as its first associate member in June 1999 and its full membership came with the accession of Hungary to the EU in May 2004.

## **2.2 The Warsaw Stock Exchange (the WSE).**

An intergovernmental agreement regarding the Warsaw Stock Exchange creation was signed in November 1990 between the two counterparties of Poland and France. The WSE establishment act was issued on the 16<sup>th</sup> of April 1991. The first trading session took place immediately the same day: shares of five newly privatized companies were under offer. Simultaneously the first Warsaw Stock Index – WIG was introduced. By the end of the calendar year nine stocks were listed with capitalization less than 0,2% of Polish GDP (or US 0,15 bn). In contrast to the BSE, the WSE traded actively: by the end of 1991 nine companies were traded with 877 average transactions per day. The frequency of trading sessions increased gradually from one in 1991 to five sessions a week in 1994. The new WSE index – WIG 20 was launched in 1994. However, it was the last year of such a high level of trading – the market cooled down after the introduction of Bank Śląski shares for trading, which provoked the “bubble” and led to a decline in value of nearly all companies listed on the

market. In the following years despite the increase in number of listed equities the number of trades decreased significantly.

In 1999 the WSE became an associate member of FESE. The launch of the new Warsaw Stock Exchange Trading System (WARSET) at the end of 2000 improved the Exchange's efficiency and market transparency. Further, in early 2003 a post-auction trading phase in the continuous trading system was introduced. The WSE became a full member of FESE in 2004 after Poland joined the EU. In September 2008 the stock exchange was recognized as an "Advanced Emerging" exchange by FTSE, alongside markets from such countries as South Korea and Taiwan.

### **2.3 The Prague Stock Exchange (the PSE).**

The Prague Stock Exchange was established on November 24, 1992 and its first trading session, where shares of seven companies were offered, took place on April 6, 1993. Due to the mass privatization of that period trading environment was more than favorable in the Czech Republic – about 1000 of stocks were introduced to the newly created Exchange within the next two months of 1993. The PSE market index - PX50 was created on April 7, 1994. By the end of 1995 there were 1716 share listings with the total value of 47% of the Czech GDP (or US 24,5 bn). In Mid-1998 the PSE opened a market segment on which Czech blue chips - stocks of well-established companies with stable earnings and no extensive liabilities - started to be traded. By the end of 2003 the PSE number of equity listings decreased to 65 and the total capitalization dropped to 27% of GDP. The main reason for a drastic decline in the shares listed was the mass privatization programme implemented in the early and mid-1990s, accompanied by a massive collapse of privatized companies, the need to bailout banks and as a consequence withdrawal of many listings from the PSE in 1997.

In June 2001 the PSE became an Associate Member of FESE and automatically a full member when the Czech Republic entered the EU in May 2004. The same month the U.S. Securities and Exchange Commission officially granted the status of a "designated offshore securities market" to the PSE and also included it into the list of offshore exchanges reliable for investors.<sup>3,4</sup>

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3 Schotman and Zalewska, 2006

4 Egert and Kocenda, 2010

## **2.4 The PFTS Ukrainian Stock Exchange.**

Ukraine entered its transition period in 1991 and establishment of the country's stock market was closely tied up to the privatization process – transfer of enterprise property rights from the state to the private hands.

Privatization of the early and mid-1990s was chaotic and unbalanced, among its main drawbacks<sup>5,6</sup>:

- rapidity with no strategic privatization plan;
- dominance of insider privatization through leasing and privatization certificates;
- lack of legislative rules regulating privatization and property rights;
- not transparent tenders with information asymmetry, collusion among tender participants, inequality of participants;
- “quantity” rather than “quality” emphasis.

All in all, the main privatization criteria - the buyer is the one with the highest price - was not met and concentrated investor was out of the privatization scope. As the national market was developing in such hard and specific conditions, it took several years to found the first Ukrainian stock exchange – the PFTS.

The first trading session on the Ukrainian Stock Exchange PFTS took place in July 1996. By the end of the year there were 64 companies and banks in the PFTS Association. The number of listed companies was increasing throughout the period up till the first quarter of 2008. When the financial market was overheated in January, 2008 the PFTS index reached its historical maximum of 1208.3 points but then it dropped to around 200 points in March of 2009 at a time of financial crisis<sup>7</sup>.

CEEC stock exchanges history dates from the early nineties with political, legal changes and restructuring in financial sector. By the time of joining the EU in 2004, the WSE, PSE and BSE became full members of the FESE, which will be the next important step for the Ukrainian PFTS stock exchange.

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<sup>5</sup> Elborgh-Woytek and Lewis, 2002

<sup>6</sup> Pivovarsky, 2003

<sup>7</sup> <http://www.pfts.com/uk/history/>

### 3. Theoretical Framework

This section covers definitions and explanations of the terms of market integration and portfolio diversification, as well as literature overview. Measures of market integration are discussed in terms of CAPM theory and econometric methodology of VAR and GARCH approaches. Portfolio measures - expected return and volatility - are presented from the point of view of the international investors who act as risk-averse agents and want to minimize their portfolio risk and maximize portfolio returns, therefore they invest money into financial markets of those countries which have low correlation with the EU equity market, which means that they diversify their portfolios. In the literature overview we present articles which deal with market financial integration in general and in CEE region in particular.

#### 3.1 Integration

There are several approaches to define market integration in modern academic literature. In international macroeconomics, for example, interest rate parity conditions are used to test for financial integration of money markets.

In financial economics, markets are said to be integrated when only common risk factors are priced and segmented when local risk factors also determine equilibrium returns. Estimates of this definition of integration employ capital asset pricing model (CAPM):<sup>8</sup>

$$E_{t-1}(r_{i,t}) = \lambda_w \beta_{iw} + \lambda_d \beta_{id}$$

where  $r_{i,t}$  is an excess return on the local portfolio  $i$ ,  $\lambda$  is the market risk premium,  $\beta_{iw}$  is the risk of portfolio  $w$  defined as  $\beta_{iw} = cov_{t-1}(r_{i,t}, r_{w,t})/var_{t-1}(r_{i,t})$  and  $\beta_{dw}$  correspondingly for domestic market portfolio  $d$ . The null hypothesis of full integration requires that  $\lambda_d = 0$ , i.e. the local portfolio is only priced relative to the global portfolio. Therefore CAPM implies that expected local returns in a fully integrated market depend only on non-diversifiable international factors.

Various econometrical methodologies were employed to test this concept. Earlier works used VAR models and generally found rising cross-market correlations and growing regional interdependence. More recent studies use generalized autoregressive conditional heteroscedasticity (GARCH) framework to take into account the existence of autoregressive conditional heteroscedasticity (ARCH) effects in data of higher frequency.

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<sup>8</sup> Hunter, 2006; Schotman and Zalewska 2006; Rockinger and Urga, 2001

Another, more general definition relates market and economic integration to a strengthening of the financial and real linkages between economies. Estimates of this approach are usually conducted by investigating the changes in the co-movements across countries between selected financial asset returns.<sup>9</sup> In this paper we focus on the this type of tests.

### 3.2 Diversification

Theoretical background of portfolio diversification was first discussed by Markowitz in 1952. According to modern portfolio theory, risk-averse market agents tend to maximize portfolio return and minimize portfolio risk by making up their portfolios of low correlated assets. Portfolio theory deals with terms of expected return  $E[R]$  as a portfolio return measure and variance  $V$  as a portfolio risk measure.

