A new risk history: The Eastern Europe case

JOSEP MARIA CARDONA
Universitat Rovira i Virgili
Departament de Gestio d'Empreses
Av. Universitat 1, 43204 Reus
SPAIN
josepmaria.cardona@urv.cat

JORDI ANDREU
Universitat Rovira i Virgili
Departament de Gestio d'Empreses
Av. Universitat 1, 43204 Reus
SPAIN
jordi.andreuc@urv.cat

SEBASTIAN CANO
Universitat Rovira i Virgili
Departament d'Economia
Av. Universitat 1, 43204 Reus
SPAIN
sebastian.cano@urv.cat

Abstract: Eastern European Emerging Markets (EEEM's) have been superficially analysed in the literature. In this paper, the authors use a T-GARCH and E-GARCH approach to model volatility in eleven EEEM's, being one of the most comprehensive analysis in terms of number of markets. Data includes daily returns from 2004 to 2011. Main findings show higher unconditional volatility in EEEM's than in developed markets, but risk premium is statistically negative or non significant in this markets. Almost all markets show an important and significant leverage effect, contrary to previous results in the literature. According to the news impact and decay parameters, volatility is more difficult to predict in EEEM's than in developed markets. Greece, Hungary, Poland and Turkey seem to be the maturest EEEM's markets. Finally, no significant differences are found among countries inside and outside European Union.

Key–Words: Eastern European Markets, EU, Integration, European markets, volatility dynamics, GARCH.

1 Introduction

During the last 30 years, internationalization and globalization have become specially important. Citizens, enterprises, governments and financial markets have been obligated to think in global terms, and investors and fund managers have never had world assets as available as now.

Emerging markets have become an important economic pole, and rising interest in investment opportunities in these markets has spread among investors. Latin American, Asian, Pacific and Eastern European countries have received increasing incoming capital from developed countries, even after the 90's emerging market crisis. In the last three decades, three extraordinary important processes have taken place inside Europe:

1. Eastern European countries' transition from command to market economy.
2. An increase in integration among European Countries (including some of these former socialist countries).
3. The birthday of the Euro.

These great challenges suggest important structural changes, specially in fundamentals, macroeconomic conditions, trade, competition and financial market behaviour. For that reason, this framework became a fertile research field, and thousands of studies have explored it with detail from a macro or policy making point of view.For example, [24][1]; [11] analyse several strategies for economic policy in the European Economic and Monetary Union (EMU), finding that the European Central Bank's (ECB) monetary and inflation targeting supposes a good strategy for a wide range of shocks; [22] examine the macroeconomic strategies followed by the ECB after the Central and Eastern European Countries joined to the EMU, finding the EMU enlargement do not suppose an increase in the welfare on the current members of the EMU; [33] analyses the effectiveness of the cohesion policy in the European Union, concluding this policy helped the cohesion among countries, and finding a convergence pattern between new members and the European average; even some authors like [15] has dedicated their papers to the study of happiness of european citizens through these European great changes.

From a financial market point of view, studies regarding the three commented European challenges are more scarce. The main conclusions of existing financial markets literature can be summarized in two key issues:

First, a risk reduction. Since stock prices reflect expectations of future dividends, interest rates an risk premia, new macroeconomic conditions derived from the European Integration should affected them. Using a Markov Regime Switching Model, [20]

[1] The authors displays a study of trade among Spain, Hungary, Slovakia, Czech Republic and Slovenia.

found unconditional variance reduction among Western European countries[2], meanwhile [19] found a similar pattern in Eastern European Emerging Markets (EEEM's) as the integration with the EU proceeds[3]. However, [2] shows that volatility increases in the Euro Area after the launch of the common currency[4].

Second, an increase in correlation and cointegration. Even studies that use old data, as [14][5] found low correlation among EEEM's and developed countries, [35] found European country long-run linkages generally strengthened after the Economic and Monetary Union[6]. Similar patterns are obtained in [31] and [32] that conclude EEEM's display stronger linkages with their mature counterparts in the EU. In that line, the pattern of information flow among countries has been also analysed, for example, in [18] and [32].

EEEM's are specially interesting both among European countries and Emerging Markets, because they have suffered all three commented processes. Despite their high growth rates and investment opportunities, research on volatility analysis (one of the most important issues that has worried researchers in last years) remains limited. Volatility dynamics in EEEM's remains quite unexplored, that is why our paper focuses on it, concretely in three items: volatility dynamics and its differences among markets (unconditional volatility, news parameter, decay parameter and asymmetry and kurtosis of the errors), the existence of leverage effects, and the existence of risk premia.

Regarding volatility dynamics, [14] analyses 6 EEEM's markets using a GARCH-M approach. The authors found alphas between 0.1745 and 0.3257, meanwhile betas range from 0.3739 to 0.7039. [18], analysing 4 EEEM's markets with 7 different GARCH approaches[7] founding alpha parameters lower than 0.20 in almost all markets (Hungary showed higher values, between 0.3919 and 0.6749). Betas values are between 0.7800 and 0.9196 in most markets, being Hungary again the exception (beta among 0.3244 and 0.7760). [32], using a E-GARCH approach[8], found similar results. EEEM's news parameter (α) is between 0.190 and 0.499, and the decay parameter (β) is high (between 0.900 and 0.943) in most EEEM's (with the exception of Poland with a $\beta = 0.114$). Analysing these results, alphas are higher in EEEM's markets than in developed markets as, for example, DAX or S&P 500. This mean volatility reacts intensively to market shocks in EEEM's. In contrast, persistence (β) is lower in most EEEM's than in developed markets. Similar patters are observed in our empirical study.

