J. Basic. Appl. Sci. Res., 2(1)150-155, 2012

ISSN 2090-4304
Journal of Basic and Applied Scientific Research
www.textroad.com

Forecasting Volatility in Tehran Stock Market with GARCH Models

Mehdi Parvaresh[1,*] ,Morteza Bavaghar[2]

[1,2] Department of Accounting, Roodan Branch, Islamic Azad University, Roodan, Iran

ABSTRACT

The aim of this paper is Forecasting Volatility in Tehran Stock Market with GARCH Models. The data consist of 1884 daily observations of the closing value of the Tehran stock market from 9/28/1997 to 8/20/2010. The sample is divided in two parts. The first 2800 observations (from 9/28/1997 to 8/20/2009) are used as the in-sample for estimation purposes, while the remaining 315 observations (from 8/21/2009 to 8/20/2010) are taken as the out-of-sample for forecast evaluation purposes. The estimation and test results for models suggest that the leverage effect term, , is significant in EGARCH model(even with a one-sided test). So there does appear to be an asymmetric effect in Tehran stock market. In addition Evaluation forecasting with MSE criteria indicate that GARCH models in this paper have a same forecasting power, but when Log-Likelihood is evaluation criteria, CGARCH has the best forecasting power.

KEY WORDS: Forecasting, Volatility, Tehran Stock Market, GARCH Models.

1. INTRODUCTION

The ability to forecast financial market volatility is important for portfolio selection, valuation of stocks, asset management, predictability of risk premiums and designing optimal dynamic hedging strategies for options and Futures. While most researchers agree that volatility is predictable in many asset markets (see for example the survey by Bollerslev et al.,1992, 1994), they differ on how this volatility predictability should be modeled. 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, Christle, 1972, Nelson, 1991, Pagan and Schwert, 1990, Sentena, 1992, Campbell and Hertschel, 1992, Engle, 1993, 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 Christie, 1982, 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 compare the performance of GARCH, TARCH, EGARCH and component ARCH (CARCH) fitted to daily Tehran Stock Market (TSM) returns and test whether asymmetry is present. There are not any studies which focus explicitly on modeling the volatility in the TSM. 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 and estimates of the relationship between news and volatility for the candidate models. The final section provides a brief summary and conclusion.

2. *Modeling volatility*

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

***Corresponding Author:** Mehdi Parvaresh, Postal address: Parvaresh alley, Daroopakhsh street, Bandarabbas, Iran, Postal code: 7915873389, Telephone: 00987616667232, Fax:00987664221110 E-mail: parvaresh2009@gmail.com,

variance are $y_t = E(R_t|\Omega_t), h_t = \text{var}(R_t|\Omega_t)$ respectively. Given this definition, the unexpected return at time t is $\varepsilon_t = R_t - y_t$. This paper follows Engle and Ng (1993) in treating ε_t as a collective measure of bad news (unexpected decrease in returns) if $\varepsilon_t < 0$ and good news (unexpected increase in price) if $\varepsilon_t \geq 0$. Further, a large value of $|\varepsilon_t|$ implies that the news is "significant" or "big" in the sense that it produce a large unexpected change in returns.

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

$$R_t = \delta + \varepsilon_t, \varepsilon_t = \eta_t\sqrt{h_t}, \quad \eta_t \sim N(0,1) \tag{1}$$

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

where $\omega,\ \alpha_i,\ \beta_j,\ \gamma$ 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: $\omega > 0$, $\alpha_1, \ldots\ldots \alpha_p \geq 0$ and $\beta_1, \ldots\ldots, \beta_q \geq 0$. 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.

Glosten, jagannathan and Runkle (1993), hereafter GJR, Defined GJR Asymmetric Volatility model as follow:

$$h_t = \omega + \alpha\varepsilon_{t-1}^2 + \beta h_{t-1} + \gamma s_{t-1}^- \varepsilon_{t-1}^2 \tag{4}$$

Where $s_t^- = 1$ if $\varepsilon_t < 0$, and 0 otherwise.

