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Forecasting Volatility: Evidence from the Bucharest Stock Exchange

Assoc. Prof. Erginbay UĞURLU[1]
[1]*Hitit Üniversitesi, FEAS, Department of Economics, Çorum, 19030, Turkey*
Tel: +903642257700, Fax: +903642257710, e-mail: erginbayugurlu@hitit.edu.tr

Abstract: Financial series tend to be characterized by volatility and this characteristic affects both financial series of developed markets and emerging markets. Because of the emerging markets have provided major investment opportunities in last decades their volatility has been widely investigated in the literature. The most popular volatility models are the Autoregressive Conditional Heteroscedastic (ARCH) or Generalized Autoregressive Conditional Heteroscedastic (GARCH) models. This paper aims to investigate the volatility of Bucharest Stock Exchange, BET index as an emerging capital market and compare forecasting power for volatility of this index during 2000-2014. To do this, this paper use GARCH, TARCH, EGARCH and PARCH models against Generalized Error distribution. We estimate these models then we compare the forecasting power of these GARCH type models in sample period. The results show that the EGARCH is the best model by means of forecasting performance.

Keywords: stock returns; volatility; GARCH models; emerging markets.

JEL classification: C13, C32 C51, C52, G17

1. Introduction

The conditional variance of financial time series is important for measuring risk and volatility of these series. Conditional distributions of high-frequency returns of financial data have excess of kurtosis, negative skewness, and volatility pooling and leverage effects. Volatility of stock exchange indices and forecasting of their volatility have enormously increasing literature for both investors and academicians. The prices of financial securities have constant inconsistency and their returns over the various periods

[1] *Hitit University,FEAS, Department of Economics, Çorum, 19030, Turkey, Tel: +903642257700, Tel: +903642257710, Fax: +902123351000, e-mail: erginbayugurlu@hitit.edu.tr*

of time are notably volatile and complicated to forecast. The modelling volatility started with the Autoregressive Conditional Heteroskedasticity (ARCH) model, introduced by Engle (1982) and generalized by Bollerslev (1986) in GARCH model. Although ARCH and GARCH models capture volatility clustering and leptokurtosis, they fail to model the leverage effect. After these two papers, various types of GARCH models were proposed to solve this problem such as the Exponential GARCH (EGARCH) model , the Threshold GARCH (TARCH) model and the Power ARCH (PARCH) model.

Aim of this paper is to investigate the volatility and of Bucharest Stock Exchange, namely Bucharest Exchange Trading Index (BET) as an emerging capital market for the last decade. Also we aim to compare forecasting power of GARCH-type models to find the relevant GARCH-type model for BET. We investigate the forecasting performance of GARCH, EGARCH, TARCH and PARCH models together with the Generalized Error Distribution (GED).

Bucharest Exchange Trading Index (BET) is a capitalization weighted index which was developed with a base value of 1000 as of September 22, 1997. BET is the first index developed by the BSE and comprised of the most liquid 10 stocks listed on the Bucharest Stock Exchange BSE tier 1. Currently, the Bucharest Stock Exchange calculates and publishes a few indices: BET, BET-C, BET-FI, ROTX, BEX-XT, BET-NG, RASDAQ-C, RAQ-I, RAQ-II. BET. (Pele et al.,2013; Bloomberg,2013)

Investigating volatility of returns of stock markets and comparing forecasting accuracy of returns of stock markets have achieved attractiveness all over the world. Because of aim of the paper we focused on paper about European and emerging stock markets.

[Emerson et al.,1997], [Shields ,1997], and [Scheicher,1999] investigates Polish stock returns. [Scheicher,2001], [Syriopoulos,2007] and [Haroutounian and Price, 2010] analyze the emerging markets in Central and Eastern Europe. [Vošvrda and Žıkeš, 2004] is another research about the Czech, Hungarian and Polish stock markets. [Rockinger and Urga, 2012] make a model for transition economies and established economies. [Ugurlu et al., 2012] and [Thalassinos et al. 2013] investigate the forecasting performance of GARCH-type model to European Emerging Economies and Turkey and Czech Republic stock exchange respectively.

This paper is organized as follows. Section 2 describes the volatility models which are used in this paper. Section 3 shows empirical application results. Section 4 contains summary of the paper and some concluding remarks.