Regarding the existence of leverage effects, it is well known in the literature that negative shocks could have a higher effect on volatility than positive shocks. This characteristic, called leverage effect, has not been found in EEEM's markets. [30] found negative but statistically non robust leverage effect. Moreover, [18], [28][9], [21][10] and [32] conclude also than no important leverage effect on volatility can be found in EEEM's. In contrast, [25] found mostly asymmetric behaviour of volatility using the Central European Stock Index for the period 1996-2002, and [12] test the predictive power of 12 GARCH models in EEEM's[11], concluding those models that incorporate asymmetry, improve forecasting results (APARCH, EGARCH, LOGGARCH and T-GARCH fit better the data). As commented previously, our paper focuses on that point, finding important leverage effect, in contrast with previous studies.

Finally, regarding the existence of risk premia, [26] and [21] conclude, using a GARCH-in-Mean model, that volatility does not explain expected returns for the vast majority of EEEM's markets. In that line, our empirical study seems to reach similar results.

Our paper supposes an exploratory analysis of 11 EEEM's (plus Germany and US for comparative reasons) using a T-GARCH and E-GARCH approach. Our paper extends literature in different ways. First of all, it presents one of the most comprehensive analysis in terms of number of countries. Second, using

[2]France, Germany, Spain, Italy, UK and US are analysed using data from January 1988 to May 2000. Results are not maintained with a test for equality of unconditional variance in a GARCH(1,1) framework.

[3]The authors analyse Poland, Czech Republic, Hungary, Slovakia and Slovenia for the 1994-2006 period.

[4]The author analyses eleven Euro Area countries, three non-Euro Area countries and US, covering the period from 1989 to 2010.

[5]The authors analyse Czech Republic, Greece, Poland, Hungary, Poland, Russia, Slovakia and Turkey for the period 1988-2002.

[6]The authors analyse Germany, France, Italy, Netherlands, Spain, Finland, Belgium, Portugal, Ireland, Austria, Luxembourg, and use UK and US as control variables. Data ranges from January 1996 to June 2001.

[7]The authors analyse Poland, Czech Republic, Hungary and Slovakia using GARCH, NGARCH, EGARCH, GJR-GARCH, AGARCH, NAGARCH and VGARCH for the period 1992-1998.

[8]The author analyse Poland, Czech Republic, Hungary, Slovakia, Germany and US, using data from January 1997 to September 2003.

[9]Using data for the 1995-1997 period for Czech Republic, Hungary and Poland.

[10]The authors show evidence on Croatia, Czech Republic, Hungary, Poland, Russia and Slovakia.

[11]The authors analyse Bulgaria, Czech Republic, Estonia, Hungary, Latvia, Lithuania, Poland, Romania, Slovenia and Slovak Republic during the period 1991-2008.

a modern data set (2004-2011) it focuses on volatility dynamics of recent EU member, specially in the leverage effect and risk premia. And third, it is the only study that uses a T-GARCH approach to analyse EEEM's countries. Major findings are EEEM's are riskier than developed markets, however do not exists risk-return relationship. Moreover, important leverage effects are found in EEEM's in contrast with existing literature that found no significant leverage effect. Finally, EEEM's show significant differences with delevoped markets in terms of the news parameter (α) and persistence parameter (β).

The article is structured as follows: in section 2, data and methodology is presented; in section 3, results of the T-GARCH and E-GARCH models are provided and commented; in section 4 and 5 we drawn conclusions and references.

2 Data and Methodology

Our data is presented in Table 1. We consider eleven Eastern European Emerging Markets (EEEM's) and their respectivelly market indices. On one hand, nine of them are into the European Union: Greece (FTASE), Hungary (BUX), Estonia (TALSE), Latvia (RIGSE), Lithuania (NSEL30), Czech Republic (PX50), Poland (WGI), Bulgaria (SOFIX) and Romania (BET). On the other hand, two of them are not still in the European Union: Serbia (BELEXLIN) and Turkey (TR20I). We also consider two developed markets to compare results: US (DJIA) and Germany (DAX). All indices are value weighted indices, except DJIA from US, which is price weighted. Furthermore, we calculate daily log returns from 2004/01/01 to 2011/12/19[12]. Our whole period includes a economic boom period (until 2007), and a crises period (from 2007 to end 2011). As can be seen in Figure 1, this fact has significant implications for volatility dynamics[13]. Volatility are clearly not constant over time, and it raises dramatically during the period 2008-2010 due to the Subprime crises and the beginning of the European Debt Crisis.

Financial market research using stock market time series has been widely spread. Since the first Random Walk tests [9] researchers have developed more powerful techniques and models as VAR, Multiple Imputation[14] or Autoregressive Moving Average (ARMA) models[15].

Nevertheless, since the creation of the original

Market	Index	Entrance
USA	DJIA	-
Germany	DAX	1952
EU members		
Greece	FTASE	1981
Hungary	BUX	2004
Estonia	TALSE	2004
Latvia	RIGSE	2004
Lithuania	NSEL30	2004
Czech Rep.	PX50	2004
Poland	WGI	2004
Bulgaria	SOFIX	2007
Romania	BET	2007
No EU members		
Serbia	BELEXLIN	-
Turkey	TR20I	-

Table 1: *Index:* DJIA (Down Jones Industrial Average), DAX (DAX30), FTASE (FTSE/ASE 20 Index), BUX (Budapest Stock Exchange Index), TALSE (OMX Tallin Index), RIGSE (OMX Riga Index), NSEL30 (Lithuania NSEL30), PX50 (Prague Stock Exchange), WGI (Warsaw General Index), SOFIX (SOFIX Index), BET (Bucharest Stock Exchange),BELEXLIN (BELEXLIN Index), TR20I (Dow Jones Turkey Titans 20). Available data ranges from 2004/01/01 to 2011/12/19 on daily basis. Entrance means the year of entry in the European Union.

