Impacts of News on Stock's Return Volatility under Different Economic Conditions: Evidence from Stock Exchange of Thailand

Jiranart Sutthirat[1]

Abstract

Not only is a well-specified model required in estimation of financial market volatility, sample period used in such estimation is needed to represent only one economic condition. This paper uses the ARCH-class models to show that using symmetric model over sample period covering more than one economic condition could mislead the volatility estimates. This is because investors perceive differently between good and bad news, which are factors determining volatility. During period full of good news as Thai economic was stellar, another good-news would not surprise investor as much as bad news. On the other hand, over period market clouded by many bad news as in recession period, investors are pessimistic and do not expect any good news. Using the day Thailand floated the baht as change in economic condition, this paper finds evidence suggesting that the impact of good and bad news are diverse under different economic conditions. As a result, to predict market volatility, practitioners and researchers need to be careful in selecting the sample period by excluding sample under one economic condition from another. Moreover, the volatility estimators used in such estimation should be asymmetric in which difference between good and bad news is captured. Otherwise, the volatility estimates could be misleading.

I. INTRODUCTION

For several years, practitioners and researchers in the field of finance and economics have developed estimators in order to forecast volatility in financial market. Precision in volatility estimation is very crucial for portfolio selection, asset management, and asset pricing. For instance, Markowitz (1952) constructs an efficient frontier of common stocks by minimizing portfolio volatility for each level of expected return. The asset pricing model, especially the CAPM of Sharpe (1964) and Lintner (1965), states the relation between expected return of asset and its associated systematic risk. Such risk is expressed as the co-movement between the volatility of the asset's return and that of the market. Moreover, the option-pricing model of Black and Schole (1976) suggests that price of an option could be derived using volatility of the underlying asset.

In the first stage of development, volatility models were static. They had been contemporaneous since Engle (1982) introduced the autoregressive conditional heteroskedasticity (ARCH) model. Under the ARCH framework, current volatility is determined by shocks or news occurred previously. Subsequently, numbers of literatures studying conditional volatility have applied the class of ARCH models. Among those, the most popular one is Bollerslev (1986)'s generalized ARCH (or GARCH) model.

---

[1]Program Director and Lecturer of Finance, Business Administration Department, Mahidol University International College, Mahidol University, Salaya Campus, Nakhonpathom

This section discusses specification of each model.

GARCH(1,1)

$$h_t = \omega + \beta h_{t-1} + \alpha (\varepsilon_{t-1})^2 \tag{1}$$

where h_t is the conditional variance of stock return estimated at time *t*; ε_{t-1} is the unexpected shock at time *t-1*; and ω, β and α are constant parameters.

GJR

$$h_t = \omega + \beta h_{t-1} + \alpha(\varepsilon_{t-1})^2 + \gamma[D_{t-1}(\varepsilon_{t-1})^2] \tag{2}$$

where D_{t-1} is the dummy variable whose value equals one if ε_{t-1} is negative; and γ is another constant parameter. The term $D_{t-1}(\varepsilon_{t-1})^2$ is aimed to capture the impact of bad news on volatility. As a result, good news has an impact of α, while bad news has an impact of $\alpha + \gamma$.

EGARCH(1,1)[2]

$$\log(h_t) = \omega + \beta \log(h_{t-1}) + \alpha[\frac{|\varepsilon_{t-1}|}{\sqrt{h_{t-1}}}] + \gamma[\frac{\varepsilon_{t-1}}{\sqrt{h_{t-1}}}] \tag{3}$$

The term $\varepsilon_{t-1}/\sqrt{h_{t-1}}$ is aimed to capture the impact of bad news on volatility. Comparing to GJR, the impact of bad news in this model is exponential, rather than quadratic.

2.2 Measurement of Impact of News and the News Impact Curve

We use the process suggested in Engle and Ng (1993) in measuring the impact of news. In their paper, the impact of news is defined as the relation between past return shock (ε_{t-1}) and current conditional variance (h_t), holding constant the information dated t-2 and earlier; and is illustrated using the curve so-called the *"news impact curve"*. This curve shows how volatility estimates take into account new information.

For the GARCH model, the news impact curve is symmetric, quadratic, and centers on the point where $\varepsilon_{t-1} = 0$. For the GJR model, the curve is also quadratic, but has different slope parameters for the positive and negative shocks. For the EGARCH model, the curve is exponentially increasing in both directions but with different parameters. The curves for the GJR and EGARCH reach their minimum at $\varepsilon_{t-1} = 0$.

