Economics Bulletin

Volume 31, Issue 3

Modeling Volatility Using GARCH Models: Evidence from Vietnam

Tran MANH Tuyen
Paris Nord University and CEPN UMR 7234

Abstract

We explore the relevance of GARCH models in explaining stock return dynamics and volatility on the Vietnamese stock market. Although the evidence suggests that volatility is prevalent on this market, the effects of shocks on volatility are symmetric. The standard GARCH(0,1) model provides the best description of return dynamics. The results of GARCH-M do not show any relation between expected returns and expected risk. There exists only Bull effect, one characteristic of the emerging market. However, we could not find Friday, and low_transaction effects on Vietnamese stock market.

Citation: Tran MANH Tuyen, (2011) ''Modeling Volatility Using GARCH Models: Evidence from Vietnam'', *Economics Bulletin*, Vol. 31 no.3 pp. 1935-1942.
Submitted: Feb 14 2011. **Published:** July 03, 2011.

1. Introduction

One of the most prominent tools for capturing such changing variance was the Autoregressive Conditional Heteroskedasticity (ARCH), developed by Engle (1982). The primary feature of the Autoregressive Conditional Heteroskedasticity (ARCH) is that the conditional variance of the errors varies over time. Generalized ARCH (GARCH) models were developed by Bollerslev (1986) and Nelson (1991). Recently, a few modifications to the GARCH model have been proposed, which take account of skewed distributions. The weighted innovation models such as exponential GARCH (Nelson, 1991) and Threshold Autoregressive GARCH or TAR-GARCH model (Glosten et al., 1993, henceforth, GJR; Engle and Ng, 1993) have been advanced. This line of research highlights the asymmetric effect by emphasizing that a negative shock to returns will create more volatility than a positive shock of equal magnitude.

The first trading of HOSE (Hochiminh Stock Exchange) was only started on 28/07/2000 with only two securities and the first trading of HNX (Hanoi Stock Exchange) on 14/07/2005. The index of all stocks listed on HOSE is called Vn-index, on HNX called HNX-index. The number of listed companies has been increased quickly. From only 2 listed companies in July 2000, to 422 listed companies in November 2009 and 652 listed companies in January 2011, with the market capitalization around US$50 billion approximately 45% GDP of Vietnam. However, the volume of stock transaction is quite small, around 1000-2000 billion Vietnam dong (around $50-100 million) par days.

By employing GARCH(p,q) model, EGARCH, TGARCH and GARCH in Mean, the main purpose of this paper is to examine whether stock return volatility changes over time and whether it is predictable. We then study the relation between market risk and expected return. Besides, we examine the Bull, Friday and low transaction effect in the market.

Several studies investigate the performance of GARCH models in explaining volatility of emerging stock markets. Mecagni and Sourial (1999) examine the behaviour of stock returns as well as the market efficiency and volatility effects in the Egyptian stock exchange using GARCH models. The results show significant departures from the efficient market hypothesis, tendency for returns to exhibit volatility clustering and a significant positive link between risk and returns. Ronald Mangani (2005) examines expected return and volatility on the JSE Securities Exchange of South Africa using GARCH models. The results show that volatility is prevalent on this market, it is established that the effects of shocks on volatility are symmetric, and that volatility is not a commonly priced factor. Finally, Christos Floros (2008) models volatility by using GARCH models for Egypt and Israel. The results show that daily returns can be characterized by the GARCH models. For both markets, he concludes that increased risk will not necessarily lead to a rise in the returns.

In this study, we add three dummy variables in our model including Bull, Low_transaction and Friday variables in order to examine whether or not the bull, low transaction and Friday effects affect to the Vietnamese stock market. The paper is organized as follows: Section 2 provides data information. Section 3 presents the methodology, section 4 shows the main empirical results. Finally, section 5 gives out conclusion and our findings.