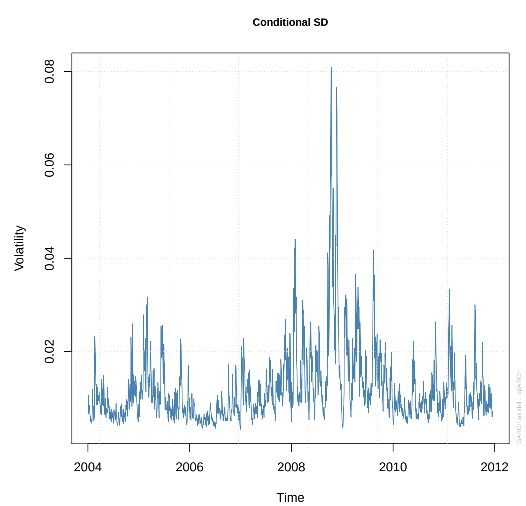

Figure 1: Bulgaria (SOFIX) Conditional Volatility on daily basis, from 2004 to 2010, considering the T-GARCH model.

[12]Most EEEM's joined the European Union during 2004; Our data base covers until 2011.

[13]The study of structural changes are not included in the GARCH specification. Then, it will be considered in future research.

[14]See [8] for an application of Multiple Imputation to the analysis of financial time series.

[15]The ARMA processes provide a parsimonious description of a stationary stochastic process through two parts: the autoregressive part (AR) and the moving average part (MA)[7]

ARCH in [10], financial time series research focused on changing volatility. From there, ARCH models grew rapidly into a rich family of empirical models for volatility forecasting during the last two decades. [4] generalized the ARCH model of [10], the well known GARCH model, which extends the specification of the conditional variance of [10], allowing the conditional variance to depend on its past values, which renders the model more parsimonious than the ARCH model[16]. Hence, the general equation of a GARCH(p,q) is given by:

$$\sigma_t^2 = \omega + \sum_{i=1}^{p} \alpha_i \epsilon_{t-i}^2 + \sum_{j=1}^{q} \beta \sigma_{t-j}^2.$$

Numerous variations and refinements of the GARCH model have been developed to test stylized facts observed in financial markets. These extensions recognize that there may be important non-linearity, asymmetry, and long memory properties in the volatility process[17]. For example, it is possible to cite GARCH-t, GARCH-M, GARCH-GJR, T-GARCH, E-GARCH, apARCH, etc. In accordance with [12], in this article is used a T-GARCH and E-GARCH approach, to allow us to analyse non-linearities and asymmetric effects on volatility. The model specification is as follows:

$$r_t = \mu + \phi r_{t-1} + \lambda \sigma_t + \epsilon_t \quad (1)$$

$$\epsilon_t | \Omega_{t-1} \sim S_u(\mu, \sigma, \nu, \tau) \quad (2)$$

$$\sigma_t = \omega + \alpha|\epsilon_{t-1}| + \gamma|\epsilon_{t-1}| I(\epsilon_{t-1} < 0) + \beta\sigma_{t-1} \quad (3)$$

$$log\sigma_t^2 = \omega + \alpha|\epsilon_{t-1}| + \beta log\ \sigma_{t-1}^2 + \delta\epsilon_{t-1} \quad (4)$$

The description of the parameters can be summarized in Table 2:

Equations 1 and 2 are the mean equation and the conditional error distribution equation, respectively. We consider a Johnson S_u distribution, following the model in [16]. Similar studies dealing with volatility in EEEM's like [17], use a Student's t-distribution. Nevertheless, the main reason we consider a Johnson S_u distribution is that we attempt to describe the errors more accurately through four parameters: μ, σ, ν, τ,

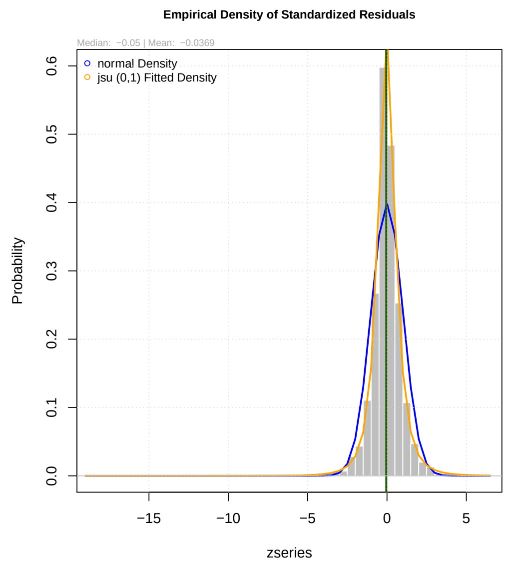

Figure 2: Empirical density of standardized residuals plot of Lithuania (NSEL30). Yellow line refers to Johnson S_u distribution, while blue line refers to normal distribution.

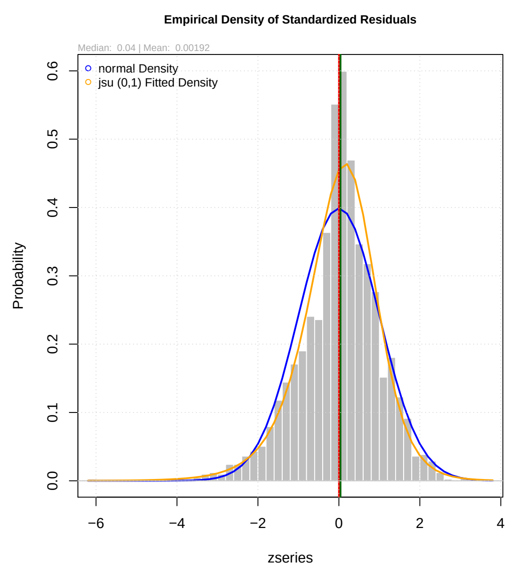

Figure 3: Empirical density of standardized residuals plot of United States (DJIA). Yellow line refers to Johnson S_u distribution, while blue line refers to normal distribution.

trying to capture financial data asymmetry and excess of kurtosis. Figures 2 and 3 show how a Johnson S_u distribution allows a better fitting of the residuals distribution using two of our analysed markets as examples (NSEL30 and DJIA).