The expected return  $E[R]$  is calculated as:

$$E[R] = \sum_{i=1}^N w_i \mu_i,$$

where  $\mu_i$  is return and  $w_i$  is the weight of asset  $i$ ;

The portfolio variance  $V$  is calculated as:

$$V = \sum_{i=1}^N \sum_{j=1}^N w_i w_j \sigma_i \sigma_j \rho_{ij},$$

where  $w_i$  is the weight of asset  $i$  and  $w_j$  is the weight of asset  $j$ ;

$\sigma_i$  is the standard deviation of  $i$ ;

$\sigma_j$  is the standard deviation of asset  $j$ ;

$\rho_{ij}$  is the correlation between assets  $i$  and  $j$ <sup>10</sup>.

From the portfolio variance equation above it can be seen that there exists a direct relationship between the assets' correlation and portfolio risk. This is the dependence, which determines investor's behavior: the lower correlation of assets, included in their portfolio, the less risky portfolio they have.

On the international level, if returns from investments in different national stock markets are not perfectly correlated and the correlation is stable (which means that low volatility of correlation is observed), there exist potential gains from international portfolio diversification. On the contrary, if international stock markets share common trends, this implies no significant gains from portfolio diversification<sup>11</sup>.

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<sup>9</sup> Cappiello et al, 2005

<sup>10</sup> Markowitz, 1952

<sup>11</sup> Syriopoulos, 2004

International portfolio diversification is justified only if there are gains from it. With increasing integration of international equity markets, the diversification benefits will tend to decline as the correlations become positive and strengthen.<sup>12</sup>

Therefore, the stock market correlation between the CEE stock returns and the EU stock returns could be a decision-making indicator for the investor's portfolio diversification choice. If investor observes low correlation between equity returns of developed market and any of CEE countries he/she would invest into these equity markets to minimize portfolio risk. Therefore developing markets could become new profitable area for investors from developed markets.

### **3.3 Previous research**

There exists a significant number of studies, which focus on emerging stock markets and their integration with the developed markets: some of them are dedicated to stock markets of Latin America (Fujii, 2004; Hunter, 2006, Bekaert, Harvey and Ng, 2005), Asia (Fujii, 2004; Bekaert, Harvey and Ng, 2005; Fujita, 2008) or particular African countries (Ahmed, 2010, Lee 2001). We are, however more interested in those studies which deal with CEEC (Central and Eastern European Countries).

Most of the CEEC markets started to operate in the mid-1990s, so due to the short sample period and data problems the literature on them is not as extensive as on developed markets. Among the CEEC, those of Poland, Hungary and the Czech Republic have attracted most of the attention of academics due to their economies' faster growth relative to their regional counterparts (Slovakia, Slovenia, Bulgaria, Croatia and Baltic countries), in addition to political stability and their (successfully realized) prospects of joining the European Union.

Various studies on market integration of CEEC equity markets with developed countries employ different kinds of market integration definition, different data and methodology.

Relevant studies deal with monthly (Bekaert, Harvey and Ng, 2005; Chelley-Steeley, 2005; Gelos and Sahay, 2000), weekly (Caporale, 2010; Kouwenberg and Mentink, 2006; Anatolyev, 2005), daily returns of stock indices (Cappiello et al, 2006; Rockinger and Urga, 2001; Lucey et al, 2005 etc), or even intraday data (Egert and Kocenda, 2007, 2010).

Developed markets are defined as either separate countries' markets (UK, Germany, France or US), or as Eurozone or European Monetary Union (EMU) countries (market value weighted average indices are used in that case). Studies employ either Morgan Stanley Capital

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<sup>12</sup> Lucey and Voronkova, 2006

International (MSCI) indices, or the local exchanges indices (BUX for Hungary, PX500 for the Czech Republic, WIG for Poland, DAX for Germany, CAC for France, FTSE for the UK, S&P or DJI for the USA).

A wide range of methodologies has been used to empirically test the stock market integration. Following the work of Engle and Granger (1987) and Johansen (1988), the cointegration methodology has been employed to study co-movements between stock markets. Stock markets that are cointegrated exhibit stable long-run behavior, and shocks to the stock prices are temporary rather than permanent. In the short-run, stock prices across markets may deviate from each other, but market forces, investors' tastes, and preferences, and government regulations will bring stock prices back to their long-run equilibrium.<sup>13</sup> The relevant methodology includes multivariate cointegration techniques with the concept of error correction models, Johansen cointegration procedure, Granger causality and impulse response functions (Richard, 1996; Voronkova, 2004; Kouwenberg and Mentink, 2006; Gilmore and McManus, 2001) and a variety of multivariate generalized autoregressive conditional heteroskedasticity models (Lucey and Voronkova, 2005; Caporale and Spagnolo, 2010; Egert and Kocenda, 2007). Some simple methods such as rolling historical correlations and exponential smoothing are widely used as well (Fratzscher, 2001).

The existing literature also focuses on different aspects of market integration. For instance, Schotman and Zalewska (2006) investigate the integration of CEEC stock exchanges with the stock markets of Germany, UK and US, accounting for non-synchronous trading issues. Their findings are that the correlations with developed markets increased substantially during the Asian crisis, and the predictability of CEE countries has decreased over time. Belke et al. (2009) study the importance of different economic sentiments, e.g. consumer moods, for the Central and Eastern European countries (CEECs) during the transition process.

The earlier studies on the topic, which focused on the period from 1994 to approximately 1997 suggested that there is little or no evidence of cointegration between developed and emerging markets, therefore investors can obtain benefits from international diversification into these markets (Gilmore and McManus, 2001; Röckinger and Urga, 2001).

However, most of the recent studies confirm that integration of the CEE countries with developed markets has increased over time (Gelos and Sahay, 2000; Lucey and Voronkova, 2005; Chelley-Steeley, 2005; Syriopoulos, 2004), and strengthened after their EU accession (Wang and Moore, 2008; Cappiello et al., 2005; Caporale and Spagnolo, 2010).

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<sup>13</sup> Syriopoulos, 2007

## 4. Methodology

This section provides description of two methods to compute correlation: the rolling window and dynamic conditional correlation. We state main advantages and limitations of the methods, as well as state methods' principal logics and express it with the formulas, stressing upon application of the formulas for our particular data and research purpose.

### 4.1 Rolling Window Correlation

Rolling window method is quite easy to compute, therefore we introduce it first. The contemporaneous correlation of return series is defined as:

$$\hat{\rho}_{EU,CEE,t} = \frac{cov_t(EU, CEE)}{\sqrt{var_t(EU) * var_t(CEE)}}$$

where  $EU_t$  stands for the European Union equity market return series on day  $t$  and  $CEE_t$  for the equity market return of a particular country of the Central and Eastern Europe.

We use a rolling-window correlations (RWC) approach to calculate correlations between log-returns of the EU and each of the selected CEE countries. The length of the window equals to 63 days (a quarter of a year), which means that variances and covariances are computed for every 63 days.

$$var(CEE) = \frac{1}{63} \sum_{i=1}^{63} (CEE_i - \overline{CEE})^2;$$

$$cov(CEE, EU) = \sum_{i=1}^{63} \frac{(CEE_i - \overline{CEE})(EU_i - \overline{EU})}{63}.$$

The overlapping window method is straightforward and easy to implement, it captures the time variation and “clustering” (here, quarter clustering) of EU-CEE log-return correlation.<sup>14</sup> However, it has a significant drawback - a so-called “ghost effect”<sup>15</sup>: the obtained series of correlations may contain biased estimates, due to presence of extreme values in the original return series. Another disadvantage of the method is based on equal weighting of observations, which slows down adjustment of correlation estimates to new information.