2. Method

In this section we review the GARCH-type models which are used in the empirical application section of this paper.

Engle (1982) developed Autoregressive Conditional Heteroscedastic (ARCH) model. ARCH models based on the variance of the error term at time t depends on the realized values of the squared error terms in previous time periods. The model is specified as:

$$y_t = u_t \quad (1)$$

$$u_t \sim N\left(0, \sigma_t^2\right)$$

(2)

$$\sigma_t^2 = \alpha_0 + \sum_{t=1}^{q} \alpha_j u_{t-i}^2 \tag{3}$$

This model is referred to as ARCH(q), where q refers to the order of the lagged squared returns included in the model. [Bollerslev, 1986] and [Taylor, 1986] proposed the GARCH(p,q) random process. The process allows the conditional variance of variable to be dependent upon previous lags; first lag of the squared residual from the mean equation and present news about the volatility from the previous period which is as follows:

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{p} \alpha_i u_{t-i}^2 + \sum_{j=1}^{q} \beta_i \sigma_{t-i}^2 \tag{4}$$

All parameters in variance equation must be positive and $\sum_{i=1}^{q} \alpha_i + \sum_{i=1}^{p} \beta_i$ is expected to be less than one but it is close to 1. If the sum of the coefficients equals to 1 it is called an Integrated GARCH (IGARCH) process.

[Nelson, 1991] proposed the Exponential GARCH (EGARCH) model as follows:

$$\ln(\sigma_t^2) = \omega + \sum_{t=1}^{p} \left(\alpha_i \left| \frac{\varepsilon_{t-i}}{\sigma_{t-i}} \right| + \gamma_i \frac{\varepsilon_{t-i}}{\sigma_{t-i}} \right) + \sum_{j=1}^{q} \beta_i \ln(\sigma_{t-i}^2) \tag{5}$$

In the equation γ_i represent leverage effects which accounts for the asymmetry of the model. While the basic GARCH model requires the restrictions the EGARCH model allows unrestricted estimation of the variance. If $\gamma_i < 0$ it indicates presence of leverage effect which means that leverage effect bad news increases volatility.

Threshold GARCH (TARCH) model was developed by [Zakoian ,1994]. In TARCH model the leverage effect is expressed in a quadratic form as follows:

$$\sigma_t^2 = \omega + \sum_{j=1}^{p} \alpha_i u_{t-i}^2 + \sum_{k=1}^{r} \gamma_k u_{t-k}^2 I_{t-k}^- + \sum_{i=1}^{q} \beta_j \sigma_{t-j}^2$$

(6)

where $I_{t-k}^- = \begin{cases} 1 & u_{t-i} < 0 \\ 0 & u_{t-i} = 0 \end{cases}$

The effect of the $u_{t-i} > 0$ represents the good news and $u_{t-i} < 0$ represents the bad news have different outcomes on the conditional variance. The impact of the news is asymmetric and the leverage effects exist when $\gamma_k \neq 0$.

The power-ARCH (PARCH) specification proposed by [Ding et al. ,1993] generalises the transformation of the error term in the models as follows:

$$\sigma_t^\delta = \omega + \sum_{j=1}^{p} \alpha_i (|u_{t-i}| - \gamma_i u_{t-i})^\delta + \sum_{i=1}^{q} \beta_j \sigma_{t-j}^\delta$$

(7)

where δ is power parameter, γ_i is an optional threshold parameter

3. Empirical Application

We use daily data in stock exchanges of BET Index for the period 1/5/2004-6/10/2014 thus we have 2607 observations. Data collected from Reuters. We use return series as follows:

$$return = \log\left(\frac{BET_t}{BET_{t-1}}\right)$$

(8)