Equation 3 is the specification of T-GARCH model according to the previous work in [36], and equation 4 is the specification of E-GARCH, according to the model presented in [23]. E-GARCH and T-GARCH models fit accurately EEEM's stock mar-

[16]GARCH models are now considered as essential tools in financial econometrics, thus they are available in common econometrics software.

[17]Many of these models are surveyed in [5] and [6].

Parameter	Description
μ	Unconditional mean
λ	Risk premium
α	News parameter
β	Decay parameter
γ	Asymmetric coefficient
ν	Skewness
σ_y	Unconditional volatility
τ	Kurtosis coefficient

Table 2: Parameter's description.

ket index returns, as can be seen in Figure 4[18].

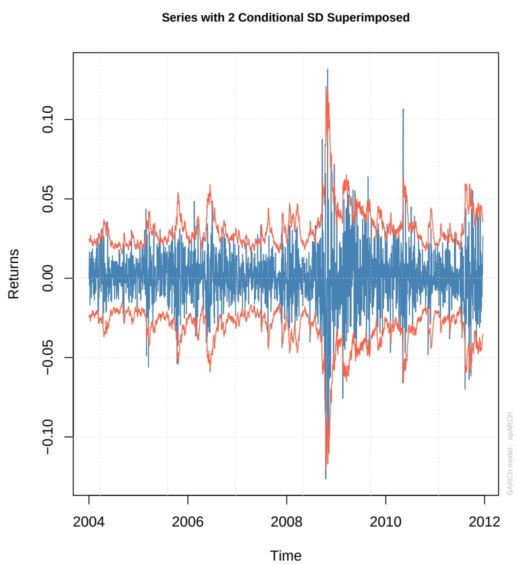

Figure 4: Hungary (BUX) Conditional Volatility fitting the stock market returns with T-GARCH model (Daily basis from 2004 to 2011).

3 Empirical Results

The summary statistics for the thirteen markets are shown in Table 3. We consider four relevant variables: mean, standard deviation, skewness and kurtosis. We find that ten of thirteen markets have positive daily mean returns (only Greece, Bulgaria and Serbia exhibit negative daily mean returns). The most profitable market is Turkey (0.00049) whereas Greece exhibits the lowest level of mean returns. However, the mean values are close to zero. Related to the standard deviation, Greece is the riskiest country, while Serbia exhibit the lowest standard deviation level. The skewness and kurtosis indicate departures from normality in all return series. Eight of thirteen markets show negative skewness indicating that negative big surprises are more likely. In addition, all series exhibit kurtosis greater than three (except Turkey), specially Lithuania (20.17), Czech Republic (13.75) and Serbia (11.18), indicating the presence of fat tails.

[18]The E-GARCH approach shows a very similar pattern.

Country	Mean	St. dev.	SK	KT
United States	0.00005	0.012	-0.05	10.41
Germany	0.00017	0.014	0.06	7.26
Greece	-0.00074	0.019	0.21	5.38
Hungary	0.00030	0.017	-0.11	6.24
Estonia	0.00030	0.012	0.18	8.47
Latvia	0.00012	0.013	0.21	6.28
Lithuania	0.00024	0.013	-0.33	20.17
Czech Rep.	0.00012	0.016	-0.56	13.75
Poland	0.00027	0.013	-0.46	3.37
Bulgaria	-0.00019	0.013	-0.94	9.33
Romania	0.00032	0.018	-0.60	6.56
Serbia	-0.00001	0.010	0.25	11.18
Turkey	0.00049	0.018	-0.05	2.46

Table 3: Descriptive statistics from 2004/01/01 to 2011/12/19 on daily basis. Number of observations: 2077 except in Serbia: 1881. St. dev refers to the standard deviation, SK refers to the skewness and KT refers to the kurtosis.

Empirical results of the application of T-GARCH and E-GARCH models are showed in Table 4. Considering a T-GARCH model, the vast majority of markets exhibit positive statistically significant mean (μ). Moreover, EEEM's show higher unconditional mean than developed markets[19]. These results are consistent with [13], [27] and [1], who also find that emerging markets show higher mean returns than developed markets. Related to the rest of results, they can be classified in three lines.

First, the volatility dynamic analysis. The unconditional volatility (σ_y) indicates that almost all EEEM's are more volatile than developed markets. The highest unconditional volatility is found in Greece ($\sigma_y = 0.0237$) and Romania ($\sigma_y = 0.0180$). On the other hand, the less volatile markets are United States ($\sigma_y = 0.0113$) and Serbia ($\sigma_y = 0.0105$). Nevertheless, it cannot be noted great differences among EU members and non-EU members. It

[19]Greece (FTASE) exhibits the highest unconditional mean of returns, the highest negative risk premium and the highest unconditional volatility of returns considering both the T-GARCH and E-GARCH models.

may indicates that being a EU member do not has effect in risk terms. Regarding news parameter (α), innovations (news) have more influence on volatility in EEEM's than in developed markets. As can be seen in Figures from 5 to 16, innovations have more influence in EEEM's than in Germany except in Greece, Hungary, Poland and Turkey. For instance, we remark the coefficients of Serbia ($\alpha = 0.2544$) and Bulgaria ($\alpha = 0.318$). One possible explanation is that investors have less available information about EEEM's so they are more responsive to innovations in these stock markets. Moreover, we may observe that markets with higher (α) display lower decay parameter (β), indicating that when a shock occurs, its effect persists a short time period. For example, in Hungary a shock on volatility decay slowly. However, in Serbia a shock on volatility decay rapidly. Therefore, forecasting volatility in these markets could lead less accurate estimates. Four interesting results are Greece ($\alpha = 0.0755$ and $\beta = 0.9386$), Poland ($\alpha = 0.0697$ and $\beta = 0.9342$), Hungary ($\alpha = 0.0963$ and $\beta = 0.9064$) and Turkey ($\alpha = 0.0817$ and $\beta = 0.8941$) indicating that innovations have a lower effect in volatility than in developed markets and the shock persists a large time period. Thereby, volatility estimation will be more accurately in this markets. It indicates that Greece, Poland, Hungary and Turkey have similar patterns to developed markets. In terms of errors asymmetries (ν), we find negative skewness in two developed markets. However, almost all EEEM's show not statistically significant skewness[20]. On the other hand, all return series exhibit excess of kurtosis indicating the presence of fat tails and departures from normality. EEEM's show higher excess of kurtosis than developed markets[21], except Greece ($\tau = 1.1800$), Hungary ($\tau = 1.0292$), Poland ($\tau = 0.9542$) and Turkey ($\tau = 0.8773$) which show very low values. Then, considering skewness and kurtosis altogether we find that negative big surprises are more probable in developed markets, whereas it seems to be the same probability of positive and negative big surprises in EEEM's[22].