It can be concluded that rolling window correlation is not an absolutely reliable indicator of time-varying co-movements and therefore we implement an alternative, more sensitive approach – dynamic conditional correlation generalized autoregressive conditional heteroscedasticity (DCC-GARCH and one of its specifications DCC-EGARCH).

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<sup>14</sup> Andersson et al, 2008

<sup>15</sup> Alexander, 1996

## 4.2 Dynamic Conditional Correlation

Since we are interested in modeling dynamics between two definite markets at a time, we employ a more advanced - bivariate DCC-GARCH model, developed by Engle (2002). DCC-GARCH estimation method presumes that volatilities of data series change over time, which results into changes of conditional correlations over time. This approach is argued to have the flexibility of univariate GARCH models and to provide at the same time parsimonious correlation specifications without the computational difficulties of multivariate GARCH models, due to a two-step approach.<sup>16</sup>

For the bivariate GARCH case we have two return series:  $r_t=(r_{1t}, r_{2t})'$ . We assume that conditional returns are normally distributed with zero expectations and conditional covariance matrix

$$H_t=E[r_t r_t' | \Psi_{t-1}].$$

which implies that:

$$r_t = \sqrt{H_t} * \varepsilon_t \text{ and } r_t | \Psi_{t-1} \sim N(0, H_t)$$

where  $\varepsilon_t \sim N(0, I)$

and  $\Psi_{t-1}$  is the  $\sigma$ -algebra generated by all the available information up through time (t-1).

Conditional covariance matrix can be further decomposed into

$$H_t \equiv D_t R_t D_t$$

where  $D_t$  is a diagonal matrix of time-varying standard deviations of residuals of the mean equation of univariate GARCH models:

$$D_t = \text{diag} \{ \sqrt{h_t} \} = \begin{bmatrix} \sqrt{h_{1t}} & 0 \\ 0 & \sqrt{h_{2t}} \end{bmatrix}$$

and  $R_t$  is a time dependent conditional correlation matrix of the standardized disturbances  $\varepsilon_t$ :

$$R_t = \begin{bmatrix} 1 & q_{21} \\ q_{12} & 1 \end{bmatrix}$$

$$\varepsilon_t = D_t^{-1} r_t \sim N(0, R_t)$$

$R_t$  can be further decomposed into  $R_t = Q_t^{*-1} Q_t Q_t^{*-1}$  with a conditional correlation matrix  $Q_t = (q_{12,t})$ .

The dynamic covariance structure  $q_{12,t}$  follows a GARCH process:

$$q_{12,t} = \bar{\rho}_{12} + \alpha(\varepsilon_{1,t-1} \varepsilon_{2,t-1} - \bar{\rho}_{12}) + \beta(q_{12,t-1} - \bar{\rho}_{12}),$$

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<sup>16</sup> Engle, 2002

where  $\bar{\rho}_{12}$  is the unconditional correlation of standardized disturbances  $\varepsilon_{1,t}$  and  $\varepsilon_{2,t}$ .<sup>17</sup>:

$$\bar{\rho}_{12} = Cov(\varepsilon_t \varepsilon_t') \text{ and } \rho_{12,t} = q_{12};$$

$\alpha$  and  $\beta$  are scalars.

It should be noted, that by the definition of covariance,  $H_t$  has to be positive definite, which means that  $R_t$  has to be positive definite as well. To guarantee this, restrictions on parameters are imposed, namely:

$$\alpha \geq 0; \beta \geq 0$$

$$\alpha + \beta < 1$$

The last requirement ensures that the estimated model preserves mean reversion of correlation (mean-reverting DCC-GARCH).

The DCC log-likelihood function is:

$$L = -\frac{1}{2} \sum_{t=1}^T [n * \log(2\pi) + \log|D_t R_t D_t| + r_t' D_t^{-1} R_t^{-1} D_t^{-1} r_t]$$

and can be separated into two parts: the volatility part and the correlation part, and a relevant two-step estimation procedure can be used.

$$L = L_{vol} + L_{cor},$$

where:

$$L_{vol} = -\frac{1}{2} \sum_{t=1}^T [n * \log(2\pi) + \log|D_t|^2 + r_t' D_t^{-2} r_t];$$

$$L_{cor} = -\frac{1}{2} \sum_{t=1}^T [\log|R_t| + \varepsilon_t' R_t^{-1} \varepsilon_t - \varepsilon_t' \varepsilon_t].$$

The two-stage algorithm that we implement is as follows.

**In the first step**, the volatility-dependent part of the likelihood function  $L_{vol}$ , a set of univariate GARCH models is estimated for  $n$  series (for a bivariate case  $n=2$ ). Here the mean equation for each of our return series nested in a univariate GARCH model for the conditional variance is estimated.

Conditional variance is defined as:

$$h_t \equiv E(\varepsilon_t^2 | \Psi_{t-1}).$$

We also assume that  $h_t$  follows the GARCH (1,1) process, hence conditional variance  $h_t$  equals:

$$h_{i,t}^2 = \omega_i + \alpha_i * \varepsilon_{t-1}^2 + \beta_i * h_{i,t-1}^2, \text{ where}$$

$$\omega \geq 0, \alpha \geq 0, \beta \geq 0^{18}.$$

**In the second step**, the dynamic conditional correlations are estimated given the maximizing values of variances obtained in step one.

<sup>17</sup> Andersson et al, 2008

<sup>18</sup> Tsui and Y, 1999

Summing up, the model is estimated in two stages as in Engle (2002): the univariate GARCH models in the first stage and the conditional correlation matrix in the second stage. Parameters are also estimated in stages. DCC model can be estimated consistently using a two step approach to avoid the dimensionality problem of the most multivariate GARCH models. The above DCC model has two major advantages: it is parsimonious and ensures that time varying correlation matrices between the stock exchange returns are positive definite.

#### 4.2.1 The Exponential GARCH Model (EGARCH) specification for DCC

As we deal with developing stock markets, which are rather instable and sensitive to even subtle changes, a symmetric GARCH model can disregard some specific asymmetric effects if they are present. Hence, we also try to apply EGARCH(1,1) model specification instead of GARCH(1,1), to see if any asymmetric effects in volatility are present and if this model specification outperforms GARCH. The assumption for EGARCH model is that bad and good news have different effect on volatility.

The EGARCH model was first introduced by Nelson in 1991. We use this model specification as suggested in Eviews software:

$$\log(\sigma_t^2) = \omega + \alpha \log(\sigma_{t-1}^2) + \beta \left| \frac{\varepsilon_{t-1}}{\sigma_{t-1}} \right| + \gamma \frac{\varepsilon_{t-1}}{\sigma_{t-1}},$$

where  $\alpha$  measures persistence in volatility,

$\beta$  and  $\gamma$  capture volatility spillovers.

If  $\gamma \neq 0$  there exists an asymmetry in variance equation, which implies the following:

if  $\gamma > 0$ , then negative shocks increase variance more than positive shocks;

if  $\gamma < 0$ , then good news increases variance more than bad news.

Thus, this exponential type of GARCH specification allows capturing the asymmetric equity return volatility phenomena, where negative shocks are supposed to have a higher effect on stock return volatility compared to positive shocks of the same scale.<sup>19</sup>

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<sup>19</sup> Brooks, 2008

## 5. Data

In this section we introduce data, used further in our estimations, explain how we transformed and treated it. We also plot the data and present the basic descriptive statistics and unit root tests on it.

We use daily observations of the stock indices, measured in US dollars, of the following markets: the European Union, Poland, Hungary and Czech Republic, constructed by the Morgan Stanley Capital International (MSCI). MSCI indices are used since they are designed to be directly comparable across national exchanges, constructed on a value weighted basis of freely investible shares. The sample period is from November 06, 1997 to March 23, 2010, however, we drop the last several observations during the computation process, which limits the sample period by March 19, 2010. The MSCI data is obtained from the Datastream, and Microsoft Excel was used to transform the data. To obtain empirical estimates software package E-Views 6.0 was used.

