Journal of Applied Science and Agriculture, 9(2) February 2014, Pages: 566-571

AENSI Journals

Journal of Applied Science and Agriculture

ISSN 1816-9112

Journal home page: www.aensiweb.com/jasa/index.html

Modeling Tehran Stock Exchange Volatility; GARCH Approach

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ARTICLE INFO

Article history:
Received 23 December 2013
Received in revised form 25 February 2014
Accepted 26 February 2014
Available online 20 March 2014

Keywords:
GARCH Volatility
Forecast Tehran Stock Exchange

ABSTRACT

Background: The volatility of financial markets has been the object of numerous developments and applications over the past two decades, both theoretically and empirically. Portfolio managers, option traders and market makers all are interested in the possibility of forecasting volatility, with a reasonable level of accuracy. That is so important, in order to obtain either higher profits or less risky positions. **Objective:** we have compared different GARCH models with both Gaussian and fat-tailed conditional distribution for residuals in terms of their ability to describe and forecast volatility. **Results:** The best model based on MSE criteria is GARCH with normal distribution, second model is GARCH with t distribution and third model is EGARCH (1,1) with normal distribution. **Conclusion:** Results indicate that leverage effect exists in asymmetric models with normal distribution, but this effect does not exist in asymmetric models with t-student and GED distributions.

To Cite This Article: Esmaiel Abounoori, Zahra (Mila) Elmi, Younes Nademi., Modeling Tehran Stock Exchange Volatility; GARCH Approach. ***J. Appl. Sci. & Agric.,*** *9(2): 566-571, 2014*

INTRODUCTION

The volatility of financial markets has been the object of numerous developments and applications over the past two decades, both theoretically and empirically. Portfolio managers, option traders and market makers all are interested in the possibility of forecasting volatility, with a reasonable level of accuracy. That is so important, in order to obtain either higher profits or less risky positions. In this respect, the most widely used class of models is that of GARCH models (see e.g. Bollerslev, Engle, and Nelson (1994) for an overview). Tehran Stock Exchange (TSE) opened officially in February 1967 with only six listed companies compared to the 420 companies that individual and institutional investor trade today. The first ten years of the TSE was marked by a brisk activity where capitalization rose from IRR 6.2 billion to IRR 240 billion and the listed companies grew to 105. After 1978, the Islamic revolution and Iraq's invasion to Iran reduced exchange activities significantly and capitalization fell again to IRR 9.9 billion in 1982. After the Iraq-Iran war ended, the TSE was perceived as one of the most important mechanisms to foster economic development by channeling savings into investment. This goal quickly accelerated the number of listed companies from 56 in 1988 to 422 in 2006 [www. Tse.ir]. Over the past several decades the evidence for predictability has led to variety of approaches. The most interesting of these approaches are the “asymmetric” or “leverage” volatility models, in which good news and bad news have different predictability for future volatility (see, for example, Black, 1976, Nelson, 1991, Pagan and Schwert, 1990, Campbell and Hertschel, 1992, Henry, 1998, and Friedmann, Sanddorf-Köhle, 2002). In most these studies researchers have documented strong evidence that volatility is asymmetric in equity markets: negative returns are generally associated with upward revisions of the conditional volatility while positive returns are associated with smaller upward or even downward revisions of the conditional volatility (see, for example, Cox and Ross, 1976, Engle and Ng, 1993, Henry, 1998,). Researchers (see Black, 1976 and Schwert, 1989) believe that the asymmetry could be due to changes in leverage in response to changes in the value of equity. Others have argued that the asymmetry could arise from the feedback from volatility to stock price when changes in volatility induce changes in risk premiums (see Pindyck, 1984, French et al., 1987, Campbell and Hentschel, 1992, and Wu, 2001). The presence of asymmetric volatility is most apparent during a market crisis when large declines in stock prices are associated with a significant increase in market volatility. Asymmetric volatility can potentially explain the negative skewness in stock return data, as discussed in Harvey and Siddique (1999). There is no general agreement as to how the predictability should be modeled and, in particular how to condition such models for asymmetric nature of the stock return volatility. In this paper we have compared the performance of GARCH, TARCH, EGARCH, component ARCH (CARCH)

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and PARCH fitted to daily Tehran Stock Exchange (TSE) returns and test whether asymmetry is present. This paper is organized as follows. In section II of this paper various models of stock return volatility, both symmetric and asymmetric are outlined. Section III describes the data. Section IV presents empirical results. The final section provides a brief summary and conclusion.