Second, we analyse the leverage effect. Unlike the previous literature, the leverage effect parameter (γ) indicates that negative innovations have more influence in volatility than positive innovations in almost all markets. As can be seen in Table 4 (*Panel A*), the leverage effect is higher in two developed markets than in EEEM's[23]. This fact indicates that negative innovations (news) have more impact in developed markets volatility than in EEEM's volatility. However, there is no significant difference between EU members and non-EU members.

And **third, we consider the risk premium (λ).** Two developed markets and four EEEM's[24] exhibit no significant risk-return relationship. This finding are consistent with [14], who find that five of the seven analysed markets do not show significant risk-return relationship. In this sense, [3] also find no risk-return relationship in all analysed markets. However, we find that some EEEM's exhibit statistically significant negative risk premia[25]. Then, our results are also consistent with the findings in [30] and [29], who find no time varying risk-return relation in Hungary using several GARCH models.

One of the most remarkable findings is that results do not differ among EEEM's EU members and EEEM's non-EU members. We do not find any significant differences between nine European Union markets and two non-EU markets, in line with [20], but contrary to [34]. Our findings show that European Union market integration seems not to have important effects on unconditional volatility of EEEM's. Presented results are robust to our two models: T-GARCH and E-GARCH.

4 Conclusions

In this paper we analyse the main characteristics of volatility in several recent EU members and two still non EU members. Then, we present a wide database which includes eleven EEEM's and two developed markets. The analysed period ranges from 2004 to 2011. Using daily observations, we calculate the log returns and carry out two GARCH approaches: T-GARCH and E-GARCH models. Empirical results are classified in three lines: volatility dynamic, leverage effect and risk premium. We find similar results considering a T-GARCH and E-GARCH models, indicating robustness of our conclusions. Main finding can be summarized as follows:

We find that almost all markets exhibit positive unconditional mean, and generally EEEM's show higher (μ) than developed markets. EEEM's markets

[20] Only Latvia (RIGSE) exhibit positive statistically significant asymmetry at 1% level

[21] The highest excess of kurtosis is shown by Lithuania (NSEL30) $\tau = 28.351$.

[22] Except in Greece, Hungary, Poland and Turkey.

[23] In *Panel B*, α indicates the leverage effect while γ indicates the news impact, just the opposite than in *Panel A*.

[24] Hungary, Bulgaria, Romania and Turkey.

[25] Namely, Greece, Latvia, Lithuania, Czech Republic, Poland and Serbia show statistically significant negative risk premium considering the T-GARCH model, and the same markets plus Bulgaria considering the E-GARCH model.

show higher volatility than developed markets, but no important differences in risk can be noticed among UE and non-EU members. All EEEM's exhibit high levels of kurtosis except Greece, Hungary, Poland and Turkey

Innovations and news have more influence on volatility in EEEM's markets than in developed markets, being also the decay parameter lower in EEEM's than in developed markets. It implies that volatility is more difficult to estimate in EEEM's. Then, is more difficult for an investor to analyse the portfolio risk including these markets. Nevertheless, we find that Greece, Hungary, Poland and Turkey also exhibit low news impact parameter and high decay parameter.

One of the main findings in this article is an important leverage effect in EEEM's, contrary to what is defended in previous literature.

Most EEEM's show non statistically significant risk-premia or even statistically significant negative risk-premia. Then, the extra risk assumed investing in EEEM's, might not be rewarded to an investor.

Finally, taking into account the news parameter, the decay parameter and kurtosis, Greece, Hungary, Poland and Turkey show similar patterns to developed markets, indicating that they may be the maturest EEEM's.

Volatility analysis in EEEM's has considerable implications for international investors and asset management. A good characterization of return moments is absolutely necessary for an international portfolio construction and efficient asset allocation. A portfolio risk reduction through international diversification is not possible without a correct variance analysis. Our main findings show some implications for investors. First, to invest in EEEM's is riskier than in developed markets and this extra risk might not be rewarded. Second, to construct a well diversified portfolio might be less accurate including some EEEM's, due to the greater difficulty to predict volatility. Third, both Greece, Hungary, Poland and Turkey seem to be the maturest EEEM's, indicating that to invest in these markets might be less riskier than in others emerging markets. And forth, non relevant differences are observed between EU members and non-EU members.

Acknowledgements: The research was supported by the Grant URV-AIRE2010.

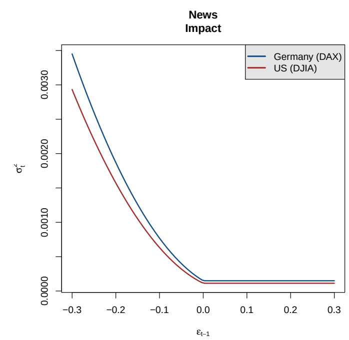

Figure 5: News impact (α) plot. Blue line refers to Germany and red line refers to United States. T-GARCH model.