Since the stock exchanges for the countries under consideration are open approximately over the same hours during the day, there should be no non-synchronous trading effects. Asynchronicity may arise because there are instances in which markets are closed in one country and open in another, as national holidays and administrative closure do not fully coincide. However, we choose not to adjust for the non-simultaneous closures, and since the sample size we use is very large, we just assume that the daily returns we investigate are synchronous.<sup>20</sup>

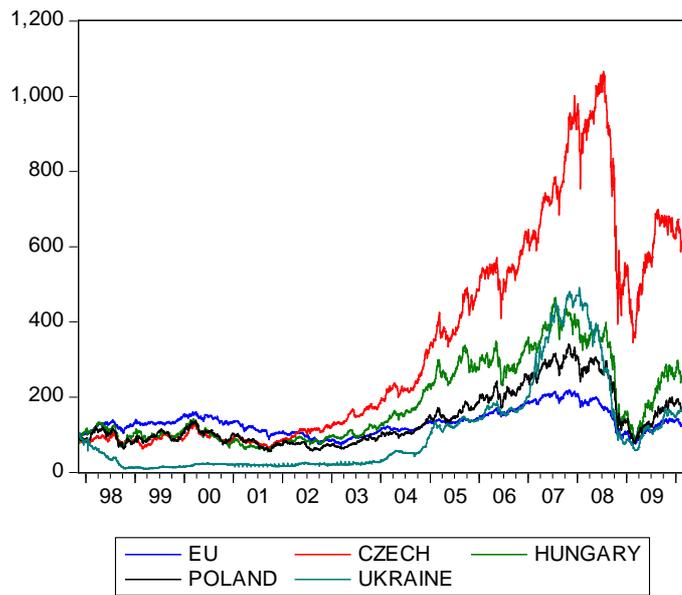
Since the data for the MSCI index for Ukraine is available only starting from May 31, 2006, we use PFTS Ukraine Stock Exchange index, the index of Ukraine's primary bourse, data for which is available starting from November 3, 1997 (in our estimations, however, we use return observations starting from November 6, 1997). Since this index is measured in local currency hryvnya (UAH), we also collect the data on the exchange rate between UAH and the US dollar from the National Bank of Ukraine's official website, and convert the PFTS index in the US dollars. The reason for this is to make all the data comparable – indices measured in different currencies may fluctuate not only due to the movements of stock markets, but also because of the changes in the exchange rate.

Figure 1 plots the indices that for comparison purposes are normalized to equal 100 on 11/06/1997.

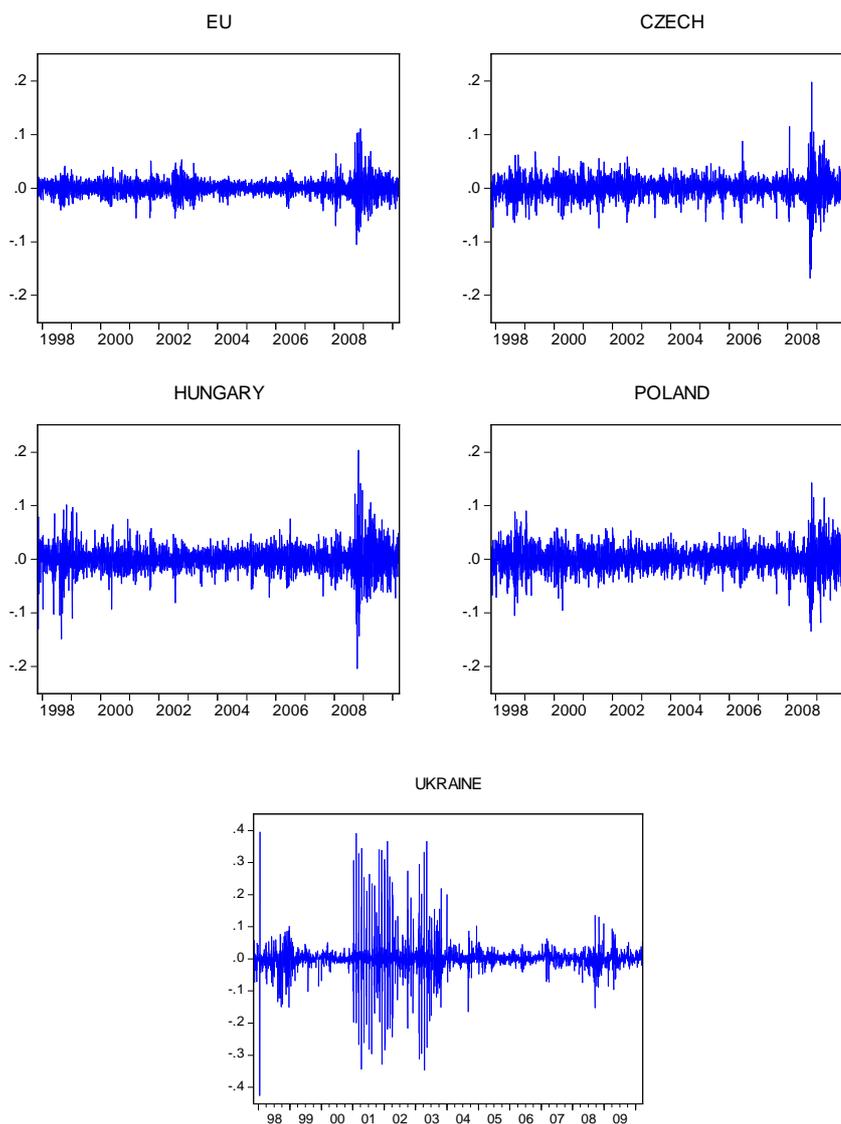
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<sup>20</sup> Cappiello et al, 2006

**Figure 1 Stock market indices**



**Figure 2 Daily Stock Index returns**



Then continuously compounded returns are calculated as:

$$R_t = \log P_t - \log P_{t-1}$$

Figure 2 plots the daily stock index returns for each market.

Table 1 reports summary statistics relative to daily returns on equity market indices. The daily data set starts on November 6, 1997 and ends on March 19, 2010, which makes 3227 return observations. Table 1 reports mean, median, maximum and minimum daily returns. It be seen, that mean returns were the highest for the Czech Republic: 0,057%, and the lowest for the European Union market. At the same time, EU market is the least volatile, with the standard deviation of 0,014, while the standard deviation for the most volatile Ukrainian market is 0,045. Ukrainian market also has the most extreme maximum and minimum values of returns, compared to other markets. As could have been expected, European market has the least extreme maximum and minimum values.

Table 1 also reports skewness, kurtosis, and Jarque-Bera test statistics, which show that the normality hypothesis is rejected for all markets. In addition, the stock return dynamics is asymmetric and leptokurtic since the skewness and kurtosis coefficients are statistically significant. The negative skewness is a sign of nonlinearity in the dynamics of stock markets, and implies that the distribution of the series (around the mean) has a long left tail. Skewness is positive for Ukraine, hence the right tail of the distribution is longer than the left one.