The GJR model is closely related to the threshold ARCH or TARCH model of Rabemananjara and Zakoian (1993) and Zakoian (1994). Providedthat $\gamma > 0$, the GJR model generates higher values for h_t given $\varepsilon_{t-1} < 0$ than for a $\varepsilon_t > 0$ of equal magnitudes.

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:

$$\sigma_t^2 - q_t = a(\varepsilon_{t-1}^2 - q_{t-1}) + \beta(\sigma_{t-1}^2 - q_{t-1}) \quad (5)$$

$$q_1 = \omega + \rho(q_{t-1} - \omega) + \phi(\varepsilon_{t-1}^2 - \sigma_{t-1}^2) \quad (6)$$

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

$$\sigma_t^2 = (1-\alpha-\beta)(1-\rho)\omega + (\alpha+\phi)\varepsilon_{t-1}^2 - (\alpha\rho + (\alpha+\beta)\phi)\varepsilon_{t-1}^2 + \beta - \phi)\sigma_{t-1}^2 - (\beta\rho - (\alpha+\beta)\phi)\sigma_{t-2}^2$$
(7)

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:

$$R_t = x_t'\pi + \varepsilon_t \quad (8)$$

$$q_t = \omega + \rho(q_{t-1} - \omega) + \phi(\varepsilon_{t-1}^2 - \sigma_{t-1}^2) + \theta_1 z_{1t} \quad (9)$$

$$\sigma_t^2 - q_{t-1} = \alpha(\varepsilon_{t-1}^2 - q_{t-1}) + \gamma(\varepsilon_{t-1}^2 - q_{t-1})d_{t-1} + \beta(\sigma_{t-1}^2 - q_{t-1}) + \beta(\sigma_{t-1}^2 - q_{t-1}) + \theta_2 z_{2t} \quad (10)$$

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.

3. Data Description

The data consist of 1884 daily observations of the closing value of the Tehran stock market from 9/28/1997 to 8/20/2010. The sample is divided in two parts. The first 2800 observations (from 9/28/1997 to 8/20/2009) are used as the in-sample for estimation purposes, while the remaining 315 observations (from 8/21/2009 to 8/20/2010) are taken as the out-of-sample for forecast evaluation 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 0.6. 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 positive, showing that the upper tail of empirical distribution of the return is longer than the lower tail, that is positive 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)
0.0683	0.5865	-5.45	5.26	0.55	20.02	22835.49	135.89	143.53
p-value:						[0.00]	[0.00]	[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 $\chi^2(12)$. 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.

4. Empirical Results

We have used quasi-maximum likelihood (QML) covariance and standard errors using the methods described by Bollerslev and Woldridy (1992) for estimation GARCH models.

The estimation and test results for models suggest that the leverage effect term, γ, is significant in EGARCH model(even with a one-sided test). So there does appear to be an asymmetric effect. In EGARCH model the estimated coefficient on the asymmetry term $\hat{\varepsilon}_{t-1}/\hat{\sigma}_{t-1}$ is -0.0194, which is significant at conventional levels.

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
MSE	**0.2910**	**0.2910**	**0.2910**	**0.2910**	**0.2910**

Evaluation forecasting with MSE criteria indicate that GARCH models in this paper have a same forecasting power, but with Log-Likelihood criteria, CGARCH has the best forecasting power.

5. conclusion

We have used quasi-maximum likelihood (QML) covariance and standard errors using the methods described by Bollerslev and Woldridy (1992) for estimation GARCH models. The estimation and test results for models suggest that the leverage effect term, γ , is significant in EGARCH model(even with a one-sided test). So there does appear to be an asymmetric effect in Tehran stock market. In addition Evaluation forecasting with MSE criteria indicate that GARCH models in this paper have a same forecasting power, but when Log-Likelihood is evaluation criteria, CGARCH has the best forecasting power.

REFERENCES

[1]. Black, F., 1976. Studies of stock price volatility changes. Proceedings of the 1976 Meetings of the AmericanStatistical Association, Business and Economical Statistics Section, pp. 177– 181.

[2]. Bollerslev, T., 1986. Generalized autoregressive conditional heteroskedasticity. Journal of Econometrics 31, 307–327.