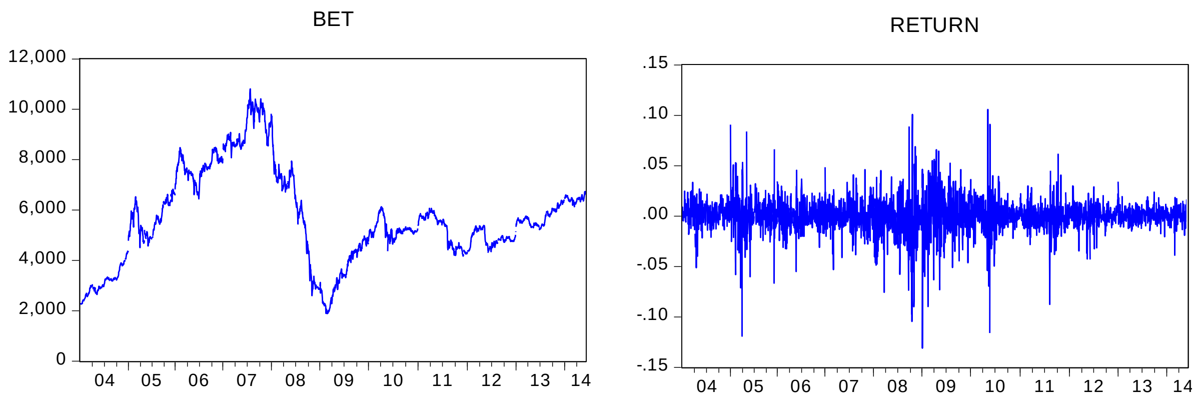

Figure 1: Graph of BET and Return Series of BET

Source: Authors

Table 1: Descriptive Statistics

	Return
Mean	0.000416
Median	0.000647
Maximum	0.105645
Minimum	-0.131168
Std. Dev.	0.017425
Skewness	-0.544454
Kurtosis	10.69096
Jarque-Bera	6551.549
Probability	0.000000
Observations	2606

Source: Authors

Table 1 summarizes descriptive statistics of return series. Because the skewness of the variable is negative and kurtosis is higher than 3, the descriptive statistics indicate that the return of BET has negative skewness and high positive kurtosis. These values signify that the distributions of the series have a long left tail and leptokurtic. Jarque-Bera (JB) statistics reject the null hypothesis of normal distribution at the 1% level of significance for the variable.

Before the variance of the series is to estimate the mean model of the mean equation should be estimated. To estimate the mean equation we find the exact ARIMA(p,d,q) model. In the model; p is the number of autoregressive terms, d is the number of differencing operators, and q is the number of lagged forecast errors in the prediction equation.

Before the model is chosen unit root test must be used to see d part of the model. Table 2 shows unit root tests results of the variable. ADF and DF-GLS tests results conclude that return is stationary then *d* part of the model is “0” then ARMA(p,q) model must be used instead of ARIMA(p,d,q).

Table 2: Unit Root Test Results of Return

	Intercept	Trend and Intercept
ADF	-47.0073(0)***	-47.0239(0)***
DF-GLS	-46.66605(0)***	-46.84999(0)***
PP	-47.08005 (12) ***	-47.08553(12) ***

Notes: The figures in square brackets show the lag length by SIC for ADF and Bartlett Kernel for PP test. *, ** and *** indicate statistical significance at the 10, 5 and 1% levels, respectively

Source: Authors calculation

The correlogram of the return series shows no systematic pattern according to autocorrelation function (ACF), and partial autocorrelation function (PACF) (See:Appendix). We set the maximum lag ARMA(2,2) in order to estimate mean equation and consider (1,1), (1,2), (2,1) and (2,2) as specifications for choosing the best model. Existence of ARCH effect in these mean models is tested by ARCH-LM test. If the value of the ARCH LM test statistic is greater than the critical value from the χ^2 distribution, the null hypothesis of there is no ARCH effect is rejected. After the ARMA(p,q) model is defined as a mean part of the series we will estimate the GARCH-type models. We set the maximum lag order in the GARCH-type part to 2 and consider (1,1), (1,2), (2,1) and (2,2) too as used in ARMA part. To compare ARMA(p,p) models and GARCH-type models, we use the Akaike Information Criterion (AIC) [Akaike, 1973], Schwarz Information Criterion (SIC) [Schwarz, 1978], Hannan-Quinn Criterion (HQC) [Hannan and Quinn, 1979], log-likelihood and R squared. The model which has smaller AIC, BIC and HQC value and the greater R squared and loglikelihood value is the better the model.