**Table 1: Descriptive Statistics of daily returns on equity market indices (% ), 1997-2010**

	EU	CZECH	HUNGARY	POLAND	UKRAINE
Mean	0,00	0,000576	0,000335	0,000192	0,000242
Median	0,000558	0,000876	0,00087	0,00028	0,000133
Maximum	0,110636	0,197205	0,203114	0,142343	0,394922
Minimum	-0,105049	-0,167469	-0,203493	-0,133781	-0,425544
Std. Dev.	0,014287	0,018969	0,023035	0,021583	0,044769
Skewness	-0,124266	-0,18188	-0,253125	-0,164104	0,511531
Kurtosis	10,56614	13,41837	11,77393	6,445449	30,66194
Jarque-Bera	7705,578	14612,22	10385,32	1610,655	103025,9
Probability	0,00	0,00	0,00	0,00	0,00
Sum	0,274225	1,857692	1,082028	0,620954	0,782052
Sum Sq. Dev.	0,658491	1,16073	1,711795	1,502713	6,465888
Observations	3227	3227	3227	3227	3227

Notes: Jarque-Bera test for normality combines excess skewness and kurtosis and is asymptotically distributed as  $\chi^2$  with 2 degrees of freedom.

Table 2.1 reports the unconditional (or contemporaneous) correlation matrix of the returns data for the new EU members for different periods: the whole sample period, from November 6, 1997 to April 30, 2004, and from May 3, 2004 to March 19, 2010. This is done to check if the unconditional correlation coefficient is higher for the period after EU accession of the CEE countries analyzed, which took place in May 2004. As we can see, unconditional correlation coefficients are about 1,7 times higher for the second subsample, which may indeed evidence that higher level of integration can be associated with the EU accession.

**Table 2.1 Unconditional correlation matrix of returns for the new EU members**

Period		CZECH	HUNGARY	POLAND
11/06/1997 – 3/19/2010	EU	0,5889	0,603022	0,57464
	CZECH		0,577358	0,567992
	HUNGARY			0,613506
11/06/1997 – 4/30/2004	EU	0,408356	0,428792	0,373481
	CZECH		0,42938	0,381456
	HUNGARY			0,445895
5/03/2004 – 3/19/2010	EU	0,715016	0,721983	0,734068
	CZECH		0,677409	0,714976
	HUNGARY			0,743548

Notes: Table reports correlation coefficients calculated as:  $\hat{\rho}_{x,y} = \frac{cov(x,y)}{\sqrt{var(x)*var(y)}}$

Table 2.2 reports the unconditional correlation coefficients between the EU and Ukrainian stock markets for the same periods as in Table 2.1. We can see that for Ukraine the significant increase in correlation with EU market can also be traced, since the correlation coefficient for the first sub-period is negative and equal to -0,0007, but for the second sub-period – positive and equal to 0,267. However, it is still quite low compared to the correlation coefficients of the new EU members.

**Table 2.2 Unconditional correlation coefficient between EU and Ukraine**

Period	Value
11/06/1997 – 3/19/2010	0,062534
11/06/1997 – 4/30/2004	-0,000654
5/03/2004 – 3/19/2010	0.266817

We applied three unit root tests to test for stationarity of the series investigated, to avoid one-sided conclusions. All stock price index series were found to be non-stationary in levels (tests were applied on log-levels) and stationary in differences. Table 3 reports the unit root tests results.

**Table 3 Unit Root Tests**

	Log Levels					
	ADF		PP		KPSS	
	constant	constant and trend	constant	constant and trend	constant	constant and trend
EU	-1,729	-1,634	-1,740	-1,674	1,468*	0,606*
Czech	-0,465	-2,040	-0,436	-1,981	6,794*	0,780*
Hungary	-1,176	-1,878	-1,034	-1,889	4,951*	0,669*
Poland	-1,341	-2,051	-1,279	-2,034	4,317*	0,708*
Ukraine	0,143	-1,349	-0,160	-1,564	4,686*	0,516*

	1st differences					
	ADF		PP		KPSS	
	constant	constant and trend	constant	constant and trend	constant	constant and trend
EU	-27,146*	-27,149*	-56,206*	-56,202*	0,110	0,100
Czech	-52,853*	-52,846*	-52,759*	-52,752*	0,182	0,170
Hungary	-26,886*	-26,881*	-51,077*	-51,070*	0,092	0,085
Poland	-51,562*	-51,555*	-51,520*	-51,513*	0,087	0,079
Ukraine	-8,270*	-8,371*	-82,057*	-82,337*	0,593	0,320*

Notes: ADF, PP; and KPSS are the Augmented Dickey-Fuller, the Phillips-Perron, and the Kwiatkowski-Phillips-Schmidt-Shin unit root tests respectively. The null hypothesis for the ADF and PP tests is the presence of a unit root; for the KPSS test, the null hypothesis is stationarity. For the ADF test, lag length is chosen using the Schwartz information criterion, and the Newey-West kernel estimator is used for the PP and KPSS tests.

\* denotes the rejection of the null hypothesis (here if hypotheses are rejected, they are rejected at 1% level).

For the KPSS test, critical values are given by Kwiatkowski et al. (1992): 0.739 at the 1% and 0.463 at the 5% significance level for the case with a constant, and 0.216 at the 1% level and 0.146 at the 5% level of significance for the KPSS test with a constant and trend.

The critical values for the ADF and PP test statistics are calculated as in MacKinnon (2010) and for the given sample size (3227 observations) are: -3.435 at the 1% and -2,863 at the 5% significance level for the case with a constant and -3,966 at the 1% and -3,414 at the 5% significance level for the case with a constant and a trend.

Now that we have described, processed the data, and tested it for stationarity, we can proceed directly to the estimation section.

## 6. Estimation results

In this section we report the empirical results of the methodology applied to our data. We present maximum likelihood estimates of DCC-GARCH and of DCC-EGARCH models and using information and forecasting ability criteria discuss which model specification fits data better. We also discuss the descriptive statistics and plots of rolling window correlation and dynamic conditional correlation series, obtained through the modeling.

From the Table 4.1 we can see that the estimated DCC-GARCH(1,1) models appear statistically highly significant for all countries, except Ukraine. The coefficients  $\alpha$  and  $\beta$  are positive for all the other countries and the sum of  $\alpha$  and  $\beta$  estimates in the conditional covariance equation is less than unity and consequently the estimated models preserve mean reversion of the stock return correlations. All estimations are significant at 1% level, except for the intercept in Poland's mean equation, which is significant only at 95% confidence level.

As for the DCC-GARCH(1,1) estimations for Ukraine, the intercept in the mean equation is insignificant, and both coefficients  $\alpha$  and  $\beta$  are negative, which violates the restrictions of the model. Therefore, we conclude that this model doesn't fit the data for Ukraine, and proceed with estimation of DCC-EGARCH(1,1) model for all the countries.