Methodology:

Let R_t be the rate of return of a stock, or a portfolio of stocks from time $t-1$ to t and Ω_{t-1} be the past Information set containing the Realized value of all relevant variables up to time $t-1$. So the conditional mean and variance are $y_t = E(R_t|\Omega_t), h_t = \mathrm{var}(R_t|\Omega_t)$ respectively. Given this definition, the unexpected return at time t is $\varepsilon_t = R_t - y_t$. In order to model the effect of ε_t on returns we present ARCH models. ARCH models were Introduced by Engle (1982) and generalized as GARCH models by Bollerslev (1986). In developing GARCH (p, q) we will have to provide mean and variance Equation

$$R_t = x_t'\gamma + \varepsilon_t \tag{1}$$

$$h_t = \omega + \sum_{i=1}^{p} \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^{q} \beta_j h_{t-j} \tag{2}$$

where ω, α_i, β_j, γ are constant parameters and x_t contains exogenous and predetermined regressors. As h_t is variance it must be nonnegative which impose the following conditions: $\omega > 0$, $\alpha_1,.......\alpha_p \geq 0$ and $\beta_1,.........,\beta_q \geq 0$. The conditional variance under ARCH (p) model reflects only information from time $t-p$ to $t-1$ with more importance being placed on the most recent innovation implying $a_i < a_j$ for $i > j$. To avoid long lag lengths on ε_t in ARCH (p) and difficulty in selecting the optional length p, and ensuring the non-negativity of coefficients of conditional variance equation (2) , Bollerslev (1986) present GARCH(P, q). A common parameterization for the GARCH model that has been adopted in most applied studies is the GARCH (1, 1) specification under which the effect of a shock to volatility declines geometrically over time. One problem with ARCH (p) and GARCH (p, q) is that good news and bad news with some absolute size have the same effect on h_t. This fact is symmetric effect. However, the market may react differently to good and bad news. It is important, to be able to test for and allow asymmetry in the ARCH type specification. Nelson (1991) proposes the exponential GARCH (EGARCH) model as a way to deal whit this problem. Under the EGARCH (1, 1) the h_t is given as:

$$\log(h_1) = \omega + \alpha\left[\left|\frac{\varepsilon_{t-1}}{\sqrt{h_{t-1}}}\right| - \sqrt{2/\pi}\right] + \beta \log h_{t-1} + \gamma \frac{\varepsilon_{t-1}}{\sqrt{h_{t-1}}} \tag{3}$$

The EGARCH news Impact differs from the GARCH new Impact in four ways: (1) it is not symmetric. (2) Big news can have a much greater impact than in the GARCH model. (3) Log construction of Equation 3 ensures that the estimated h_t is strictly positive, thus non-negativity constraints used in the estimation of the ARCH and GARCH are not necessary. (4) Since the parameter of γ typically enters equation 3 with a negative sign, bad news generates more volatility than good news. The Component GARCH (CGARCH) model by Engle and Lee (1993) decomposes returns uncertainty into a short-run and a long-run component by permitting transitory deviations of the conditional volatility around a time-varying trend, q_t, modeled as:

$$\sigma_t^2 - q_t = a(\varepsilon_{t-1}^2 - q_{t-1}) + \beta(\sigma_{t-1}^2 - q_{t-1}) \tag{4}$$

$$q_t = \omega + \rho(q_{t-1} - \omega) + \phi(\varepsilon_{t-1}^2 - \sigma_{t-1}^2) \tag{5}$$