Table 3: Estimation results of the ARMA Models

Coefficient	ARMA (1,1)	ARMA (1,2)	ARMA (2,1)	ARMA (2,2)
intercept	0.000417	0.000417	0.000412	0.000414
AR(1)	0.014048	-0.40397	0.500484	-0.36794***
AR(2)	-	-	-0.05005	-0.68256***
MA(1)	0.06824	0.486967	-	0.43619***
MA (2)		0.04123	-	0.716625***
R^2	0.00673	0.006829	0.006969	**0.009398**
AIC	-5.2663	-5.26563	-5.26547	**-5.26715**
SIC	-5.25954	-5.25662	-5.25646	**-5.25589**
HQC	-5.26385	-5.26236	-5.26221	**-5.26307**
Loglikelihood	6862.349	6862.478	6859.645	**6862.833**
ARCH (1)	302.4293***	304.0687***	300.4242***	297.6099***
ARCH(5)	361.9099***	363.0508***	359.8138***	357.2484***

Notes: The bold fonts show the selected criteria. *, ** and *** indicate statistical significance at the 10, 5 and 1% levels, respectively

Source: Authors calculation

Table 3 shows the results of ARMA(p,q) models. All criteria indicate that the ARMA(2,2) is the best model, also only this model has significant coefficients. In the second step, we estimate a set of GARCH-type processes with a generalized error distribution using GARCH, EGARCH, TARCH and PARCH models with ARMA(2,2) process in mean equation.

Table 4: Estimation results of the GARCH Type Models

Coefficient	GARCH (1,1)	GARCH (1,2)	GARCH (2,1)	GARCH (2,2)	EGARCH (1,1)	EGARCH (1,2)	EGARCH (2,1)	EGARCH (2,2)
ω	5.74E-06***	7.15E-06***	2.83E-06***	1.27E-06***	-0.6169***	-0.6795***	-0.4672***	-0.3190***
$\alpha 1$	0.180984***	0.2352***	0.3075***	0.3024***	0.3491***	0.4249***	0.4788***	0.4883***
$\alpha 2$			-0.2130***	-0.2577***			-0.2091***	-0.2816***

γ1					-0.0365**	-0.0500**	-0.0439	-0.0488
γ2							0.0176	0.0304
β1	0.813674***	0.2668***	0.9002***	1.2654***	0.9583***	0.4127***	0.9693***	1.0315
β2		0.4889***		-0.3125****		0.5451***		-0.0506***
V	1.2520***	1.2610***	1.2703***	1.2776***	1.2679***	1.2854***	1.3118***	1.2789***
R^2	0.0077	0.0076	0.0076	0.0076	0.0079	0.0076	0.0076	0.0075
AIC	-5.7705	-5.7750	-5.7800	-5.7826	-5.7716	-5.7809	-5.7783	-5.7792
SIC	-5.7503	-5.7525	-5.7575	**-5.7578**	-5.7491	-5.7561	-5.7513	-5.7500
HQC	-5.7632	-5.7669	-5.7719	-5.7736	-5.7635	-5.7719	-5.7685	-5.7686
Logl.	7522.264	7529.0810	7535.5840	7539.9270	7524.6460	7537.7430	7535.3800	7537.5710
ARCH(5)	6.5621	3.1579	2.3140	1.7614	7.2362	3.3227	2.4836	3.5863
	TARCH (1,1)	TARCH (1,2)	TARCH (2,1)	TARCH (2,2)	PARCH (1,1)	PARCH (1,2)	PARCH (2,1)	PARCH (2,2)
ω	6.73E-06***	7.95E-06***	2.99E-06***	1.15E-06**	8.93E-05***	0.0001	2.84E-05	3.61E-06
α1	0.1601***	0.2102***	0.3008***	0.2877***	0.1944***	0.2476***	0.2996***	0.2856***
α2			-0.2092***	-0.2460			0.1010	0.1485**
γ1	0.0576*	0.0592	0.0098***	-0.0012***	0.0921**	0.0899*	-0.1974***	-0.2476***
γ2							0.1264	0.1734***
β1	0.8005***	0.2665**	0.8976***	1.2956***	0.8162***	0.2827**	0.9030***	1.3499***
β2		0.4809***		-0.3392***		0.4843***		-0.3862***
δ					1.4121***	1.3828***	1.4957***	1.7051***
V	1.2731***	1.27E-06***	1.2704***	1.2867***	1.2589***	1.2680***	1.2753	1.2872***
R^2	0.0078	0.0078	0.0077	0.0078	**0.0079**	0.0078	0.0077	0.0078
AIC	-5.7697	-5.7751	-5.7794	**-5.7840**	-5.7719	-5.7767	-5.7799	-5.7836
SIC	-5.7471	-5.7503	-5.7546	-5.7569	-5.7471	-5.7497	-5.7506	-5.7521
HQC	-5.7615	-5.7661	-5.7704	**-5.7742**	-5.7629	-5.7669	-5.7693	-5.7722
Logl.	7522.0990	7530.1880	7535.7360	7542.7370	7526.0450	7533.2400	7538.4340	**7544.2610**
ARCH(5)	4.6202	2.5684	2.0927	1.4294	7.2958	3.5841	2.8717	2.3598

