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Evaluating the Forecasting Performance of GARCH Models. Evidence from Romania

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Abstract

Modeling and forecasting the volatility of stock markets has been one of the major topics in financial econometrics in the last years. The aim of the study is to evaluate the forecasting performance of GARCH-type models in terms of their in-sample and out-of-sample forecasting accuracy in the case of Romanian stock market. We use daily stock index return data from Romania (BET index) covering the period 09/03/2001 to 02/29/2012.We find that the TGARCH model is the most successful in forecasting the volatility of BET index. Our results have important significance in the calculation of Value-at-Risk (VaR) and in risk management process.

Keywords: Volatility modelling; volatility forecasting; GARCH model; Romanian stock market; Value-at-Risk;

1. Introduction

Modeling and forecasting financial markets volatility have been an important empirical and theoretical research topic in the last three decades. The main reasons for such intense concern are the facts that volatility is one of the features of today financial markets and the forecast of volatiliy has numerous application in the field of finance, i.e., risk management (Value-at-risk, hedging), portfolio management, option pricing, capital asset pricing, and monetary policy making. As a result, there are numerous articles and working papers that study forecasting performance of various volatility models.

The aim of this paper is to evaluate the forecasting performance of various GARCH models using data for BET (Bucharest Exchange Trading) index covering the period 09/03/2001 to 02/29/2012. Comparing with other papers, we employed a wider selection of GARCH models, three error distribution assumptions, and a longer period of time.

The rest of the paper is organized as follows. In the next section a review of the existing literature is provided. In section three, an explanation of the data and models used is given. Section four discusses the empirical findings and section five concludes the paper.

2. Literature review

ARCH(Autoregressive Conditional Heteroskedasticity) and Generalized ARCH (GARCH) models have emerged as the most proeminent tools for estimating volatility, because they are adequate to capture the random movement of

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the financial data series. Many researchers have studied over time the performance of GARCH models on explaining volatility of mature stock markets, but only a few have tested GARCH models using daily data from Central and Eastern European stock markets (see, for example, Kash-Haroutounian and Price, 2001; Poshakwale and Murinde, 2001; Murinde and Poshakwale, 2002; Patev and Kanaryan, 2006; Lupu and Lupu, 2007; Miron and Tudor, 2010; Harisson and Moore, 2011; Kovačić, 2011). The focus of our paper is on forecasting stock market volatility in Romania, a market which has not been thoroughly investigated.

Several studies results have confirmed that asymmetric GARCH-models fit better stock markets returns volatility for emerging CEE countries. Lupu and Lupu (2007) found that an EGARCH (Exponential GARCH) model is suitable for the logarithmic returns of the Romanian composite index BET-C covering the period 03/01/2002-17/11/2005.Miron and Tudor (2010) employed different asymmetric GARCH-family models (EGARCH, PGARCH, and TGARCH) using U.S. and Romanian daily stock return data corresponding to the period 2002-2010. They found that volatility estimates given by the EGARCH model exhibit generally lower forecast error and are therefore more accurate than the estimates given by PGARCH and TGARCH models.

One of the latest paper (Harisson and Moore, 2011) has studied the stock market volatility in 10 stock exchanges in CEE countries (Bulgaria, Czech Republic, Estonia, Hungary, Latvia, Poland, Romania, Slovenia, and Slovak Republic) covering the period 1991-2008. Their results confirmed that models which allow for asymmetric volatility consistently outperform all other models considered.

3. Data and Methodology

The data consist of 2,737 daily observations of the BET index from the period 09/03/2001 to 02/29/2012. The series were obtained from *Datastream International*. The first part of the sample, consisting of 2519 observations (09/03/2001 to 04/29/2011), was used to calculate returns summary statistics and for estimation of GARCH models. The second part of the sample, consisting of 218 observations (05/02/2011 to 02/29/2012), was left for examination of the out-of-sample forecasting accuracy.BET index is a value-weighted index of the shares of the 10 companies with the highest market capitalization that are traded on Bucharest Stock Exchange. Daily returns are computed as logarithmic price relatives: $R_t = \ln (P_t/P_{t-1})$, where P_t is the daily price of the BET at time *t*.

ARCH models have their roots in a study by Robert Engle (1982) and have been generalized (GARCH - Generalized Autoregressive Conditional Heteroscedasticity) by Bollerslev (1986) and Taylor (1986), becoming extremely useful tools in applied financial econometrics. These models have been further extended in order to cover the asymmetric impact (or leverage effect) of returns on volatility and long memory property in the volatility. In order to capture the asymmetry of the volatility Nelson (1991) developed the exponential GARCH model (EGARCH). An overview of the GARCH models used in the analysis is presented in table 1 (See Poon & Granger (2003), Xiao & Aydemir (2007), and Andersen et al. (2006a,b) for an extensive review of volatility forecasting models developed in the last years). To perform a more thorough evaluation, the normal distribution function, the Student-t distribution function, andGeneralized Error Distribution (GED)were chosen as possibile distributions for the error terms.