Here σ_t^2 is still the volatility, while q_t takes the place of ω and is the time varying long run volatility. The first equation describes the transitory component, $\sigma_t^2 - q_t$ which converges to zero with powers of ($\alpha + \beta$). The second equation describes the long run component q_t, which converges to ω with powers of ρ. Typically ρ is between 0.99 and 1 so that q_t approaches ω very slowly. We can combine the transitory and permanent equations and write

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$$\sigma_t^2 = (1-\alpha-\beta)(1-\rho)\omega + (\alpha+\phi)\varepsilon_{t-1}^2 - (\alpha\rho + (\alpha+\beta)\phi)\varepsilon_{t-1}^2 + \beta - \phi)\sigma_{t-1}^2 - (\beta\rho - (\alpha+\beta)\phi)\sigma_{t-2}^2 \quad (6)$$

which shows that the component model is a (nonlinear) restricted GARCH (2, 2) model. In addition, GARCH(1, 1) is a special case of the CARCH in which $\alpha = \beta = 0$. We can include exogenous variables in the conditional variance equation of component models, either in the permanent or transitory equation (or both). The variables in the transitory equation will have an impact on the short run movements in volatility, while the variables in the permanent equation will affect the long run levels of volatility. The asymmetric component combines the component model with the asymmetric TARCH model. This specification introduces asymmetric effects in the transitory equation and estimates models of the form:

$$R_t = x_t'\pi + \varepsilon_t \quad (7)$$

$$q_t = \omega + \rho(q_{t-1} - \omega) + \phi(\varepsilon_{t-1}^2 - \sigma_{t-1}^2) + \theta_1 z_{1t} n \quad (8)$$

$$\sigma_t^2 - q_{t-1} = \alpha(\varepsilon_{t-1}^2 - q_{t-1}) + \gamma(\varepsilon_{t-1}^2 - q_{t-1})d_{t-1} + \beta(\sigma_{t-1}^2 - q_{t-1}) + \beta(\sigma_{t-1}^2 - q_{t-1}) + \theta_2 z_{2t} \quad (11)$$

Where z are the exogenous variables and d is the dummy variable indicating negative shocks. $\gamma > 0$ indicates the presence of transitory leverage effects in the conditional variance. Suppose information is held constant at time $t-2$ and before, Engle and Ng (1993) describe the relationship between ε_{t-1} and h_t as the news impact curve. The news impact curves of GARCH and CGARCH models are symmetric and centered at $\varepsilon_{t-1} = 0$. The news impact curves of EGARCH and TARCH are asymmetric with different slopes.

To estimate the model, we follow the quasi-maximum likelihood. Both the conditional mean and the conditional variance are estimated jointly by maximizing the log-likelihood function which is computed as the logarithm of the product of the conditional densities of the prediction errors. The ML estimates are obtained by maximizing the log-likelihood with the Broyden, Fletcher, Goldfarb, and Shanno (BFGS) quasi-Newton optimization algorithm in the MATLAB numerical optimization routines.

Forecast evaluation is a key step in any forecasting exercise. A popular metric to evaluate different forecast models is given by the minimization of a particular statistical loss function. However, the evaluation of the quality of competing volatility models can be very difficult because, as remarked by both Bollerslev, Engle and Nelson (1994) and Lopez (2001), there does not exist a unique criterion capable of selecting the best model. Thus, even though rather criticizable, so far most of the literature has focused on a particular statistical loss function, the Mean Squared Error (MSE). In this paper we have used MSE criterion for evaluation of competing volatility models. This loss function is:

$$MSE = n^{-1}\sum_{t=1}^{n}\left(\hat{\sigma}_{t+1}^2 - \hat{h}_{t+1|t}\right)^2 \quad (24)$$

where $\hat{\sigma}_{t+1}^2$ is the actual volatility that we have used the squared return for the measure of daily volatility and $\hat{h}_{t+1|t}$ is the forecasted volatility based on period of forecasting.