2.3 Estimation of News

News is measured by the unexpected part (or shock) of the stock returns. Engle and Ng (1993) use the procedure similar to that of Pagan and Schwert (1990) to find unexpected return. They remove the expected part of the return series by adjusting day-of-the-week effect and an autocorrelation. They first regress stock return (Y_t) on four day-of-the-week dummy variables (Tuesday to Friday) and get the primary residual, u_t. Then, the primary residual is regressed on its own lag to obtain the secondary residual, ε_t, which is the unexpected stock return or shock. The regression equations are expressed as follows:

---

[2]Note that the EGARCH model used in this paper differs slightly from Nelson's original model. However, it will yield identical estimates except for the intercept term, ω, which will differ by $\alpha[\sqrt{2/\pi}]$

Day-of-the- Week Effect Adjustment

$$Y_t = \beta_0 + \beta_1 TUE + \beta_2 WED + \beta_3 THU + \beta_4 FRI + u_t \quad (4)$$

Autocorrelation Adjustment

$$u_t = \beta_5 + \beta_6 u_{t-1} + \varepsilon_t \quad (5)$$

where β_0 to β_6 are regression coefficients. The dummy variables, *TUE*, *WED*, *THU*, and *FRI*, represent Tuesday to Friday, respectively.

They, then, use the unexpected return series to estimate conditional variance using the model described in Equations (1) to (3).

Since volatility is dynamic, expected return should also be time-varying given information on conditional variance. Instead of using static (unconditional) model like Equation (4) and (5) to estimate return shocks or residuals, we use the conditional mean equation in which information on the conditional variance (h_t) and the previous return (Y_{t-1}) are incorporated. This model is known as the GARCH in mean (or GARCH-M) in which mean (or the expected part), residual (or the unexpected part), and variance are time-varying and conditional to their previous values. The model can be specified as follows:

Conditional Mean Equation

$$Y_t = \beta_0 + \beta_1 TUE + \beta_2 WED + \beta_3 THU + \beta_4 FRI + \beta_5 h_t + \beta_6 Y_{t-1} + \varepsilon_t \quad (6)$$

The conditional variance (h_t) can then be obtained through one of the three ARCH-class model expressed in Equations (1) to (3). For comparison, the results of the analyses using the model of Engle and Ng (1993) are also shown with the suffix (E&N).

2.4 Diagnostic Tests

To investigate whether the volatility model is well specified, we use three tests proposed by Engle and Ng (1993). These tests include the *Sign Bias Test,* the *Negative Size Bias Test,* and the *Positive Size Bias Test* as well as a joint test of the three.

The basic concept of these tests is that if there are some variables, which are observed in the past and are not included in the volatility model, that can predict the squared standardized residual ($\varepsilon_t / \sqrt{h_t}$); the volatility model under consideration is misspecified. The test statistics are actually the t-statistics of coefficients on these variables.

For the Sign Bias test, we regress the squared standardized residual on a dummy variable, D_{t-1}, whose value equals one if ε_{t-1} is negative, zero otherwise. If the dummy variable can significantly explain the shock, it suggests that the model being used does not capture the different impacts of good and bad news on volatility.

For the Negative Size Bias test, we regress the squared standardized residual on the interaction of variables (D_{t-1} and ε_{t-1}). If the interaction variable can significantly explain the shock, it suggests that the model being used does not take into account whether the bad news occurred previously is small or large.

For the Positive Size Bias test, we regress the squared standardized residual on the interaction of variables ($D_{t-1}(+)$ and ε_{t-1}), where $D_{t-1}(+) = 1 - D_{t-1}$. Similar to the Negative Size Bias test, if the interaction variable can significantly explain the shock, it suggests that the model being used does not capture well the difference in size of the good news.

For the joint test, we regress the squared standardized residual on the three variables mentioned above. The test statistic for the joint test is the LM test statistic with Chi-Square distribution and three degrees of freedom; and is equal to number of observations multiplied by the R-squared from the regression.

In addition to the tests above, we also employ the Ljung-Box test to test whether the model can capture well the previous news or shocks. Since the model forecasts expected return and conditional variance using previous news, if the model works well, the residual which are not predicted by the model should not be explained by such news or shocks. In contrast, if the autocorrelation of the squared standardized residual, and hence the Ljung-Box statistic, is significant, it suggests that the model being used is misspecified. The Ljung-Box test is conducted for the sixth-, twelfth-, and twenty-fourth- orders serial correlation.