2. Data

The data employed in this study comprise 197 daily observations on the Vietnam's stock market (Vn-index) covering the period 02/01/2009 – 16/10/2009. Closing prices for stock indices were obtained from *Phutoan.com*. Table 1 gives the descriptive statistics for daily stock market prices and returns. Using the close daily index, a series of daily simple gross return of Vn-index, denoted Rt, were computed as first differences of this series. After the necessary computational data adjustments, the final sample had 196 observations for Rt. Figure 1a is plot of daily close price of Vn-index. Figure 1b is plot of returns of Vn-index. We assume that at the first day of our data, on 02/01/2009, returns of Vn-index equals 1.00.

From table 1, the kurtosis is about 2.4978, indicating that the series of daily simple gross return of Vn-index (Rt) from 02/01/2009 to 16/10/2009 have short tails, indicating that the distribution puts less mass on the tails of its support than a normal distribution. The skewness is about 0.0125, indicating that the series of daily simple gross return of Vn-index (Rt) are significantly skewed to the right at the 5% level. The return series have positive skewness implying that the distribution has a short right tails. The Augmented Dickey-Fuller (ADF) statistic, used in the test, is about -10.58. We will use this value to compare with the critical values at 1% (-3.4637), at 5% (-2.8761) and at 10% (-2.5746). The more negative it is, the stronger the rejection of the hypothesis that there is a unit root at some level of the confidence 1%, 5% and 10%. We reject the null hypothesis and accept the alternative hypothesis. This means that the series of daily simple gross return of Vn-index (Rt) is *stationary*. So, the samples have all financial characteristics: volatility clustering and platykurtic. The daily returns for the indices (presented in Figure 1b) show that volatility occurs in bursts. Furthermore, in terms of stationarity, and therefore, time-series models can be used to examine the behaviour of volatility over time.

Figure 1a: Plot of daily close prices of Vn-index (02/01/2009-16/10/2009)

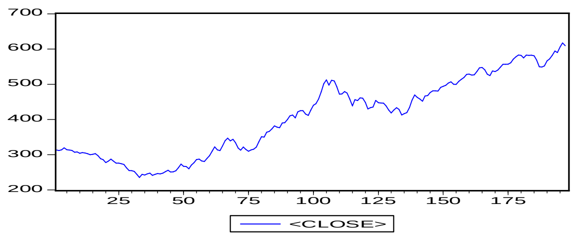


Figure 1b: Plot of returns of Vn-index (02/01/2009-16/10/2009)

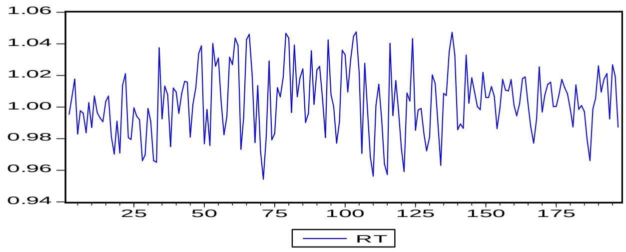


Table 1: Descriptive Statistics & ADF Tests

A Price	**Vn-index**
Mean	406.1280
Median	419.4800
Maximum	617.3800
Minimum	235.5000
Std. Dev.	110.8156
Skewness	0.091082
Kurtosis	1.684961
Jarque-Bera	14.46729
Probability	0.000722
Observations	197

B. Return	**Vn-index**
Mean	1.003627
Median	1.002637
Maximum	1.047564
Minimum	0.954360
Std. Dev.	0.021365
Skewness	0.012540
Kurtosis	2.497897
Jarque-Bera	2.064018
Probability	0.356290
Observations	196
ADF (Level) ADF (1st diff)	-10.58820 -11.51058

- ADF critical values: (1%) –3.4637, (5%) –2.8761, (10%) –2.5746.