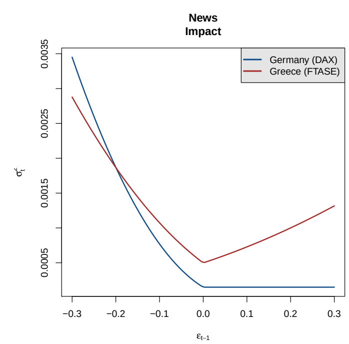

Figure 6: News impact (α) plot. Blue line refers to Germany and red line refers to Greece. T-GARCH model.

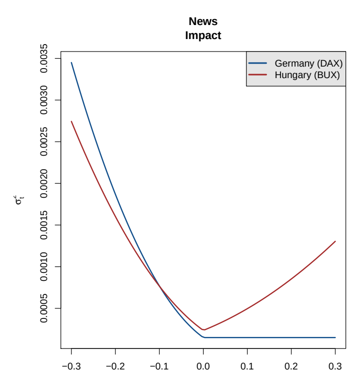

Figure 7: News impact (α) plot. Blue line refers to Germany and red line refers to Hungary. T-GARCH model.

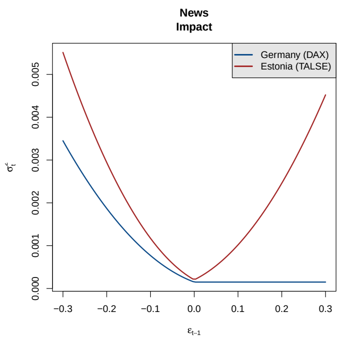

Figure 8: News impact (α) plot. Blue line refers to Germany and red line refers to Estonia. T-GARCH model.

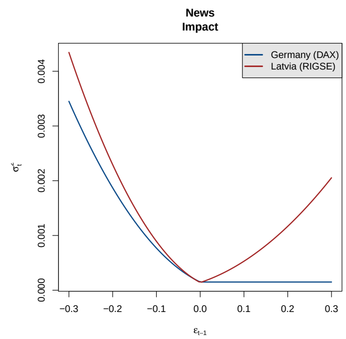

Figure 9: News impact (α) plot. Blue line refers to Germany and red line refers to Latvia. T-GARCH model.

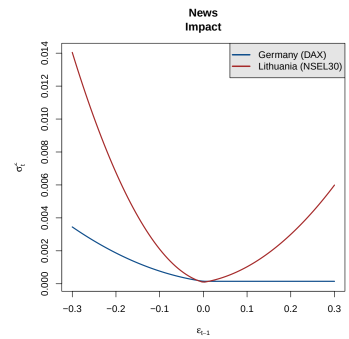

Figure 10: News impact (α) plot. Blue line refers to Germany and red line refers to Lithuania. T-GARCH model.

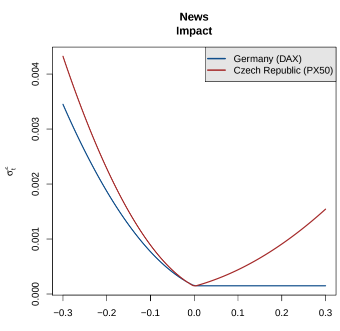

Figure 11: News impact (α) plot. Blue line refers to Germany and red line refers to Czech Republic. T-GARCH model.

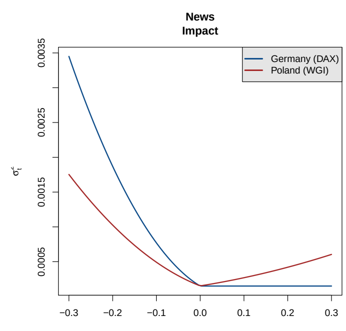

Figure 12: News impact (α) plot. Blue line refers to Germany and red line refers to Poland. T-GARCH model.

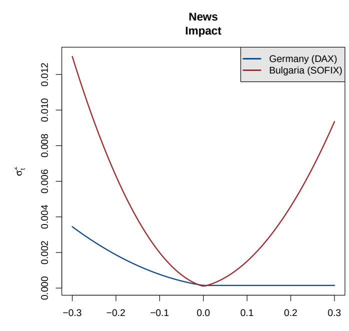

Figure 13: News impact (α) plot. Blue line refers to Germany and red line refers to Bulgaria. T-GARCH model.

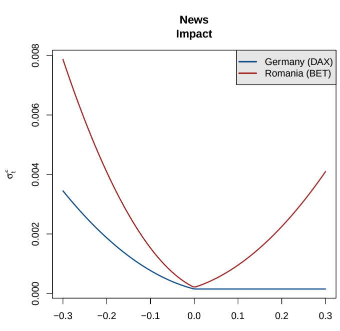

Figure 14: News impact (α) plot. Blue line refers to Germany and red line refers to Romania. T-GARCH model.

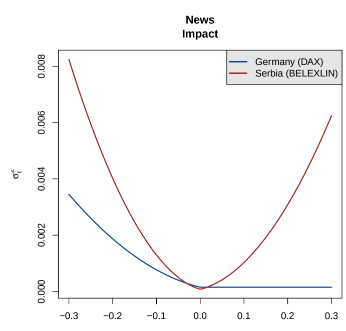

Figure 15: News impact (α) plot. Blue line refers to Germany and red line refers to Serbia. T-GARCH model.

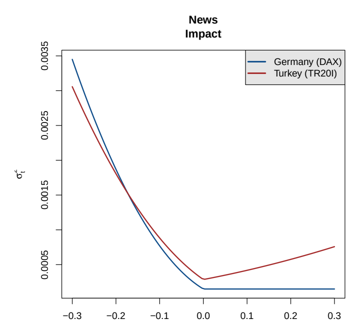

Figure 16: News impact (α) plot. Blue line refers to Germany and red line refers to Turkey. T-GARCH model.