[3]. Bollerslev, T.,Wooldridge, J., 1992. Quasi-maximum likelihood estimation and inference in dynamic models with time-varying covariances. Econometric Reviews 11, 142–172.

[4]. Bollerslev, T., Chou, R.Y., Kroner, K.F., 1992. ARCH modeling in finance. Journal of Econometrics 52, 5– 59.

[5]. Box, G., Pierce, D., 1970. Distribution of residual autocorrelations in autoregressive-integrated moving average time series models. Journal of the American Statistical Association 65, 1509– 1526.

[6]. Breusch, T.S., Pagan, A.R., 1980. The Lagrange multiplier test and its applications to model specification in econometrics. Review of Economic Studies 47, 239–254.

[7]. Campbell, J.Y., Hentschel, L., 1992. No news is good news: an asymmetric model of changing volatility in stock returns. Journal of Financial Economics 31, 281– 318.

[8]. Campbell, J.Y., Lo, A.W., MacKinlay, A.C., 1997. The Econometrics of Financial Markets. Princeton Univ. Press, Princeton, NJ.

[9]. Christie, A.A., 1982. The stochastic behavior of common stock variances—value, leverage and interest rate effects. Journal of Financial Economics 10, 407–432.

[10]. Cox, J.C., Ross, S.A., 1976. The valuation of options for alternative stochastic processes. Journal of Financial Economics 3, 145– 166.

[11]. Engle, R., 1982. Autoregression conditional heteroskedasticity with estimates of the variance of the UK inflation. Econometrica 50, 987– 1007.

[12]. Engle, R.F., Kroner, K., 1995. Multivariate simultaneous generalized ARCH. Econometric Theory 11, 122– 150.

[13]. Engle, R.F., Ng, V.K., 1993. Measuring and testing the impact of news on volatility. Journal of Finance 48, 1749–1778.

[14]. French, K.R., Schwert, G.W., Stambaugh, R., 1987. Expected stock returns and volatility. Journal of Financial Economics 19, 3 – 29.

[15]. Glosten, L.R., Jagannathan, R., Runkle, D.E., 1993. On the relation between the expected value and the volatility of the nominal excess return on stocks. Journal of Finance 48, 1779– 1801.

[16]. Friedmann, R. and Sanddorf-Köhle, W.G. (2002) Volatility clustering and nontrading days in Chinese stock markets, Journal of Economics and Business, 54, 193-217.

[17]. Harvey, C., Siddique, A., 1999. Autoregressive conditional skewness. Journal of Financial and Quantitative

[18]. Analysis 34, 465–487.

[19]. Henry, O., 1998. Modelling the asymmetry of stock market volatility. Applied Financial Economics 8, 145-153.

[20]. Hentschel, L., 1995. All in the family: nesting symmetric and asymmetric GARCH models. Journal of Financial Economics 39, 71– 104.

[21]. Ljung, G., Box, G., 1978. On a measure of lack of fit in time series models. Biometrika 66, 67– 72.

[22]. Nelson, D.B., 1991. Conditional heteroskedasticity in asset returns: a new approach. Econometrica 59, 347–370.

[23]. Pagan, A.R., Schwert, G.W., 1990. Alternative models for conditional stock volatility. Journal of Econometrics 45, 267–290.

[24]. Pindyck, R.S., 1984. Risk, inflation, and the stock market. American Economic Review 74, 334– 351.

[25]. Rabemananjara, R., Zakoian, J.M., 1993. Threshold ARCH models and asymmetries in volatility. Journal of Applied Econometrics 8, 31–49.
[26]. Schwert, G.W., 1989. Why does stock market volatility change over time? Journal of Finance 44, 1115–1153.
[27]. White, H., 1982. Maximum likelihood estimation of misspecified models. Econometrica 50, 1– 26.
[28]. Wu, G., 2001. The determinants of asymmetric volatility. Review of Financial Studies 14, 837– 859.
[29]. Wu, G., Xiao, Z., 2002. A generalized partially linear model of asymmetric volatility. Journal of Empirical Finance 9, 287–319.
[30]. Zakoian, J.M., 1994. Threshold heteroskedastic models. Journal of Economic Dynamics and Control 18, 931–955.