3. DATA

The stock returns series used in this paper is the daily returns series of the Thai SET index from January 4, 1994 to December 30, 1999. The total observations are 1,470 daily returns. The total sample is divided into two subsample periods. The first subsample period is from January 4, 1994 to June 30, 1997 (855 observations). This subsample represents the period of bubble economy in Thailand when investors had high expectation about future growth and price. During this period, market was full of good news. The second subsample starts from July 2, 1997, the day the Thai Baht was floated, to December 30, 1999 (615 observations). This subsample represents the period the Thai financial market was clouded by mostly bad news. The first and the second subsamples are named "Before-Float" and "After-Float", respectively.

4. EMPIRICAL RESULTS

4.1 Estimations of Unexpected Return (ε_t)

Table 1 presents the unexpected return estimation using GARCH-M, GJR-M, and EGARCH-M models, along with the model used in paper of Engle and Ng (1993) for the whole sample (Jan 4, 1994 - Dec 30, 1999). The results suggest statistical significances of the day-of-the-week and autoregressive variables. The lower panel shows the summary statistics of the unexpected return obtained from each model. All models generate very similar unexpected return distribution. The ε_t obtained using the model of Engle and Ng (1993) is perfectly center around 0.0000% mean, whereas ones obtained from the others model are slightly deviated.

Overall, the ε_t obtained from all models are normally distributed around zero mean; with no autocorrelations (the Ljung-Box statistics and Jarque-Bera statistics are statistically insignificant).

For the two subsamples: Before-Float and After-Float, the results are shown in Table 2 and 3, respectively. The distribution of ε_t generated using model of Engle and Ng (1993) is normal and center on 0.000%.

For the Before-Float subsample, the distribution of ε_t obtained using GARCH-M model shows higher deviation from zero mean to -0.1147%, while the distributions of ε_t from the other two asymmetric models do not change.

For the After-Float subsample, the EGARCH-M model yields obviously different result from other models. The average unexpected return is 0.1505%. GARCH-M and GJR-M generate the ε_t series similar to that of Engle and Ng (1993).

In summary, except for GARCH-M in the Before-Float subsample and EGARCH- M in the After-Float subsample, the zero mean distribution of ε_t is consistent with the assumption of the GARCH class models[3].

4.2 Estimations of Conditional Variances

The Overall Period

The conditional variances estimation results and diagnostic tests for the overall period are presented in Table 4. The results shows that the parameters corresponding to the term $D_{t-1}(\varepsilon_{t-1})^2$ in GJR and GJR(E&N) are almost insignificant and positive; the parameters corresponding to the term $\varepsilon_{t-1}/\sqrt{h_{t-1}}$ in EGARCH and EGARCH(E&N) are insignificantly negative at all levels. These results indicate that bad news does not cause higher volatility than good news. As a result, the symmetric model, like GARCH (1, 1), should be used in estimating volatility.

The diagnostic tests also confirm the results. Even though all models fails the Positive Size Bias test and the joint test, as well as showing the existence of autocorrelation, GARCH(1,l) almost passes the joint test, whereas GJR and EGARCH show strongly significance.

At this point, it seems to be that using GARCH(l,l) is the best way to estimate volatility for the Thai stock returns. Yet, another story is revealed after the sample is divided into two subsamples representing two different economic conditions.

The Before-Float Period

Table 5 shows the volatility estimation results and diagnostic tests for period from January 4, 1994 to June 30, 1997. The term $D_{t-1}(\varepsilon_{t-1})^2$ in GJR and GJR (E&N) now has positive and strongly significant parameters. Also, the parameters corresponding to the term $\varepsilon_{t-1}/\sqrt{h_{t-1}}$ in EGARCH and EGARCH (E&N) models are negative and strongly significant. These results strongly indicate that negative return shocks (or bad news) cause higher volatility than positive return shocks (or good news). Moreover, the log likelihood value of the GARCH(l,l) is much lower than those of GJR and EGARCH. Therefore, the model used in predicting volatility should be asymmetric.

Note that the diagnostic tests show interesting results. All models using method of Engle & Ng (1993) in estimating ε_t fails the Negative Size Bias and Joint tests, while all of our models passes all tests, except for EGARCH in the Positive Size Bias test.

The After-Float Period

Table 6 shows the volatility estimations results and diagnostic tests for period from July 2, 1997 to December 30, 1999. The parameters corresponding to the term $D_{t-1}(\varepsilon_{t-1})^2$ in GJR and GJR(E&N) is significant, however, negative. In addition, the term $\varepsilon_{t-1}/\sqrt{h_{t-1}}$ in EGARCH has positively, statistically insignificant parameter. This parameter in EGARCH(E&N) is also positive and significant. The results indicate that good news have higher impact on volatility than bad news. Again, the model used to estimate volatility should be asymmetric. The GJR, comparing to others, has the highest log likelihood value of -1,414.392.