**Table 4.1 Maximum Likelihood Estimates of the DCC-GARCH(1,1) Model**

	CEE country							
	Czech Republic		Hungary		Poland		Ukraine	
	Estimate	z-statistic	Estimate	z-statistic	Estimate	z-statistic	Estimate	z-statistic
$\gamma_{CEE}$	0,001	5,016	0,001	3,968	0,001*	2,441	0,002***	1,219
$\gamma_{EU}$	0,001	3,667	0,001	3,667	0,001	3,667	0,001	3,667
$\omega_{CEE}$	0,000	4,706	0,000	3,961	0,000	3,581	0,0003	3,608
$\omega_{EU}$	0,000	3,590	0,000	3,590	0,000	3,590	0,000	3,590
$\alpha_{CEE}$	0,098	7,031	0,089	6,099	0,061	5,912	1,608	0,432
$\alpha_{EU}$	0,094	6,901	0,094	6,901	0,094	6,901	0,094	6,901
$\beta_{CEE}$	0,875	58,781	0,892	55,367	0,926	81,985	0,235	3,491
$\beta_{EU}$	0,897	71,281	0,897	71,281	0,897	71,281	0,897	71,281
$\alpha$	0,025	6,653	0,025	6,553	0,011	4,827	-0,003	-33,875
$\beta$	0,968	180,184	0,968	176,660	0,988	372,753	-0,003***	-0,0003

Notes:

Table 4.1 reports the maximum likelihood estimates of the following DCC-GARCH (1,1) model:

1. Mean equation:  $r_{i,t} = \gamma_i + \varepsilon_{i,t}$

2. Conditional variance equation for GARCH (1,1) process:  $h_{i,t}^2 = \omega_i + \alpha_i \varepsilon_{i,t-1}^2 + \beta_i h_{i,t-1}^2$

3. Time-conditional covariance between a certain CEE country and EU log-returns:

$$q_{EU,CEE,t} = \bar{p}_{EU,CEE} + \alpha \left( \varepsilon_{EU,t-1} \varepsilon_{CEE,t-1} - \bar{p}_{EU,CEE} \right) + \beta \left( q_{EU,CEE,t-1} - \bar{p}_{EU,CEE} \right)$$

\*statistically significant at 5%, but not at 1% level

\*\*\* statistically insignificant

From the Table 4.2 we can see that the estimated DCC-EGARCH(1,1) models are statistically highly significant for all countries, including Ukraine. The coefficients  $\alpha$  and  $\beta$  are positive for all the countries and the sum of  $\alpha$  and  $\beta$  estimates in the conditional covariance equation is less than unity. All estimations are significant at 1%, 5% or 10% level, except for the intercept in Poland's mean equation, which is statistically insignificant.

**Table 4.2 Maximum Likelihood Estimates of the DCC-EGARCH(1,1) Model**

	CEE country							
	Czech Republic		Hungary		Poland		Ukraine	
	Estimate	z-statistic	Estimate	z-statistic	Estimate	z-statistic	Estimate	z-statistic
$c_{CEE}$	0,001	3,878	0,001	2,953	0,0004***	1,422	0,002**	1,867
$c_{EU}$	0,0004*	2,118	0,0004*	2,118	0,0004*	2,118	0,0004*	2,118
$\omega_{CEE}$	-0,403	-6,288	-0,281	-5,651	-0,191	-5,630	-2,976	-6,141
$\omega_{EU}$	-0,275	-6,861	-0,275	-6,861	-0,275	-6,861	-0,275	-6,861
$\alpha_{CEE}$	0,193	8,095	0,166	6,100	0,107	6,155	0,991	8,492
$\alpha_E$	0,151	7,650	0,151	7,650	0,151	7,650	0,151	7,650
$\gamma_{CEE}$	-0,057	-3,380	-0,057	-3,137	-0,037	-3,463	-0,107*	-2,433
$\gamma_{EU}$	-0,083	-6,260	-0,083	-6,260	-0,083	-6,260	-0,083	-6,260
$\beta_{CEE}$	0,969	143,750	0,980	200,323	0,9866	287,466	0,645	9,112
$\beta_{EU}$	0,983	263,160	0,983	263,160	0,983	263,160	0,983	263,160
$\alpha$	0,024	6,136	0,033	8,087	0,010	4,435	0,007	6,410
$\beta$	0,967	165,270	0,954	148,537	0,989	384,121	0,974	16072,6

Notes:

Table 4.2 reports the ML estimates of the following DCC-EGARCH (1,1) model:

1. Mean equation:  $r_{i,t} = c + \varepsilon_t$

2. Conditional variance equation for EGARCH (1,1) process:

$$\log(\sigma_t^2) = \omega + \alpha \left| \frac{\varepsilon_{t-1}}{\sigma_{t-1}} \right| + \gamma \frac{\varepsilon_{t-1}}{\sigma_{t-1}} + \beta \log(\sigma_{t-1}^2)$$

3. Time-conditional covariance between a certain CEE country and EU log-returns:

$$q_{EU,CEE,t} = \bar{p}_{EU,CEE} + \alpha(\varepsilon_{EU,t-1}\varepsilon_{CEE,t-1} - \bar{p}_{EU,CEE}) + \beta(q_{EU,CEE,t-1} - \bar{p}_{EU,CEE})$$

\*statistically significant at 5%, but not at 1% level

\*\* statistically significant at 10%, but not at 1% or 5% level

\*\*\* statistically insignificant

We can conclude that EGARCH(1,1) model fits the data for Ukraine better, than GARCH(1,1) model. To find out whether this holds for the rest of the countries, we apply information criteria and test forecasting abilities of the models. Table 4.3 contains the summary on the information criteria:

**Table 4.3 Comparison between GARCH and EGARCH models using information criteria**

Criterion	Model specification	Country				
		EU	Czech	Hungary	Poland	Ukraine
AIC	GARCH(1,1)	-6,081	-5,408	-5,054	<b>-5,0461</b>	<b>-4,080</b>
	EGARCH(1,1)	<b>-6,098</b>	<b>-5,416</b>	<b>-5,059</b>	-5,0457	-4,070
	DCC-GARCH	X	5,362	<b>5,310</b>	<b>5,292</b>	5,668
	DCC-EGARCH	X	<b>5,360</b>	5,319	5,294	<b>5,664</b>
BIC	GARCH(1,1)	-6,073	-5,401	-5,047	<b>-5,039</b>	<b>-4,073</b>
	EGARCH(1,1)	<b>-6,089</b>	<b>-5,406</b>	<b>-5,049</b>	-5,036	-4,060
	DCC-GARCH	X	5,366	<b>5,313</b>	<b>5,295</b>	5,671
	DCC-EGARCH	X	<b>5,363</b>	5,323	5,297	<b>5,668</b>
Log likelihood	GARCH(1,1)	9821,773	8735,376	8164,293	8151,052	<b>6591,264</b>
	EGARCH(1,1)	<b>9850,199</b>	<b>8748,871</b>	<b>8172,340</b>	<b>8151,251</b>	6575,835
	DCC-GARCH	X	-8649,889	<b>-8565,195</b>	<b>-8535,992</b>	-9143,050
	DCC-EGARCH	X	<b>-8645,809</b>	-8580,098	-8539,324	<b>-9137,180</b>

Notes: AIC stands for Akaike information criterion, and BIC – for Schwarz Bayesian information criterion; the models with lower values of AIC or BIC are preferred. The higher values of log likelihood indicate better models

Based on given information criteria values, we cannot draw any general conclusions concerning all the countries: while both criteria indicate that EGARCH model specification better fits the data on European Union, Czech and Hungary equity market returns, GARCH specification is more appropriate for Polish and Ukrainian equity markets returns. Moreover, DCC-EGARCH model specification is preferred only for the Czech Republic and Ukraine, but not for Hungary or Poland. The log likelihood values don't allow us to draw any consistent conclusions either. Therefore, we will try to see which model is better by checking their forecasting ability.

To measure forecasting performance we use Mean Absolute Percentage Error and Theil Inequality Coefficient. The summary on these measures applied to given data is presented in Table 4.4. We can see that MAPE criterion indicates that EGARCH model fits better for return series of any country, while TIC does not allow us to draw any generalized conclusions.

**Table 4.4 Forecasting abilities of GARCH and EGARCH models**

Criterion	Model specification	Country				
		EU	Czech	Hungary	Poland	Ukraine
MAPE	GARCH(1,1)	123,549	147,953	148,682	117,910	150,742
	EGARCH(1,1)	<b>112,660</b>	<b>137,249</b>	<b>137,47</b>	<b>109,398</b>	<b>144,974</b>
TIC	GARCH(1,1)	0,958	<b>0,939</b>	0,962	<b>0,968</b>	<b>0,952</b>
	EGARCH(1,1)	<b>0,974</b>	0,950	<b>0,953</b>	0,980	0,955

Notes: MAPE stands for Mean Absolute Percentage Error: the smaller the error, the better the forecasting ability of the model; TIC stands for Theil Inequality Coefficient, which lies between zero and one, where zero indicates a perfect fit.