Table 1. Overview of the GARCH-family models used

Model	Short Description	Formula
ExponentialGARCH (EGARCH)	Capture the asymmetry of the volatility	$log\sigma_t^2 = \omega + \alpha\left[\left\lvert\frac{\varepsilon_{t-1}}{\sigma_{t-1}}\right\rvert - E\left(\frac{\varepsilon_{t-1}}{\sigma_{t-1}}\right)\right] + \beta log\sigma_{t-1}^2 + \gamma\frac{\varepsilon_{t-1}}{\sigma_{t-1}}$
Power-GARCH (PGARCH)	Not only considers the asymmetric effect, but also provides another way to model the long memory property in the volatility	$\sigma_t^\delta = \omega + \alpha(\lvert\varepsilon_{t-1}\rvert + \gamma\varepsilon_{t-1})^\delta + \beta\sigma_{t-1}^\delta$
Integrated GARCH (IGARCH)	Any shock to volatility is permanent and the unconditional variance is infinite	$\sum_{i=1}^{p}\beta_i + \sum_{i=1}^{q}\alpha_i = 1$
Threshold-GARCH (TGARCH)	The asymmetric impact is incorporated into the GARCH framework by use of a dummy variable	$\sigma_t = \omega + \alpha\varepsilon_{t-1} + \beta\sigma_{t-1} + \gamma I_{t-1}\varepsilon_{t-1}$

Where $\delta>0$, $-1 < \gamma_i < 1$, α_i, β_i, γ, and ω are the parameters to be estimated.

The volatility was defined through the conditional mean and the conditional variance equations. A GARCH-M model is used to estimate the conditional mean, while for the conditional variance equation two symmetric models (GARCH and IGARCH) and three asymmetric models (TGARCH, EGARCH, and PGARCH) were tested.

4. Empirical results

Table 2 presents the main summary statistics and a few tests for the BET returns. The mean is close to zero and positive as is expected for a time series of return. We notice a large difference between the maximum and minimum return of the index. The skewness coefficient is negative for our time series, suggesting that it has a long left tail and that BET index has non-symmetric returns. The series also exhibits an excess kurtosis of 10.54, indicating that the returns are not normally distributed. The hypothesis that log returns are normally distributed is tested using the Jarque-Bera test statistic and the results confirm that the null hypothesis of normality is rejected at the significance level of 5%.

Table 2. Descriptive statistics, Normality tests, Autocorrelation Tests

Statistical analysis	Values
Mean	0.000804
Median	0.000338
Maximum	0.115445
Minimum	-0.131168
StdDev	0.017645
Skewness	-0.458519
Kurtosis	10.54251
JarqueBera value	6059.294
Probability of Jarque Bera test	0.000000

The sample has been tested for stationarity using the Augmented Dickey-Fuller Unit Root Test (Dickey & Fuller, 1979). The null hypothesis of a unit root is rejected (not presented here but available from the author upon request) and therefore the series is stationary. From the analysis we conclude that the sample has the characteristics of financial series (volatility clustering, leptokurtosis, heteroscedasticity in the residuals, and autocorrelation in the residuals) and we can employ GARCH-type models to model and forecast conditional volatility.

Table 3. Parameters estimates of GARCH models. Information criteria and log-likelihood function for GARCH models

Conditional Volatility Model	C (ω)	ARCH (-1) (α)	GARCH (-1) (β)	Leverage effects (γ_1)	AIC	SBC	Log-likelihood
GARCH	1.30E-05	0.194642	0.770926	-	-5.614760	-5.605500	7075.791
	(0.0000)	(0.0000)	(0.0000)				
EGARCH	-0.739459	0.293603	0.937481	-0.027356	-5.585180	-5.573605	7039.535
	(0.0000)	(0.0000)	(0.0000)	(0.0009)			
TGARCH	1.49E-05	0.163638	0.756344	0.075501(0.0001)	-5.617126	-5.605551	7079.770
	(0.0000)	(0.0000)	(0.0000)				
PGARCH(1,1,1)	0.001369	0.186794	0.774483	0.137289	-5.584294	-5.572719	7038.418
	(0.0000)	(0.0000)	(0.0000)	(0.0000)			
PGARCH(1,2,1)	1.48E-05	0.199470	0.756520	0.094316	-5.617114	-5.605539	7079.755
	(0.0000)	(0.0000)	(0.0000)	(0.0000)			
IGARCH	-	0.063134	0.936866	-	-5.569245	-5.564615	7016.464
		(0.0000)	(0.0000)				