Notes: The bold fonts show the selected criteria. *, ** and *** indicate statistical significance at the 10, 5 and 1% levels, respectively. v shows GED parameter. If GED parameter equals two it means normal distribution if it is less than two it means leptokurtic distribution. δ is the power of the conditional standard deviation process.

Source: Authors calculation

Table 4 shows the results of the GARCH-type models. Before interpretation of the models significance conditions for estimated parameters must be held. In this step we aim to choose best model, for this reasons we are not going to examine these conditions and only the results of criteria is going to compare. The best model for AIC and HQC is TARCH(2,2). SIC concluded that the ARCH(2,2) model is the best. PARCH (1,1) and PARCH(2,2) was selected from R squared and Loglikelihood criterion respectively. Although TARCH(2,2) model was selected by two criteria, according to the five criteria none of model has strong dominance to other.

The GARCH-type models can be compared by their forecasting performance by using forecasting error criteria. In this paper we compare estimated variance for all models for 1/03/2014-6/10/2014 in sample period using static forecast. We select the period to show 2014 year's data. Four criteria are used to evaluate the forecast accuracy for the sample namely, Mean Square Error (MSE) and Mean Absolute Error (MAE):

$$MSE_1 = n^{-1}\sum_{t-1}^{n}\left(\sigma_t^2 - \hat{\sigma}_t^2\right)^2$$

(10)

$$MSE_2 = n^{-1}\sum_{t-1}^{n}\left(\sigma_t - \hat{\sigma}_t\right)^2$$

(11)

$$MAE_1 = n^{-1}\sum_{t-1}^{n}\left|\sigma_t^2 - \hat{\sigma}_t^2\right|$$

(12)

$$MAE_2 = n^{-1} \sum_{t-1}^{n} |\sigma_t - \hat{\sigma}_t|$$

(13)

where, n is the number of forecasts, σ_t^2 is the actual volatility and $\hat{\sigma}_t^2$ is the volatility forecast at day t.

Table 5: Comparison Forecasting Performance of GARCH-type Models

Coefficient	GARCH (1,1)	GARCH (1,2)	GARCH (2,1)	GARCH (2,2)	EGARCH (1,1)	EGARCH (1,2)	EGARCH (2,1)	EGARCH (2,2)
MSE1	2.75348E-08	2.64013E-08	2.65268E-08	2.68233E-08	2.73202E-08	**2.51014E-08**	2.61637E-08	2.60132E-08
MSE2	4.70024E-05	4.51454E-05	4.46425E-05	4.44975E-05	4.62145E-05	**4.17345E-05**	4.34523E-05	4.18254E-05
MAE1	8.84287E-05	8.67443E-05	8.53613E-05	8.50496E-05	8.63471E-05	8.0017E-05	8.33985E-05	8.10262E-05
MAE2	0.005685322	0.00561891	0.005553817	0.005518952	0.005564041	0.00532046	0.005431897	**0.005312196**
	TARCH (1,1)	TARCH (1,2)	TARCH (2,1)	TARCH (2,2)	PARCH (1,1)	PARCH (1,2)	PARCH (2,1)	PARCH (2,2)
MSE1	2.81852E-08	2.66746E-08	4.81601E-08	2.66245E-08	2.70041E-08	2.5839E-08	2.60592E-08	2.66318E-08
MSE2	4.84847E-05	4.51144E-05	4.51144E-05	4.43071E-05	4.62548E-05	4.42667E-05	4.35832E-05	4.30049E-05
MAE1	9.09225E-05	8.60816E-05	8.60816E-05	8.47503E-05	**5.75549E-07**	8.43061E-05	8.31733E-05	8.24342E-05
MAE2	0.005777002	0.005585907	0.005585907	0.005518374	0.00560942	0.005523667	0.005457809	0.00537086

Notes: The bold fonts show the selected criteria.