Descriptive statistics of the rolling window and dynamic conditional correlation estimates for the CEEC equity markets with EU equity market are reported in Tables 5.1-5.3. On average, rolling window correlations for all countries are positive, with mean correlation estimates highest for Hungary: 0,506 and lowest for Ukraine: 0,095. The average conditional correlation estimates with GARCH specification are: 0,480 for the Czech Republic, 0,512 for Hungary and 0,510 for Poland. We don't report the relevant statistics for Ukraine, since the model insignificant results. Finally, Table 5.3 reports descriptive statistics for correlation series produced by DCC-EGARCH(1,1) model. Here, average conditional correlation is highest for the Polish market: 0,509, and lowest for Ukraine: 0,086. As can be seen from Tables 5.1-5.3, the rolling window and DCC estimates are quite similar to each other, only that RWC estimates contain more extreme values (this can be seen from the maximum and minimum values reported in the tables).

**Table 5.1 Descriptive statics on rolling window correlation series**

	CZECH	HUNGARY	POLAND	UKRAINE
Mean	0,483273	0,505872	0,504649	0,095258
Median	0,488584	0,50948	0,493429	0,074568
Maximum	0,843975	0,875125	0,866699	0,621753
Minimum	-0,09436	-0,06005	0,049544	-0,32434
Std. Dev.	0,194623	0,199873	0,194185	0,179367
Skewness	-0,37875	-0,52527	0,098063	0,279331
Kurtosis	2,72857	2,944071	2,055882	2,571179
Jarque-Bera	87,05861	148,8107	125,0226	66,69018
Probability	0	0	0	0
Sum	1559,522	1632,448	1628,503	307,3961
Sum Sq. Dev.	122,1952	128,8762	121,6449	103,7888
Observations	3227	3227	3227	3227

**Table 5.2 Descriptive statics on dynamic conditional correlation series – GARCH(1,1)**

	CZECH	HUNGARY	POLAND
Mean	0,479622	0,511745	0,510366
Median	0,484419	0,518636	0,478087
Maximum	0,778716	0,822311	0,800069
Minimum	0,007344	0,036276	0,215388
Std. Dev.	0,147538	0,148745	0,155325
Skewness	-0,34902	-0,44055	0,422043
Kurtosis	2,790411	3,044776	1,940024
Jarque-Bera	71,42218	104,6532	246,8695
Probability	0	0	0
Sum	1547,741	1651,4	1646,95
Sum Sq. Dev.	70,22188	71,37504	77,83016

**Table 5.3 Descriptive statics on dynamic conditional correlation series – EGARCH(1,1)**

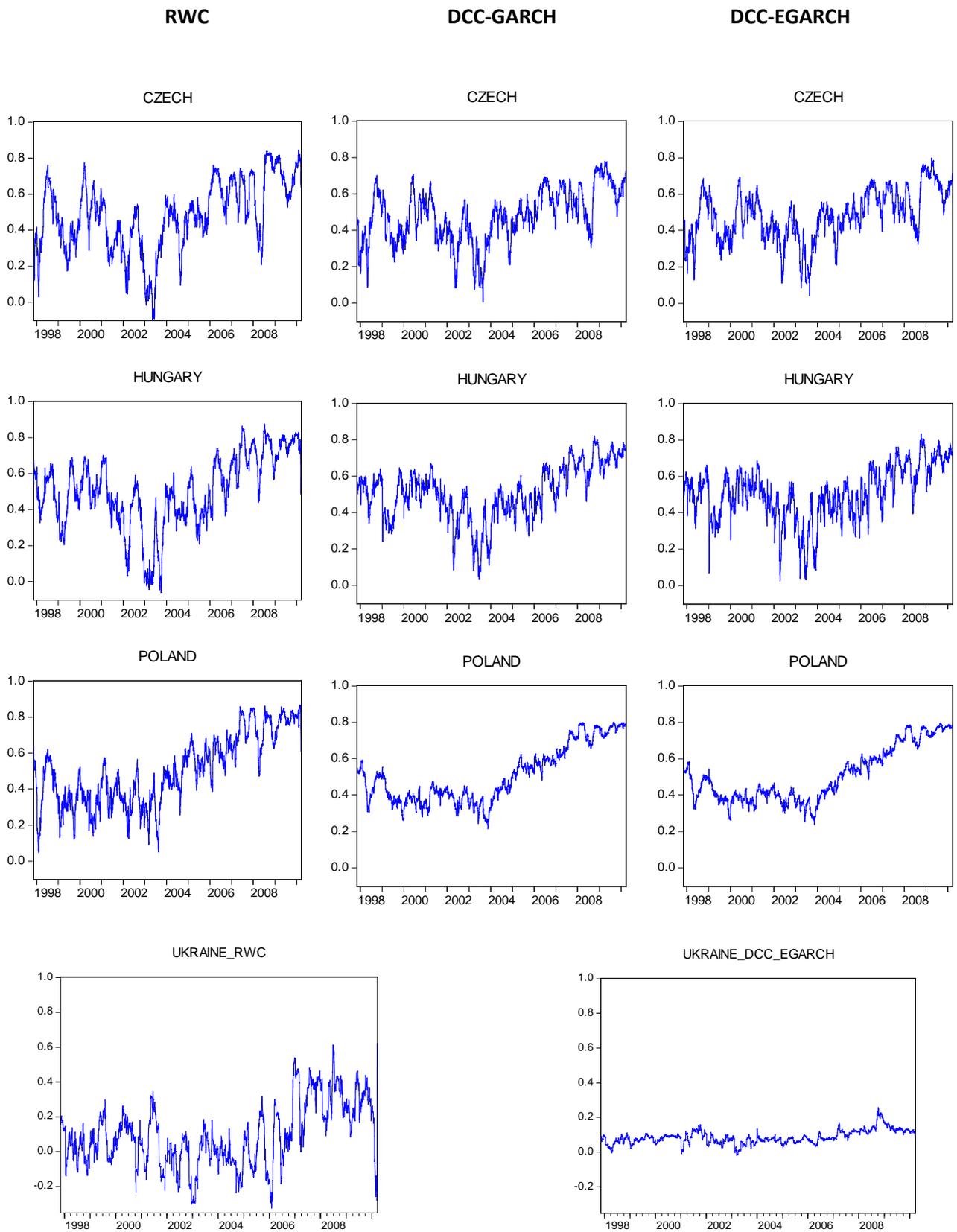
	CZECH	HUNGARY	POLAND	UKRAINE
Mean	0,482382	0,508564	0,509354	0,086035
Median	0,485251	0,515615	0,466945	0,080837
Maximum	0,797618	0,834003	0,795414	0,258251
Minimum	0,042902	0,024592	0,237241	-0,01916
Std. Dev.	0,139763	0,147303	0,149735	0,038521
Skewness	-0,27495	-0,49509	0,477172	0,694787
Kurtosis	2,804993	3,238903	1,937473	4,54401
Jarque-Bera	45,77267	139,5031	274,2595	580,1723
Probability	0	0	0	0
Sum	1556,648	1641,135	1643,686	277,6363
Sum Sq. Dev.	63,01591	69,99799	72,32894	4,787055
Observations	3227	3227	3227	3227

Developments of the rolling window and dynamic conditional correlations in the CEE countries are plotted in Figure 3. We can see that although the correlations in all three countries are positive on average, it is apparent that the relation between CEEC and European stock markets has been rather unstable over time. Moreover, the figures indicate that the correlations may change substantially in very short periods of time. For instance, in May 1998 the dynamic conditional correlation estimate between the Czech Republic and the European market was equal to 0,05, but already in August 1998, several months later, the correlation had increased to 0,5. Changes in correlations pose challenges for investors, since investment strategies and asset allocation decisions which assume constant relationship between the emerging and developed markets are obviously inappropriate and may lead to considerable losses during sudden changes in correlation structures.<sup>21</sup>

From Figure 3 it can be seen that the conditional and rolling window correlations exhibit a very similar pattern over time. However, the RWC estimates appear to be considerably more erratic than the conditional correlations produced by the DCC model.