INDEX	μ	ϕ	λ	ω	α	β	γ	ν	$shape$	σ_y	τ
Panel A:											
DJIA	**0.0002**	**-0.0518**	-0.0099	**0.0002**	**0.0725**	**0.9301**	**1.0000**	**-0.5179**	**1.9313**	**0.0113**	**1.3945**
DAX	0.0004*	-0.0168	-0.0094	**0.0003**	**0.0775**	**0.9185**	**1.0000**	**-0.6123**	**2.2798**	**0.0130**	**0.8201**
FTASE	**0.0032**	0.0371*	**-0.2268**	0.0001*	**0.0755**	**0.9386**	**0.3836**	-0.0593	**2.1064**	**0.0237**	**1.1800**
BUX	0.0020**	0.0218	-0.1000	**0.0003**	**0.0963**	**0.9064**	**0.2814**	0.0273	**2.1810**	**0.0166**	**1.0292**
TALSE	0.0002	**0.1624**	**0.0452**	**0.0002**	**0.1884**	**0.8582**	0.0620	0.0686	**1.2768**	**0.0164**	**9.2577**
RIGSE	**0.0024**	**-0.0923**	**-0.1693**	**0.0004**	**0.1458**	**0.8686**	**0.2353**	**0.1847**	**1.3332**	**0.0132**	**4.0483**
NSEL30	0.0023**	**0.1130**	-0.1608*	**0.0010**	**0.2414**	**0.7389**	**0.2172**	0.0337*	**1.1913**	**0.0113**	**28.3510**
PX50	0.0019	0.0370*	-0.1188**	**0.0004**	**0.1355**	**0.8673**	**0.3255**	-0.2096**	**1.9226**	**0.0132**	**1.7617**
WGI	**0.0013**	**0.0480**	**-0.0705**	**0.0002**	**0.0697**	**0.9342**	**0.4138**	-0.1792	**2.0602**	**0.0130**	**0.9542**
SOFIX	0.0005	**0.1431**	-0.0268	**0.0007**	**0.3184**	**0.7165**	0.0909	-0.0613	**1.3157**	**0.0127**	**3.3834**
BET	0.0010*	**0.0805**	-0.0216	**0.0011**	**0.2070**	**0.7839**	**0.1989**	-0.0013	**1.5270**	**0.0168**	**5.7488**
BELEXLIN	0.0011*	**0.3394**	-0.1579*	0.0005**	**0.2544**	**0.7714**	0.0773	0.1027	**1.4400**	**0.0105**	**4.1201**
TR20I	0.0023	0.0294	-0.0860	**0.0008**	**0.0817**	**0.8941**	**0.5665**	-0.0611	**2.1551**	**0.0180**	**0.8773**
Panel B:											
DJIA	0.0006**	**-0.0486**	-0.0702*	-0.1032**	**-0.1441**	**0.9887**	**0.1154**	**-0.4897**	**1.8507**	**0.0103**	**1.7842**
DAX	0.0010**	-0.0184	-0.0725	-0.1677**	**-0.1580**	**0.9810**	**0.1265**	**-0.5612**	**2.1243**	**0.0121**	**0.9839**
FTASE	0.0032*	0.0364	-0.2252**	-0.0510	**-0.0560**	**0.9937**	**0.1543**	-0.0629	**2.0951**	**0.0180**	**1.2128**
BUX	0.0020	0.0210	-0.0962	**-0.1700**	-0.0487*	**0.9795**	**0.1921**	0.0266	**2.1532**	**0.0157**	**1.0607**
TALSE	**0.0001**	**0.1633**	0.0452	**-0.1971**	-0.0307	**0.9784**	**0.3210**	0.0570	**1.2814**	**0.0105**	**8.6500**
RIGSE	**0.0024**	**-0.0921**	**-0.1625**	-0.2817**	**-0.0655**	**0.9680**	**0.2913**	**0.1886**	**1.3406**	**0.0122**	**3.9188**
NSEL30	**0.0026**	**0.1155**	**-0.1887**	**-0.8419**	-0.0608**	**0.9074**	**0.3820**	0.0276	**1.1872**	**0.0106**	**25.6629**
PX50	**0.0020**	0.0333*	-0.1298**	**-0.2610**	**-0.0724**	**0.9703**	**0.2622**	-0.2133**	**1.9154**	**0.0123**	**1.7845**
WGI	**0.0013**	**0.0482**	**-0.0669**	**-0.1154**	**-0.0520**	**0.9869**	**0.1338**	-0.1964*	**2.0948**	**0.0123**	**0.9105**
SOFIX	**0.0004**	**0.1460**	**-0.0208**	**-0.6029**	-0.0324	**0.9337**	**0.5481**	-0.0731	**1.3310**	**0.0106**	**3.2322**
BET	**0.0009**	**0.0824**	-0.0162	**-0.5625**	-0.0589**	**0.9323**	**0.3968**	-0.0091	**1.5273**	**0.0157**	**5.9892**
BELEXLIN	**0.0010**	**0.3545**	**-0.1493**	**-0.6872**	-0.0275	**0.9273**	**0.5274**	0.1096	**1.4945**	**0.0088**	**3.7315**
TR20I	0.0027*	0.0281*	-0.1151	-0.3093**	**-0.0783**	**0.9617**	**0.1524**	-0.0630	**2.1586**	**0.0176**	**0.8828**

Table 4: Panel A: Estimation results using a T-GARCH model. Panel B: Estimation results using a E-GARCH model. We consider daily basis from 2004/01/01 to 2011/12/19. **Bold numbers** indicate 1% level significance. ** indicate 5% level significance. * indicate 10% level significance. μ=unconditional mean; ϕ=AR coefficient; λ=risk premium; α=news parameter; β=decay parameter; γ=leverage effect; ν=error asymmetry; σ_y=unconditional volatility; τ= error excess of kurtosis.

5 References

References:

[1] R. Aggarwal, C. Inclan, and R. Leal. Volatility in emerging stock markets. *Journal of Financial and Quantitative Analysis*, 34(1), 1999.