3. Methodology

The GARCH (p,q) model is given by:

$$R_t = \mu + \varepsilon_t$$

$$\sigma_t^2 = \omega + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^{p} \beta_j \sigma_{t-j}^2 \qquad (1)$$

Where p is the order of GARCH, and q is the order of ARCH process. Error, ε_t, is assumed to be normally distributed with zero mean and conditional variance, σ_t^2 .The quantity $\sum\alpha_i+\sum\beta_i$ measures the persistence of volatility, and $(\alpha+\beta)$ is expected to be less than, but close to, unity, with $\beta>\alpha$.

ARCH-in-mean or the GARCH-in-mean models were proposed by Engel, Lilien and Robins (1987) and Bollerslev, Engel and Wooldridge (1988), Kim and Kon (1994). Standard GARCH-M model is given by:

$$\begin{aligned} R_t &= \mu + \beta_2\sigma_t^2 + \varepsilon_t \\ \varepsilon_t &\sim N(0,\sigma_t^2) \\ \sigma_t^2 &= \omega + a\varepsilon_{t-1}^2 + \beta_1\sigma_{t-1}^2 \end{aligned} \tag{2}$$

If β_2 is positive (and significant), then increased risk leads to a rise in the mean return (β_2 can be interpreted as a risk premium).

Nelson (1991), Glosten, Jaganathan and Runkle (1993), and Zakoian (1994) also suggested formulation that are useful in modeling the different impact of positive and negative shocks, a phenomenon named as ***volatility asymmetry***. A simple variance specification of EGARCH is given by:

$$\log\sigma_t^2 = \omega + \beta\log\sigma_{t-1}^2 + a\left|\frac{\varepsilon_{t-1}}{\sigma_{t-1}}\right| + \gamma\frac{\varepsilon_{t-1}}{\sigma_{t-1}} \tag{3}$$

γ_t is the leverage effect term. A leverage effect is said to exist if $\sum\gamma_t > 0$, and asymmetric volatility is established if $\sum\gamma_t \neq 0$

Another volatility model commonly used to handle leverage effects is the threshold GARCH (or TGARCH) model; see Glosten, Jagannathan, and Runkle (1993) and Zakoian (1994). A TGARCH(p,q) model assumes in form

$$\sigma_t^2 = \omega + \sum_{i=1}^{q} a_i\varepsilon_{t-i}^2 + \gamma\varepsilon_{t-1}^2 d_{t-1} + \sum_{j=1}^{p}\beta_j\sigma_{t-j}^2 \tag{4}$$

Where d_t=1 if ε_t<0 and d_t=0 otherwise

Good news has an impact of α, while bad news has an impact of $\alpha + \gamma$. If $\gamma > 0$ then leverage effect exists and bad news increases volatility, while if $\gamma \neq 0$ the news impacts is asymmetric.

4. Empirical results

Base on the correlogram of Rt, we have three possibilities: AR(1), MA(1), ARMA(1,1). Then, we have estimated all the three models. After estimating the three possibilities, we use the residual test to check the autocorrelation and partial correlation. We get the two significant models AR(1) and MA(1). We, then, use the two models to find the ARCH and GARCH effects and estimate with GARCH, we find that only AR(1) is the significant model with GARCH. (All the steps are not presented here).

After many steps, we select an AR(1) model with bull effect. The results from mean equation is presented below, all the parameters show significant. We have examined our mean equation with three cases: Bull, Low-transaction and Friday effects. The result showed that the bull effect exists while Low_transaction and Friday effects do not exist on Vietnamese stock market. See details at table 4.

Furthermore, we estimate a number of different GARCH-family models to explain conditional variance and volatility clustering. An iterative procedure is used upon the method of Marquardt algorithm. Heteroskedasticity Consistent Covariance option is used to compute quasi-maximum likelihood (QML) covariances and standard errors using the methods described by Bollerslev and Wooldridge (1992). This is normally used if the residuals are not conditionally normally distributed.