<sup>21</sup> Andersson et al, 2008

**Figure 3 RWC and DCC of CEEC equity markets with the European market**



Interestingly, Figure 3 demonstrates that the stock market correlations between CEE countries, which entered the EU, and Europe exhibit rather similar patterns over time, thereby suggesting that some common factors may determine the time-varying relation between these markets.<sup>22</sup> For all these countries, there is a sharp increase in correlation in around 1997–1998 with the occurrence of the Asian and Russian crises. This coincides with finance literature, in which international correlation increases when global factors (e.g. the oil crisis or Gulf war) dominate domestic ones and affect all financial markets.<sup>23</sup> Another similar pattern of movement can be observed among these CEEC economies: a gradual upward trend around 2004, reflecting an increase of financial market integration within the EU since these economies joined the EU in May 2004. In general, the recent high levels of correlations between the analyzed CEE countries and Europe indicate a high degree of market integration of these countries.

For Ukrainian market, RWC and DCC-EGARCH estimates differ significantly: while correlation according to RWC is very volatile and exhibits quite scattered values ranging from -0,324 to 0,62, DCC-EGARCH estimates lie within the range of 0 and 0,2, with a slight spike in 2008, probably reflecting financial crisis. This information might be useful for investors, since the correlation doesn't fluctuate substantially, and is quite low compared to other CEE countries.

Therefore, our estimation results suggest that while new EU members' equity markets become more and more integrated with European equity market, which in turn means less diversification possibilities for international investors, the equity markets of those CEE countries which have not yet entered the EU, such as Ukraine, remain quite attractive for diversification purposes.

This study can be further extended by considering more CEE countries, such as Baltic countries, Bulgaria, Slovenia, Slovakia, Lithuania etc.

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<sup>22</sup> Andersson et al, 2008

<sup>23</sup> Wang, 2008

## 7. Conclusions

The purpose of this essay was to study how the level of market integration of the transitional economies of CEE countries has changed over time. We implemented two methods to measure integration: rolling-window correlation, using variance and covariance of daily returns over a quarter; and dynamic conditional correlation, based on the GARCH and EGARCH estimates of volatility of each of the series. Both of these methods delivered similar time-varying correlation series, although for rolling window correlation estimation the series are more erratic. For the new EU members both GARCH and EGARCH model specifications work quite well, however, for Ukrainian equity market EGARCH specification definitely outperforms GARCH specification.

In general, our results confirm the results of existing studies that the level of integration of Central and East European economies with the EU has increased over the last years, especially after these countries' admission to the European Union in 2004. This does not seem strange, since as the economic linkages between Western, Central and Eastern Europe become tighter, the financial markets are expected to follow the same pattern.

The results we obtained have important implications for the strategies of portfolio management: institutional investors and hedge funds should be more cautious while considering CEE equity markets for the purposes of diversification. Since EU accession has increased the level of integration, it has also reduced the benefits of portfolio diversification. However, those CEE countries which have not entered the EU (such as Ukraine) yet, display significantly lower levels of correlation with developed markets, therefore, they can still be attractive for investors for portfolio diversification purposes. Another implication of the results obtained concerns the effectiveness of the domestic macroeconomic policies, since domestic markets of CEE countries become more exposed to external shocks.

Further research which would include more CEE countries and investigate the factors which influence the degree of integration and the CEE countries' stock market behavior following their actual participation into the EMU could enrich the present findings.

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Datastream Advanced

Eviews 6.0 Help

[www.bank.gov.ua](http://www.bank.gov.ua) – Official website of the National Bank of Ukraine

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## Appendix A

Script for Eviews 6.0 program for analyzing bivariate DCC-GARCH model<sup>24</sup>

I) Univariate GARCH estimates

1) set sample range

sample s1 1/02/1995 3/23/2010

scalar pi=3.14159

2) defining the return series in terms of y1 and y2

series y1=czech

series y2=eu

3) fitting univariate GARCH(1,1) models to each of the two returns series

equation eq\_y1.arch(1,1,m=1000,h) y1 c

OR (for EGARCH specification) equation eq\_y1.arch(1,1,egarch,m=1000,h) y1 c

equation eq\_y2.arch(1,1,m=1000,h) y2 c

OR (for EGARCH specification) equation eq\_y2.arch(1,1,egarch,m=1000,h) y2 c

3) extract the standardized residual series from the GARCH fit

eq\_y1.makeresids(s) z1

eq\_y2.makeresids(s) z2

4) extract GARCH series from univariate fit

eq\_y1.makegarch() garch1

eq\_y2.makegarch() garch2

5) calculate sample variance of series z1, z2; covariance of z1 and z2 and correlation between z1 and z2

scalar var\_z1=@var(z1)

scalar var\_z2=@var(z2)

scalar cov\_z1z2=@cov(z1,z2)

scalar corr12=@cor(z1,z2)

6) defining the starting values for the var(z1) var(z2) and covariance (z1,z2)

series var\_z1t=var\_z1

series var\_z2t=var\_z2

series cov\_z1tz2t=cov\_z1z2

7) declare the coefficient starting values

coef(2) T

II) LOG LIKELIHOOD for correlation part

1) set up the likelihood

logl dcc

dcc.append @logl logl

2) specify var\_z1t, var\_z2t, cov\_z1tz2t

dcc.append var\_z1t=@nan(1-T(1)-T(2))+T(1)\*(z1(-1)^2)+T(2)\*var\_z1t(-1),1)

dcc.append var\_z2t=@nan(1-T(1)-T(2))+T(1)\*(z2(-1)^2)+T(2)\*var\_z2t(-1),1)

dcc.append cov\_z1tz2t=@nan((1-T(1)-T(2))\*corr12+T(1)\*z1(-1)\*z2(-1)+T(2)\*cov\_z1tz2t(-1),1)

dcc.append pen=(var\_z1t<0)+(var\_z2t<0)

4) specify rho12

dcc.append rho12=cov\_z1tz2t/@sqrt(@abs(var\_z1t\*var\_z2t))

5) defining the determinant of correlation matrix and determinant of Dt

dcc.append detRt=(1-(rho12^2))

dcc.append detRdt=@sqrt(garch1\*garch2)

dcc.append pen=pen+(detRt<0)

dcc.append detRt=@abs(detRt)

6) define the log likelihood function

---

<sup>24</sup> Retrieved from Eviews forum, posted by user Hvtcapollo  
<http://forums.eviews.com/viewtopic.php?f=4&t=574>

```
dcc.append logl=(-1/2)*(2*log(2*pi)+log(detRt)+(z1^2+z2^2-2*rho12*z1*z2)/detRt)-10*pen
7) estimate the model
smpl s1
dcc.ml(showopts, m=500, c=1e-5)
8) display output and graphs
show dcc.output
graph corr.line rho12
show corr
```