Data:

The sample is 2567 observations (from 9/29/1997 to 11/27/2008) are used as the in-sample for estimation purposes. The return is calculated as $r_t = 100 \quad [\log(\frac{p_t}{p_{t-1}})]$ where P_t is the value of index at time t. Table 1 shows some descriptive statistics of the TSM rate of return. The mean is quite small and the standard deviation is around 0.3 .The kurtosis is significantly higher than the normal value of 3 indicating that fat-tailed distribution are necessary to correctly describe conditional distribution of r_t. the skewness is significant, small and negative, showing that the lower tail of empirical distribution of the return is longer than the upper tail, that is negative returns are more likely to be far below the mean than their counterparts.

Table 1: Descriptive Statistics r_t

Mean	Standard Deviation	Min	Max	Sk	Ku	$B-J$	$Q^2(12)$	LM(12)
0.0248	0.2910	-5.45	4.83	-0.68	71.75	654376.1	182.89	77.05
p-value:						[0.000]	[0.000]	[0.00]

Note: Sk and Ku are skewness and excess kurtosis. B-J is the Bera-Jarque test for normality distributed as $\chi^2(2)$. The $Q^2(12)$ statistic is the Ljung-Box test on the squared residuals of the conditional mean regression up to the twelfth order. for serial correlation in the squared return data, distributed as $\chi^2(12)$.

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LM(12) statistic is the ARCH LM test up to twelfth lag and under the null hypothesis of no ARCH effects it has a $\chi^2(q)$ distribution, where q is the number of lags. LM (12) is the Lagrange Multiplier test for ARCH effects in the OLS residuals from the regression of the returns on a constant, while $Q^2(12)$ is the corresponding Ljung-Box statistic on the squared standardized residuals. Both these statistic are highly significant suggestion the presence of ARCH effects in the TSM returns up to the twelfth order.

Results:

The parameter estimates for the different state GARCH(1,1) models with normal, t-student and GED distributions are presented respectively in Tables 2, 3 and 4. The first 2567 observations (from 9/29/1997 to 11/27/2008) are used as the in-sample for estimation purposes. Regarding the conditional mean, all the parameters for the various GARCH models are significant. The conditional variance estimates show that almost all the parameters are highly significant. Hence GARCH models perform quite well at least in sample.

Table 2: Maximum Likelihood Estimates of standard GARCH Models with Normal conditional distribution.

	GARCH	TARCH	EGARCH	CGARCH	PARCH
δ	0.0218	0.0217	0.0284	0.0208	0.0217
p-value	0.0	0.0	0.0	0.0	0.0
ω	0.0005	0.0005	-0.213	1.14	0.0005
p-value	0.0	0.0	0.0	0.0	0.0
α	0.1403	0.139	0.246	0.228	0.1402
p-value	0.0	0.0	0.0	0.0	0.0
β	0.878	0.878	0.983	0.765	0.878
p-value	0.0	0.0	0.0	0.0	0.0
γ	-	0.0001	-0.0194	-	0.0018
p-value	-	0.82	0.0	-	0.87
ρ	-	-	-	0.999	2.004
p-value	-	-	-	0.0	0.0
ϕ	-	-	-	-0.026	-
p-value	-	-	-	0.0	-
ν	-	-	-	-	-
p-value	-	-	-	-	-
Log likelihood	-642.1511	-642.1569	-620.1886	-744.0507	-642.1572

Table 3: Maximum Likelihood Estimates of standard GARCH Models with t-student conditional distribution.