Note: Numbers in parentheses are the p-values associated with the Student test

Table 3 reports the parameter estimates of all conditional volatility models employed in the analysis and information criteria and the log-likelihood function for the estimated GARCH models.The coefficients of all GARCH models are significant at all levels suggesting the strong validity of the models. With one exception (EGARCH), the sum of ARCH and GARCH coefficients is very close to one, indicating that volatility shocks are quite persistent, indicating that large changes in returns tend to be followed by large changes and small changes tend to be followed by small changes. For all asymmetric GARCH models, the coefficient γ is significantly different from zero implying that series are not symmetric and leverage effects are present. In three cases (TGARCH, PGARCH (1,1,1) and PGARCH (1,2,1)), the positive value of the coefficient γ indicates that "good news" increases the future volatility more than the "bad news".

The results presented in table 3 show that the model that obtained the lowest values for AIC and SBC, respectively the highest value for log-likelihood function is TGARCH, followed closely by PGARCH(1,2,1). These criteria reveal that TGARCH and PGARCH(1,2,1) models with normal distribution better estimate the series compared to the other models.

We re-estimate the TGARCH and the simple GARCH(1,1) models under the assumptions that residuals follow a Student distribution, respectively a GED distribution. Table 4 shows AIC, SBC and log-likelihood values for both models, confirming that volatility estimates given by TGARCH model with GED and Student distributions are more accurate than the estimates computed by the GARCH model.

Table 4. Information criteria and log-likelihood function for GARCH and TGARCH using Student and GED distributions

Model	Student Distribution			GED		
	AIC	SBC	Log-likelihood	AIC	SBC	Log-likelihood
GARCH (1,1)	-5.717744	-5.706169	7206.499	-5.720984	-5.709409	7210.579
TGARCH (1,1)	-5.719108	-5.705218	7209.217	-5.723518	-5.709628	7214.771

The forecasting accuracy of each model is measured with the root mean square error (RMSE), the mean absolute error (MAE), the mean absolute percentage error (MAPE), and Theil inequality coefficient (TIC). An extended review of forecast performance criteria can be found in Poon & Ganger (2003).

Table 5. Evaluation of out-of-sample volatility forecasts

Conditional Volatility Model	RMSE	MAE	MAPE	TIC
GARCH	0.014347	0.009664	136.7636	0.915590
EGARCH	0.014431	0.009773	156.5159	0.893616
TGARCH	0.014312	0.009623	126.5876	0.928989
PGARCH(1,1,1)	0.014416	0.009750	153.7237	0.899230
PGARCH(1,2,1)	0.014312	0.009623	126.6090	0.928958
IGARCH	0.014305	0.009648	129.6342	0.923239
GARCH_t	0.014325	0.009629	123.5612	0.927354
GARCH_GED	0.014260	0.009579	110.5784	0.953448
TGARCH_t	0.014304	0.009608	118.0937	0.935981
TGARCH_GED	0.014244	0.009566	105.9501	0.963441

Table 5 outlines the values of these forecasting accuracy criteria for the out-of-sample BET forecasts. At first sight we can conclude that the asymmetric models are better than symmetric models, but with little gain. Using a Gaussian error distribution the model that holds the best performance in 3 out of 4 criteria is TGARCH, followed closely by PGARCH (1,2,1). It can be observed that in the cases of GARCH and TGARCH models, using a Student and a GED error distribution the forecasts of the Romanian BET index perform better. However, since the out-of-sample forecast uses a small sample data, we cannot draw clear conclusions about the forecasting performance of the studied models.

5. Conclusions

Stock market volatility has numerous implications on the real economy. Changes in stock market volatility affects consumer spending (via the wealth effect), investors' willingness to hold risky assets, and corporations' investment decisions. Forecasting stock market is therefore crucial in many areas of finance such as option pricing, Value-at-Risk applications and portfolio selection.

This paper contributes to the existent literature through the expansion of the research concerning the estimation of stock market volatility using GARCH-type models and their forecasting performance in an emerging capital market from Europe.We findstrong evidence that daily returns can be characterised by the GARCH-type models.We compared the forecasting performance of several GARCH models (under different error distributions) in terms of sample fit and out-of-sample forecast ability. We find that TGARCH and PGARCH(1,2,1) are the most successful models according to information criteria (AIC and SBC) and log-likelihood function.

The GARCH models have been also evaluated based on their forecasting ability of the future returns. According to the results obtained for root mean square error (RMSE), mean absolute error (MAE), mean absolute percentage error (MAPE), and Their inequality coefficient (TIC) we conclude that TGARCH model is the most appropriate model for modelling the volatility of BET index.Our results are not consistent with the findings of Miron & Tudor (2010) and Lupu & Lupu (2007) for BET-C index from the Romanian stock market.

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