The diagnostic tests reveal that all models pass most of the tests. They show similar results between our models and those of Engle and Ng (1993). The EGARCH, again, fail the Positive Size Bias test, as well as the Negative Size Bias test.

---

[3]Even though the distribution is not normal, one can use the quasi-maximum likelihood estimation method proposed by Bollerslev and Wooldridge (1992). The method employs the BHHH numerical optimization algorithm to estimate the conditional variances. The quasi-maximum likelihood estimates will be consistent and asymptotically normal, whether or not the assumption that ε_t is normally distributed is violated

5. INTERPRETATION

Empirical results in Section 4 clearly shows that estimating volatility without separation between the normal period and the turmoil period will lead to misspecified model and wrong variance estimates. More specifically, if we estimate volatility of stock's return using sample of the returns from two different economic conditions: 1) the one full mostly of good news during economic stellar period and 2) the other full mostly of bad news during economic recession period; the model we select must be the GARCH-M model because bad and good news have about the same impact on volatility.

However, when volatility is estimated over subsample period in which different market condition is excluded, the empirical results support our hypothesis. That is bad news causes higher volatility than good news in the normal period (Before-Float), while good news causes higher volatility in the recession period (After-Float). Figure 1 and 2 illustrate these evidences by showing the news impact curves estimated by the GJR model and GARCH-M model before and after the Bank of Thailand floated the baht, respectively. Clearly, before Thailand floated the baht, previous negative return shock which is considered bad news results in higher return volatility, 1-day consequent. In contrast, the impact is opposite after the bath was floated.

Finally, I present summary statistics of the conditional variance estimated from each model for the overall, Before-Float, and After-Float periods in Table 7. The conditional variance of stock return is approximately 2 percent for Before-Float period, 6 percent for After-Float period, and 4 percent for overall period.

6. SUMMARY AND CONCLUSION

This paper shows evidence that estimation of conditional variance could be misleading if the data being used belongs to different economic conditions. We analyze the conditional variance of the Thai SET Index returns and define the news as the unexpected part of such returns. The unexpected returns or news are estimated using the GARCH-M and other modified models, EGARCH-M and GJR-M, in comparison with those estimated using the model used in Engle and Ng (1993). The empirical results suggest that, when estimating volatility from the pooled sample belonging to different economic conditions and investors' perception to news; negative and positive return shocks are of similar magnitude of impact on volatility. As a result, the best-specified volatility estimation model is GARCH-M. However, after separating sample into two subsample periods, using July 2, 1997 (when the Thai Baht was floated) as a cutting date, the results reveal another story. For the Before-Float period, bad news cause higher volatility than good news. For the After-Float period, the impacts are on positive direction. The results found in this paper suggest that not only the model specification should be considered to estimate volatility, but also the direction and magnitude of the impact of good and bad news. They clearly show that impacts of bad and good news on volatility are different from one market condition to others.

REFERENCES

Black, F., and Scholes, M. 1973. "The Pricing of Options and Corporate Liabilities." **Journal of Political Economy** 8: 637-659.

Bollerslev, T. 1986. "Generalized Autoregressive Conditional Heteroskedasticity." **Journal of Econometrics** 31: 307-327.

Bollerslev, T. and Wooldridge, J.M. 1992. "Quasi-maximum Likelihood Estimation and Inference in Dynamic Models with Time Varying Covariances." **Econometric Reviews** 11: 143-172.

Engle, R. F. 1982. Autoregressive Conditional Heteroskedasticity with Estimates of the Variance of U.K. Inflation." **Econometrica** 50: 987-1008.

Engle, R.F. and Ng, V.K. 1993. "Measuring and Testing the Impact of News on Volatility." **Journal of Finance** 48: 1022-1082.

Glosten, L.R.; Jagannathan, R. and Runkle, D. 1993. "On the Relation Between the Expected Value and the Volatility of the Normal Excess Return on Stocks." **Journal of Finance** 48: 1779-1801.

Lintner, J. 1965. "The Valuation of Risk Assets and the Selection of Risky Investments in Stock Portfolios and Capital Budgets." **The Review of Economics and Statistics** 47: 13-37.

Markowitz, H. 1952. "Portfolio Selection." **Journal of Finance** 8: 77-91.

Nelson, D.B. 1990. "Conditional Heteroskedasticity in Asset Returns: A New Approach." **Econometrica** 59: 347-370.