Table 2 reports the parameter estimates of all conditional volatility (GARCH-family) models defined in the above section. The sum of ARCH and GARCH coefficients ($\alpha_1 + \beta_1$) is very close to one, indicating that volatility shocks are quite persistent. We conclude that GARCH effects are strong for Vietnamese stock market. Moreover, the coefficient of lagged conditional variance is significantly positive and less than one, indicating that the impact of 'old' news on volatility is significant. The magnitude of the coefficient, β_1, is especially high for Vn-index, indicating a long memory in the variance.

All the coefficient of the model AR(1)-GARCH(1,0) are significant except for ω. Because this coefficient is so small, so we can omit this coefficient without changing the meaning of the equation. The other cases of the GARCH-family are not significant. See detail in the table 2 and 5. In addition, the coefficients of the conditional variance in the mean equation of GARCH-M models, denoted as β_2, are positive but insignificant. This suggests that higher market-wide risk, proxied by the conditional variance, will not necessarily lead to higher returns.

EGARCH models show an insignificant γ parameter. Moreover ω parameter is not significant. Although the evidence suggests that volatility is prevalent on this market, we cannot conclude that the effects of shocks on volatility are asymmetric.

Besides, the coefficient of the mean equation (μ) is very high, indicating that the development of this market from 02/01/2009 to 16/10/2009, about 98.51%. The bull effect is about 3.3% on the gross return. See table 2 below.

The coefficient γ of the model TGARCH is not statistically significant. So, we conclude that this model is not suitable for forecasting.

Last but not least, we also used model AR(1)-GARCH(1,0) to forecast for vn-index. See figure 2 below.

From the above output, we see that all the efficient of the forecast process might be statistically suitable. Moreover, the Theil Inequality Coefficient is quite small, 0.04, meaning that the forecast process is acceptable. Moreover, we also compare the forecast value with the real value; See table 3. The column three is the different between the real value and forecast value in absolute (%). We see that these values are all less than 1.5%, meaning that this forecast value might be suitable.

Table 2: GARCH-family Models for Volatility (Variance Specifications)

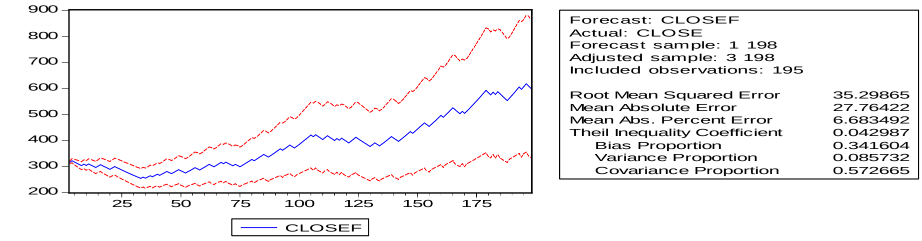
Part C	ω	α_1	γ	β_1	β_2	***AIC***
AR(1)-GARCH(1,0)	9.13E-06 (0.8351)	0		0.9466 (13.979)*		-5.866
AR(1)-EGARCH(1,0)	-0.4930 (-1.5225)	0	0.0533 (0.9566)	0.9432 (25.304)*		-5.867
AR(1)-GARCH(1,0)-M	0.0002 (1.3008)	0		-0.3827 (-0.3545)	9.3348 (0.6453)	-5.838
AR(1)-TGARCH(1,0)	7.79E-06 (2.3928)*	0	-0.0856 (-1.8083)	0.9964 (50.312)*		-5.858

Notes:

- T-statistics in the parentheses
- * Significant at the 5% level

Figure 2: forecast result with AR(1)-GARCH(1,0)

Economics Bulletin, 2011, Vol. 31 no.3 pp. 1935-1942



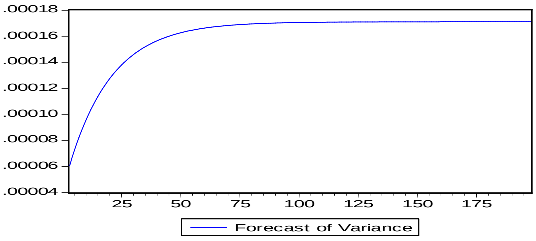


Table 3: the forecast result of Rt and the real value for the last four transaction sections