[2] M. Asal. Non-linear growth impacts of financial development in euro area. *International Journal of Economics and Finance*, 4(12):23–38, 2012.

[3] R. T. Baillie and R. P. DeGennaro. Stock returns and volatility. *Journal of financial and quantitative analysis*, 25(2):203–214, 1990.

[4] T. Bollerslev. Generalized autoregressive conditional heteroskedasticity. *Journal of Econometrics*, 31(3):307–327, 1986.

[5] T. Bollerslev, R. Y. Chou, and K. F. Kroner. Arch modeling in finance: A review of the theory and empirical evidence. *Journal of Econometrics*, 52(1):5–59, 1992.

[6] T. Bollerslev, R. F. Engle, and D. B. Nelson. Arch models. *Handbook of Econometrics*, 4:2959–3038, 1994.

[7] G. E. P. Box, G. M. Jenkins, and G. C. Reinsel. *Time series analysis: forecasting and control*, volume 734. Wiley, 2011.

[8] S. Cano and J. Andreu. Using multiple imputation to simulate time series: a proposal to solve the distance effect. *WSEAS Transactions on Computers*, 9(7):768–777, 2010.

[9] A. Cowles and H. E. Jones. Some a posteriori probabilities in stock market action. *Econometrica, Journal of the Econometric Society*, pages 280–294, 1937.

[10] R. F. Engle. Autoregressive conditional heteroscedasticity with estimates of the variance of united kingdom inflation. *Econometrica: Journal of the Econometric Society*, 50(4):987–1007, 1982.

[11] G. Haber, R. Neck, and W. J. McKibbin. Global implications of monetary and fiscal policy rules in the emu. *Open Economies Review*, 13(4):363–379, 2002.

[12] B. Harrison and W. Moore. Forecasting stock market volatility in central and eastern european countries. *Journal of Forecasting*, 31(6):490–503, 2011.

[13] Campbell R. Harvey. Predictable risk and returns in emerging markets. *The Review of Financial Studies*, 8(3):pp. 773–816, 1995.

[14] M. K. Hassan, M. Haque, and S. B. Lawrence. An empirical analysis of emerging stock markets of europe. *Quarterly Journal of Business and Economics*, 45(1/2):31–52, 2006.

[15] B. Hayo. Happiness in transition: An empirical study on eastern europe. *Economic Systems*, 31(2):204–221, 2007.

[16] N. L. Johnson. Systems of frequency curves generated by methods of translation. *Biometrika*, 36(1-2):149–176, 1949.

[17] E. Jurun, S. Pivac, and J. Arneric. Historical and prognostic risk measuring across stocks and markets. *WSEAS Transactions on Business and Economics*, 4(8):126–134, 2007.

[18] M. Kasch-Haroutounian and S. Price. Volatility in the transition markets of central europe. *Applied Financial Economics*, 11(1):93–105, 2001.

[19] T. Moore and P. Wang. Volatility in stock returns for new eu member states: Markov regime switching model. *International Review of Financial Analysis*, 16(3):282–292, 2007.

[20] C. Morana and A. Beltratti. The effects of the introduction of the euro on the volatility of european stock markets. *Journal of Banking and Finance*, 26(10):2047–2064, 2002.

[21] V. Murinde and S. Poshakwala. Volatility in the emerging stock markets in central and eastern europe: Evidence on croatia, czech republic, hungary, poland, russia and slovakia. *European Research Studies Journal*, 4(3-4):73–102, 2001.

[22] R. Neck, G. Haber, and W. Mckibbin. European monetary and fiscal policies after the eu enlargement. *Empirica*, 31(2):229–245, 2004.

[23] D. B. Nelson. Conditional heteroskedasticity in asset returns: A new approach. *Econometrica: Journal of the Econometric Society*, 59(2):347–370, 1991.

[24] M. Palazuelos-Martinez. The structure and evolution of trade in central and eastern europe in the 1990s. *Europe-Asia Studies*, 59(1):111–135, 2007.

[25] P. Patev and N. Kanaryan. Central european stock market volatility modelling and forecasting. *Working paper*, 2002.

[26] S. Poshakwale and V. Murinde. Modelling the volatility in east european emerging stock markets: evidence on hungary and poland. *Applied Financial Economics*, 11(4):445–456, 2001.

[27] G. De Santis. Stock returns and volatility in emerging financial markets. *Journal of International Money and Finance*, 16(4):561–579, 1997.

[28] M. Scheicher. The comovements of stock markets in hungary, poland and the czech republic. *International Journal of Finance & Economics*, 6(1):27–39, 2001.

[29] K. K. Shields. Stock return volatility on emerging eastern european markets. *The Manchester School*, 65(S):118–138, 1997.

[30] K. K. Shields. Threshold modelling of stock return volatility on eastern european markets. *Economics of Planning*, 30(2-3):107–125, 1997.

[31] T. Syriopoulos. International portfolio diversification to central european stock markets. *Applied Financial Economics*, 14(17):1253–1268, 2004.

[32] T. Syriopoulos. Risk and return implications from investing in emerging european stock markets. *Journal of International Financial Markets, Institutions and Money*, 16(3):283–299, 2006.

[33] M. Tvrdon. Cohesion policy, convergence and regional disparities: the case of the european union. *WSEAS Transactions on Business and Economics*, 9(2):89–99, 2012.

[34] P. Wang and T. Moore. Sudden changes in volatility: The case of five central european stock markets. *Journal of International Financial Markets, Institutions and Money*, 19(1):33–46, 2009.

[35] J. Yang, I. Min, and Q. Li. European stock market integration: Does emu matter? *Journal of Business Finance and Accounting*, 30(9-10):1253–1276, 2003.

[36] J. M. Zakoian. Threshold heteroskedastic models. *Journal of Economic Dynamics and Control*, 18(5):931–955, 1994.