Pagan, A., and Schwert, G.W. 1990. "Alternative Models for Conditional Stock Volatility." **Journal of Econometrics** 45, 267-290.

Sharpe, W.F. 1964. "Capital Asset Prices: A Theory of Market Equilibrium Under Condition of Risk." **Journal of Finance** 19: 425-442.

TABLE 1

Estimations and Summary Statistics of the Unexpected Returns for the Total Sample (Jan 4, 1994 to Dec 30, 1999)

This table reports the results of four adjustment procedures to remove day-of-the-week and autocorrelation effects from the daily return of the SET index. These procedures consist of the GARCH-M, GJR-M, EGARCH-M, and that analogous to the one in Engle and Ng (1993).

Y_t is the rate of return of the SET index from day *t-1* to day *t*. TUE, WED, THU, and FRI are dummy variables for Tuesday, Wednesday, Thursday, and Friday respectively. Each of these dummy variables takes a value of 1 on the corresponding day and a value of 0 otherwise. u_t is the primary residual of the day-of-the-week adjustment regression. ε_t is the secondary residual or the unexpected return after the day-of-the-week and autocorrelation effects are removed. The t-values are in parentheses. Ljung-Box(x) is the Ljung-Box statistics for x^{th}-order serial correlation.

Mean Adjustment Regressions

GARCH-M

$$Y_t = \underset{(-4.099)}{-0.421^{***}} + \underset{(0.788)}{0.015h_t} + \underset{(3.351)}{0.379^{***}}TUE + \underset{(3.759)}{0.511^{***}}WED + \underset{(2.241)}{0.289^{**}}THU + \underset{(4.391)}{0.544^{***}}FRI + \underset{(5.955)}{0.186^{***}}Y_{t-1} + \varepsilon_t$$

GJR-M

$$Y_t = \underset{(-3.932)}{-0.408^{***}} + \underset{(0.238)}{0.005h_t} + \underset{(3.188)}{0.360^{***}}TUE + \underset{(3.756)}{0.495^{***}}WED + \underset{(1.950)}{0.247^{*}}THU + \underset{(4.199)}{0.504^{***}}FRI + \underset{(6.115)}{0.188^{***}}Y_{t-1} + \varepsilon_t$$

EGARCH-M

$$Y_t = \underset{(-3.512)}{-0.363^{***}} + \underset{(0.122)}{0.002h_t} + \underset{(2.990)}{0.329^{***}}TUE + \underset{(3.417)}{0.460^{***}}WED + \underset{(1.441)}{0.189}THU + \underset{(3.997)}{0.472^{***}}FRI + \underset{(6.085)}{0.185^{***}}Y_{t-1} + \varepsilon_t$$

Engle and Ng (1993)

<u>*Day-of-the-Week Effect Adjustment*</u>

$$Y_t = \underset{(-3.667)}{-0.446^{***}} + \underset{(1.915)}{0.325^{**}}TUE + \underset{(3.173)}{0.538^{***}}WED + \underset{(2.435)}{0.413^{**}}THU + \underset{(3.606)}{0.612^{***}}FRI + u_t$$

<u>*Autocorrelation Adjustment*</u>

$$u_t = \underset{(-0.055)}{-0.004} + \underset{(6.920)}{0.177^{***}}u_{t-1} + \varepsilon_t$$

Summary Statistics for the Unexpected Stock Returns

	GARCH-M	GJR-M	EGARCH-M	Engle & Ng
Mean	-0.0593	-0.0066	-0.0083	0.0000
Median	-0.2011	-0.1585	-0.1628	-0.1436
Maximum	10.6278	10.6902	10.6818	10.6631
Minimum	-10.1179	-9.8672	-9.8204	-9.7838
Standard Deviation	2.0019	2.003	2.0038	2.0022
Skewness	0.6593	0.6952	0.7057	0.7248
Kurtosis	6.6553	6.6753	6.6825	6.7365
Ljung-Box (6)	1.7015	1.4809	1.3529	1.3799
Ljung-Box (12)	10.081	10.421	10.54	11.101
Ljung-Box (24)	27.969	28.369	28.454	28.646
Jarque-Bera	924.8631	945.7504	952.6111	983.8436
Number of Observations	1470	1470	1470	1470

*Significant at 90% confidence level

**Significant at 95% confidence level

***Significant at 99% confidence level

TABLE 2

Estimations and Summary Statistics of the Unexpected Returns for the Before-Float Subsample (Jan 4, 1994 to Jun 30, 1997)

This table reports the results of four adjustment procedures to remove day-of-the-week and autocorrelation effects from the daily return of the SET index. These procedures consist of the GARCH-M, GJR-M, EGARCH-M, and that analogous to the one in Engle and Ng (1993).