Trading sessions	Real value	Forecast value	The different (%)between forecast value and real value
15/10/2009	617.40	618.00	0.097%
16/10/2009	609.54	608.82	0.118%
19/10/2009	607.11	599.78	1.207%

Table 4: the estimated results for AR(1) model with three dummy variables

Model/Coefficient	*c*	Bull	Friday	Low_trans	ρ	*AIC*
AR(1) with bull effect	0.9851 (583.06)*	0.0330 (15.08)*			0.1901 (2.785)*	-5.869
AR(1) with Friday effect	1.0032 (470.36)*		0.002 (0.0033)		0.2646 (3.796)	-4.898
AR(1) with low_transaction	1.005 (330.19)*			-0.002 (-0.69)	0.2614 (3.746)*	-4.899

Table 5: GARCH Models for Volatility with different orders

Model/ coefficient	c	α_1	α_2	α_3	α_4	β_1	β_2	β_3	β_4
AR(1)-GARCH(1,1)	7.08E-06 (0.83)	0.0448 (0.7747)				0.9139 (10.64)*			
AR(1)-GARCH(1,2)	7.08E-06 (0.80)	0.1171 (0.8094)	-0.0778 (-0.4804)			0.9193 (8.9703)*			

AR(1)-GARCH(2,1)	1.20E-05 (0.80)	0.0941 (1.0164)				0.1753 (0.2433)	0.6605 (0.9511)		
AR(1)-GARCH(2,2)	1.22E-05 (0.7622)	0.1590 (1.0768)	-0.0932 (-0.4950)			0.3019 (0.4695)	0.5609 (1.0250)		
AR(1)-GARCH(3,1)	2.82E-05 (0.9160)	0.1424 (2.1809)*				-0.8311 (-13.892)	0.7142 (7.5248)*	0.8187 (9.0468)*	
AR(1)-GARCH(1,3)	8.37E-06 (0.7961)	0.1169 (0.8424)	-0.1789 (-0.8697)	0.1098 (0.7706)		0.9026 (8.0209)*			
AR(1)-GARCH(2,3)	1.16E-05 (0.7640)	0.1364 (0.9547)	-0.1196 (-0.4752)	0.0509 (0.2388)		0.4140 (0.4264)	0.4500 (0.4920)		
AR(1)-GARCH(3,2)	2.82E-05 (0.6878)	0.2449 (2.8086)*	0.1961 (2.1186)*			-1.0065 (-10.965)	0.5905 (3.8969)*	0.8306 (9.8126)*	
AR(1)-GARCH(3,3)	6.53E-07 (4.4471)*	0.0745 (4.8381)*	-0.2449 (-35.74)	0.1794 (0.1794)		1.3802 (1156.1)	0.2858 (97.014)*	-0.6788 (-406.3)*	
AR(1)-GARCH(4,1)	1.77E-05 (0.8894)	0.1057 (1.7471)				0.6477 (1.2053)	-0.7705 (-1.5179)	0.6713 (1.2287)	0.2459 (0.4824)
AR(1)-GARCH(4,2)	2.62E-05 (0.9697)	0.0907 (1.9366)	-0.0157 (-0.2850)			0.4274 (0.6786)	-0.2814 (-0.3659)	-0.1275 (-0.1562)	0.7614 (1.3223)
AR(1)-GARCH(4,3)	2.27E-05 (1.0800)	0.1248 (1.6635)	-0.0387 (-0.5118)	0.0544 (0.5408)		0.4099 (1.2500)	-0.2753 (-0.6402)	-0.1521 (-0.3565)	0.7547 (2.2336)*
AR(1)-GARCH(4,4)	2.40E-05 (0.9076)	0.1297 (1.5630)	-0.0074 (-0.0388)	0.0264 (0.1612)	0.0768 (0.4576)	0.3339 (0.4043)	-0.2014 (-0.2039)	-0.2417 (-0.2330)	0.7646 (1.0895)
AR(1)-GARCH(3,4)	1.09E-06 (2.8346)*	0.1154 (0.8294)	-0.2690 (-1.1547)	0.1856 (0.7382)	-0.0263 (-0.1770)	1.3128 (2.8974)*	0.3405 (0.3796)	-0.6653 (-1.4866)	
AR(1)-GARCH(2,4)	6.66E-07 (2.0905)*	0.0789 (0.7789)	-0.2621 (-1.7567)	0.2956 (69.680)*	-0.1090 (-2.018)*	1.9640 (48.045)	-0.9713 (-25.514)		
AR(1)-GARCH(1,4)	8.72E-06 (0.7790)	0.1077 (0.7564)	-0.1702 (-0.8008)	0.0871 (0.4417)	0.0239 (0.1890)	0.8995 (7.3364)*			