Source: Authors calculation

Table 5 reports the forecasting performance of the GARCH, EGARCH, TARCH and PARCH models. The BET volatility forecasts obtained from EGARCH(1,2) model have the greatest forecasting accuracy under MSE1 and MSE2. EGARCH(2,2) and PARCH(1,1) have greatest forecast models for BET under MAE2 and MAE1 respectively. That is, EGARCH model is a better choice than the other models in terms of BET volatility forecasting.

As it stated above significance conditions for estimated parameters must be examined. The results of the selected model which is EGARCH(1,2) is below:

$$\ln(\sigma_t^2) = -0.6795 + 0.4249 \left|\frac{\varepsilon_{t-i}}{\sigma_{t-i}}\right| - 0.0500 \frac{\varepsilon_{t-i}}{\sigma_{t-i}} + 0.4127 \ln(\sigma_{t-i}^2) + 0.5451 \ln(\sigma_{t-i}^2)$$

Except the coefficient of leverage effect is significant in 5% level rest of the coefficients are statistically significant in 1% level (Table 4). The leverage effect is negative and significant means that leverage effect bad news increase volatility in Bucharest Stock Exchange Trading Index (BET).

1. Conclusion

The first aim of the paper is to estimate the volatility model of Bucharest Exchange Trading Index (BET) by using GARCH, EGARCH, TARCH and PARCH models. The second aim is to compare forecasting performance of the used GARCH-type models to find best model for the return of the BET.

The empirical application was started with investigating excess of kurtosis, negative skewness and normality of distribution of the return series. Before the GARCH-type models were selected the ARMA models estimated to modelling the mean side of the series using several criteria. We compared the forecasting performance of several GARCH-type models using GED distribution for BET. We found that the EGARCH(1,2) model is the most promising for characterizing the behaviour of the return of BET. In other words EGARCH model might be more useful than the other models which are used in this paper for Bucharest Exchange Trading Index returns.

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Appendix

Included observations: 2604

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.016	0.016	0.6755	0.411
		2	0.002	0.001	0.6815	0.711
		3	0.000	0.000	0.6817	0.877
		4	-0.008	-0.008	0.8414	0.933
		5	0.021	0.021	1.9812	0.852
		6	-0.009	-0.009	2.1811	0.902
		7	0.006	0.007	2.2905	0.942
		8	0.056	0.055	10.384	0.239
		9	0.025	0.024	12.070	0.209
		10	-0.007	-0.009	12.214	0.271
		11	0.058	0.059	21.077	0.033
		12	0.006	0.005	21.165	0.048
		13	0.025	0.023	22.792	0.044
		14	0.046	0.046	28.394	0.013
		15	0.039	0.040	32.474	0.006
		16	0.013	0.006	32.915	0.008
		17	0.029	0.028	35.068	0.006
		18	-0.016	-0.017	35.730	0.008
		19	0.053	0.047	43.064	0.001
		20	-0.009	-0.014	43.256	0.002
		21	0.012	0.011	43.610	0.003
		22	-0.024	-0.035	45.110	0.003
		23	0.017	0.013	45.835	0.003
		24	-0.017	-0.026	46.609	0.004
		25	0.009	0.004	46.823	0.005
		26	0.012	0.004	47.191	0.007
		27	0.008	0.002	47.344	0.009
		28	0.020	0.009	48.410	0.010
		29	0.052	0.052	55.484	0.002
		30	-0.010	-0.020	55.749	0.003
		31	0.012	0.012	56.132	0.004
		32	0.019	0.016	57.059	0.004
		33	-0.024	-0.023	58.535	0.004
		34	0.020	0.012	59.563	0.004