Y_t is the rate of return of the SET index from day *t-1* to day *t*. TUE, WED, THU, and FRI are dummy variables for Tuesday, Wednesday, Thursday, and Friday respectively. Each of these dummy variables takes a value of 1 on the corresponding day and a value of 0 otherwise. u_t is the primary residual of the day-of-the-week adjustment regression. ε_t is the secondary residual or the unexpected return after the day-of-the-week and autocorrelation effects are removed. The t-values are in parentheses. Ljung-Box(x) is the Ljung-Box statistics for x^{th}-order serial correlation.

Mean Adjustment Regressions

GARCH-M

$$Y_t = \underset{(-5.495)}{-0.714^{***}} + \underset{(2.321)}{0.128^{**}}h_t + \underset{(3.354)}{0.418^{***}}TUE + \underset{(4.318)}{0.617^{***}}WED + \underset{(2.060)}{0.288^{**}}THU + \underset{(3.753)}{0.537^{***}}FRI + \underset{(4.880)}{0.205^{***}}Y_{t-1} + \varepsilon_t$$

GJR-M

$$Y_t = \underset{(-3.736)}{-0.451^{***}} + \underset{(0.009)}{0.000}\,h_t + \underset{(3.123)}{0.382^{***}}TUE + \underset{(3.852)}{0.547^{***}}WED + \underset{(1.797)}{0.239^{*}}THU + \underset{(3.779)}{0.488^{***}}FRI + \underset{(4.766)}{0.188^{***}}Y_{t-1} + \varepsilon_t$$

EGARCH-M

$$Y_t = \underset{(-3.269)}{-0.391^{***}} - \underset{(-0.299)}{0.015}\,h_t + \underset{(2.952)}{0.358^{***}}TUE + \underset{(3.313)}{0.493^{***}}WED + \underset{(1.564)}{0.211}THU + \underset{(3.545)}{0.444^{***}}FRI + \underset{(4.207)}{0.172^{***}}Y_{t-1} + \varepsilon_t$$

Engle and Ng (1993)

Day-of-the-Week Effect Adjustment

$$Y_t = \underset{(-4.201)}{-0.493^{***}} + \underset{(2.889)}{0.472^{***}}TUE + \underset{(3.187)}{0.518^{***}}WED + \underset{(1.774)}{0.288^{*}}THU + \underset{(3.309)}{0.539^{***}}FRI + u_t$$

Autocorrelation Adjustment

$$u_t = \underset{(-0.098)}{-0.006} + \underset{(4.304)}{0.145^{***}}u_{t-1} + \varepsilon_t$$

Summary Statistics for the Unexpected Stock Returns

	GARCH-M	GJR-M	EGARCH-M	Engle & Ng
Mean	-0.1147	-0.0137	-0.0051	0.0000
Median	-0.1195	-0.0531	-0.0560	-0.0199
Maximum	5.2793	6.0138	6.1063	5.8834
Minimum	-8.9934	-8.1489	-8.0091	-7.8950
Standard Deviation	1.4701	1.4651	1.4650	1.4629
Skewness	-0.4313	-0.1097	-0.0818	-0.0981
Kurtosis	5.9644	5.6733	5.6389	5.5562
Ljung-Box (6)	9.3370	7.7910	7.2770	6.3650
Ljung-Box (12)	17.1530	15.8690	15.0860	14.2450
Ljung-Box (24)	29.5000	28.9720	28.4620	27.7390
Jarque-Bera	339.5691	256.3087	249.0403	234.1586
Number of Observations	855	855	855	855

*Significant at 90% confidence level
**Significant at 95% confidence level
***Significant at 99% confidence level

TABLE 3

Estimations and Summary Statistics of the Unexpected Returns for the After-Float Subsample (Jul 2, 1997 to Dec 30, 1999)

This table reports the results of four adjustment procedures to remove day-of-the-week and autocorrelation effects from the daily return of the SET index. These procedures consist of the GARCH-M, GJR-M, EGARCH-M, and that analogous to the one in Engle and Ng (1993).

Y_t is the rate of return of the SET index from day *t-1* to day *t*. TUE, WED, THU, and FRI are dummy variables for Tuesday, Wednesday, Thursday, and Friday respectively. Each of these dummy variables takes a value of 1 on the corresponding day and a value of 0 otherwise. u_t is the primary residual of the day-of-the-week adjustment regression. ε_t is the secondary residual or the unexpected return after the day-of-the-week and autocorrelation effects are removed. The t-values are in parentheses. Ljung-Box(x) is the Ljung-Box statistics for x^{th}-order serial correlation.