	GARCH	TARCH	EGARCH	CGARCH	PARCH
δ	0.0141	0.0122	0.0121	0.0126	0.0128
p-value	0.0	0.0	0.0	0.0	0.0
ω	0.0006	0.0002	-0.158	1.061	0.0026
p-value	0.0	0.0	0.0	0.74	0.02
α	0.652	0.464	0.216	0.438	0.166
p-value	0.0	0.0	0.0	0.0	0.0
β	0.650	0.768	0.995	0.118	0.882
p-value	0.0	0.0	0.0	0.0	0.0
γ	-	-0.149	0.029	-	-0.058
p-value	-	0.0	0.0	-	0.08
ρ	-	-	-	0.999	0.624
p-value	-	-	-	0.0	0.0
ϕ	-	-	-	0.077	-
p-value	-	-	-	0.0	-
ν	3.03	3.09	3.13	4.28	3.015
p-value	0.0	0.0	0.0	0.0	0.0
Log likelihood	-1183.607	-1190.149	-1239.579	-1256.147	-1265.459

Table 4: Maximum Likelihood Estimates of standard GARCH Models with GED conditional distribution.

	GARCH	TARCH	EGARCH	CGARCH	PARCH
δ	0.0146	0.0127	0.0149	0.0134	0.0246
p-value	0.0	0.0	0.0	0.0	0.0
ω	0.0002	0.0002	-0.212	0.381	0.0048

p-value	0.0	0.0	0.0	0.0	0.0
α	0.177	0.1966	0.240	0.428	0.1597
p-value	0.0	0.0	0.0	0.0	0.0
β	0.855	0.863	0.986	0.256	0.875
p-value	0.0	0.0	0.05	0.0	0.0
γ	-	-0.061	0.0148	-	-0.030
p-value	-	0.0	0.05	-	0.38
ρ	-	-	-	0.999	0.731
p-value	-	-	-	0.0	0.0
ϕ	-	-	-	0.0309	-
p-value	-	-	-	0.0	-
ν	0.93	0.927	0.923	1.007	0.908
p-value	0.0	0.0	0.0	0.0	0.0
Log likelihood	-1118.336	-1124.019	-1150.061	-1172.739	-1160.197

Based on the “asymmetric” or “leverage” volatility models, in which good news and bad news have different predictability for future volatility. In most these studies researchers have documented strong evidence that volatility is asymmetric in equity markets: negative returns are generally associated with upward revisions of the conditional volatility while positive returns are associated with smaller upward or even downward revisions of the conditional volatility. In this paper, results indicate that leverage effect exists in asymmetric models with normal distribution, but this effect does not exist in asymmetric models with t-student and GED distributions. Since the main focus is on the predictive ability, we only present MSE criteria in Table 6, without doing any formal test.

Table 6: In sample goodness-of-fit statistics.

Model	N. of Par.	MSE	Rank
GARCH-N	4	0.006405	1
GARCH-t	5	0.007291	2
GARCH-GED	5	0.013143	10
EGARCH-N	5	0.007356	3
EGARCH-t	6	0.013872	12
EGARCH-GED	6	0.0081714	4
TARCH-N	5	0.010972	6
TARCH-t	6	0.03678	15
TARCH-GED	6	0.01493	13
CGARCH-N	6	0.010638	5
CGARCH-t	7	0.013746	11
CGARCH-GED	7	0.012271	9
PARCH-N	6	0.010983	7
PARCH-t	7	0.02254	14
PARCH-GED	7	0.011607	8

The best model based on MSE criteria is GARCH with normal distribution, second model is GARCH with t distribution and third model is EGARCH (1,1) with normal distribution.

Conclusion:

In this paper we have compared a set of standard GARCH models in terms of their ability to forecast Tehran stock market volatility. The standard GARCH models considered are the GARCH(1,1), EGARCH(1,1), TARCH(1,1), PARCH(1,1) and CGARCH(1,1). In addition, all models are estimated assuming both Gaussian innovations and fat-tailed distributions, such as the Student’s t and the GED. Results indicate that leverage effect exists in asymmetric models with normal distribution, but this effect does not exist in asymmetric models with t-student and GED distributions. The main goal is to evaluate performance of different GARCH models in terms of their ability to characterize and predict out-of-sample the volatility of TSE. I have used the squared return for the measure of real volatility. The forecasting performances of each model are measured using MSE. Overall, the empirical results show that The best model based on MSE criteria is GARCH with normal distribution, second model is GARCH with t distribution and third model is EGARCH (1,1) with normal distribution

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