5. Conclusion

In this paper, we have examined time-series features of stock returns and volatility, as well as the relation between return and volatility on Vietnamese's stock exchange. Although the evidence suggests that volatility is prevalent on this market, the effects of shocks on volatility are symmetric. We have found the Bull effect on this market but we have not found the Friday and Low-transaction effect. We found that the standard GARCH(1,0) model provides the best description of return dynamics. However, the results of GARCH-M do not show any relation between expected returns and expected risk. We also performed forecast for the daily close index for the next trading session, 19/10/2009, the result of forecast seem to be suitable statistically.

References

[1] Bollerslev, T. (1986) "Generalized Autoregressive Conditional Heteroscedasticity" *Journal of Econometrics* 31, 307-327.

[2] Bollerslev, T., R. Engel, and J. Wooldridge (1988) "A Capital Asset Pricing Model with Time Varying Covariances" *Journal of Political Economy* 96, 116-131.

[3] Cheng F. Lee (2001) "Stock Returns and Volatility on China's Stock Market" *Journal of Financial Research 4, 71-75.*

[4] Engel, R. (1982) "Autoregressive Conditional Heteroscedasticity with Estimates of the Variance of UK Inflation" *Econometrica* 50, 987-1008.

[5] Engle, R. F and V. K. Ng (1993) "Measuring and Testing the Inpact of News on Volatility" *Journal of Finance* 48, 1749–1778.

[6] Engel, R., D. Lilien, and R. Robins (1987) "Estimating Time-Varying Risk Premia in the Term Structure: The ARCH-M Model" *Econometrica* 55, 391-407.

[7] Glosten, L., R. Jagannathan, and D. Runkle (1993) "On the Relation between the Expected Value and the Volatility of Nominal Excess Return on Stocks" *Journal of Finance* 48, 1779-1801.

[8] Kim, D. and Kon, S. I. (1994) "Alternative Models for Conditional Heteroscedasticity of Stock Returns", Journal of Business Vol 67, pp. 563-598.

[9] Mangani, R. (2005) "Evidence against Static Asset Pricing on the JSE Securities Exchange of South Africa" *Working Paper No. 2005/02*, University of Malawi, Chancellor College, Zomba.

[10] Mangani, R. (2005) "Expected returns and Volatility on the JSE Securities Exchange of South Africa" *Working Paper No. 2005/10*, University of Malawi, Chancellor College, Zomba

[11] Mecagni, M. and Sourial, M. S. (1999) "The Egyptian stock market: Efficiency tests and volatility effects" IMF Working paper No. 99/48.

[12] Nelson, D. (1991) "Conditional Heteroscedasticity in Asset Returns: A New Approach" *Econometrica* 59, 347-370.

[13] Zakoian, J. (1994) "Threshold Heteroscedastic Models" *Journal of Economic Dynamics and Control* 18, 931-955.