Mean Adjustment Regressions

GARCH-M

$$Y_t = \underset{(-2.360)}{-0.854^{**}} + \underset{(1.329)}{0.072h_t} + \underset{(0.965)}{0.255TUE} + \underset{(1.513)}{0.421WED} + \underset{(1.534)}{0.444THU} + \underset{(2.235)}{0.646^{**}FRI} + \underset{(4.075)}{0.201^{***}}\,Y_{t-1} + \varepsilon_t$$

GJR-M

$$Y_t = \underset{(-1.566)}{-0.565} + \underset{(0.400)}{0.021h_t} + \underset{(1.189)}{0.317TUE} + \underset{(2.015)}{0.569^{**}WED} + \underset{(1.868)}{0.537^{*}\,THU} + \underset{(2.529)}{0.718^{**}FRI} + \underset{(3.221)}{0.184^{***}}\,Y_{t-1} + \varepsilon_t$$

EGARCH-M

$$Y_t = \underset{(-0.205)}{-0.318} - \underset{(-0.638)}{0.075\,h_t} + \underset{(1.026)}{0.287TUE} + \underset{(1.943)}{0.568^{*}WED} + \underset{(2.105)}{0.634^{**}\,THU} + \underset{(3.299)}{0.961^{***}FRI} + \underset{(2.326)}{0.145^{**}}\,Y_{t-1} + \varepsilon_t$$

Engle and Ng (1993)

Day-of-the-Week Effect Adjustment

$$Y_t = \underset{(-1.603)}{-0.384} + \underset{(0.374)}{0.125TUE} + \underset{(1.697)}{0.571^{**}\,WED} + \underset{(1.767)}{0.594^{*}THU} + \underset{(2.135)}{0.716^{**}FRI} + u_t$$

Autocorrelation Adjustment

$$u_t = \underset{(-0.121)}{-0.015} + \underset{(4.828)}{0.190^{***}}\,u_{t-1} + \varepsilon_t$$

Summary Statistics for the Unexpected Stock Returns

	GARCH-M	GJR-M	EGARCH-M	Engle & Ng
Mean	-0.0551	-0.0224	0.1505	0.0000
Median	-0.3046	-0.3244	-0.1891	-0.3228
Maximum	10.6317	10.5816	11.9313	10.5562
Minimum	-10.2801	-10.0771	-9.3270	-9.9065
Standard Deviation	2.5486	2.5507	2.5598	2.5476
Skewness	0.6090	0.7076	0.8908	0.7589
Kurtosis	4.8280	4.9446	5.3042	5.0389
Ljung-Box (6)	2.8940	1.5510	2.4530	0.9120
Ljung-Box (12)	10.9310	10.1900	14.6110	10.0710
Ljung-Box (24)	23.4230	22.3580	25.9560	21.3160
Jarque-Bera	123.4487	147.9817	217.0321	165.2872
Number of Observations	615	615	615	615

*Significant at 90% confidence level
**Significant at 95% confidence level
***Significant at 99% confidence level

TABLE 4

Estimation Results and Diagnostic Tests for the Total Sample (Jan 4, 1994 to Dec 30, 1999)

This table reports the estimation and diagnostic test results of various volatility estimator models for the daily return of the SET index. Day-of-the-week and autocorrelation effects are removed using either the class of GARCH in mean procedure or Engle and Ng (1993)'s procedure (presented by E&N) in Table 1. The volatility estimation is performed by the method of quasi maximum likelihood using the BHHH numerical optimization algorithm.

h_t is the conditional variance on day *t*. ε_{t-1} is the unexpected return on day *t-1* after the day-of-the-week and autocorrelation effects are removed. The t-values are in parentheses. Ljung-Box(x) is the Ljung-Box statistics for x^{th}-order serial correlation.

Estimation Results

GARCH(1,1)

$$h_t = \underset{(2.1368)}{0.0295^{**}} + \underset{(57.0046)}{0.9152^{***}} h_{t-1} + \underset{(5.0865)}{0.0802^{***}} (\varepsilon_{t-1})^2$$

LogL = -2924.252

GJR

$$h_t = \underset{(2.2883)}{0.0347^{**}} + \underset{(49.6823)}{0.8951^{***}} h_{t-1} + \underset{(3.4061)}{0.0714^{***}} (\varepsilon_{t-1})^2 + \underset{(1.7487)}{0.0659^{*}} [D_{t-1} (\varepsilon_{t-1})^2]$$

LogL = -2918.715

EGARCH(1,1)

$$\log(h_t) = \underset{(-5.5392)}{-0.1322^{***}} + \underset{(186.3478)}{0.9879^{***}} \log(h_{t-1}) + \underset{(5.8209)}{0.1918^{***}} [|\varepsilon_{t-1}|/\sqrt{h_{t-1}}] - \underset{(-1.6361)}{0.0379} [\varepsilon_{t-1}/\sqrt{h_{t-1}}]$$

LogL = -2913.112

GARCH(1,1)(E&N)

$$h_t = \underset{(2.2570)}{0.0305^{**}} + \underset{(59.7988)}{0.9175^{***}} h_{t-1} + \underset{(5.0604)}{0.0767^{***}} (\varepsilon_{t-1})^2$$

LogL = -2923.574

GJR (E&N)

$$h_t = \underset{(2.1601)}{0.0294^{**}} + \underset{(54.7294)}{0.9079^{***}} h_{t-1} + \underset{(3.2814)}{0.0631^{***}} (\varepsilon_{t-1})^2 + \underset{(1.6454)}{0.0542^{*}} [D_{t-1} (\varepsilon_{t-1})^2]$$

LogL = -2918.383

EGARCH(1,1)(E&N)

$$\log(h_t) = \underset{(-5.2903)}{-0.1241^{***}} + \underset{(191.3566)}{0.9874^{***}} \log(h_{t-1}) + \underset{(5.6623)}{0.1820^{***}} [|\varepsilon_{t-1}|/\sqrt{h_{t-1}}] - \underset{(-1.4555)}{0.0326} [\varepsilon_{t-1}/\sqrt{h_{t-1}}]$$

LogL = -2913.769

Diagnostic Test Results

Model	Ljung-Box (6)	Ljung-Box (12)	Ljung-Box (24)	Sign Bias	Negative Size Bias	Positive Size Bias	Joint Test
GARCH(1,1)	14.54^{***}	17.462^{*}	31.445	-1.169	0.745	2.673^{***}	7.35^{*}
GJR	12.216^{**}	16.088	29.444	-1.263	1.428	3.071^{***}	10.28^{**}
EGARCH(1,1)	$17 .881^{***}$	23.732^{**}	36.439^{**}	-1.626	1.381	3.851^{***}	14.69^{***}
GARCH(1,1)(E&N)	13.41^{**}	16.894	31.59	-0.987	0.687	2.546^{**}	7.35^{*}
GJR(E&N)	12.784^{**}	17.557	32.02	-1.423	1.385	3.215^{***}	10.28^{**}
EGARCH(1,1)(E&N)	16.592^{***}	23.67^{**}	36.985^{**}	-1.684^{*}	1.421	3.804^{***}	14.69^{***}

*Significant at 90% confidence level **Significant at 95% confidence level
***Significant at 99% confidence level

TABLE 5

Estimation Results and Diagnostic Tests for the Before-Float Subsample (Jan 4, 1994 to Jun 30, 1997)

This table reports the estimation and diagnostic test results of various volatility estimator models for the daily return of the SET index. Day-of-the-week and autocorrelation effects are removed using either the class of GARCH in mean procedure or Engle and Ng (1993)'s procedure (presented by E&N) in Table 2. The volatility estimation is performed by the method of quasi maximum likelihood using the BHHH numerical optimization algorithm.

h_t is the conditional variance on day *t*. ε_{t-1} is the unexpected return on day *t-1* after the day-of-the-week and autocorrelation effects are removed. The t-values are in parentheses. Ljung-Box(x) is the Ljung-Box statistics for x^{th}-order serial correlation.

Estimation Results

GARCH(1,1)

$$h_t = \underset{(4.3090)}{0.4690^{***}} + \underset{(7.2122)}{0.5259^{***}} h_{t-1} + \underset{(4.9839)}{0.2585^{***}} (\varepsilon_{t-1})^2$$

LogL = -1476.754

GJR

$$h_t = \underset{(2.7329)}{0.1020^{***}} + \underset{(21.0052)}{0.8462^{***}} h_{t-1} + \underset{(1.1994)}{0.0293} (\varepsilon_{t-1})^2 + \underset{(2.8459)}{0.1596^{***}} [D_{t-1} (\varepsilon_{t-1})^2]$$

LogL = -1467.954

EGARCH(1,1)

$$\log(h_t) = \underset{(-2.7783)}{-0.0790^{***}} + \underset{(67.1301)}{0.9721^{***}} \log(h_{t-1}) + \underset{(3.0859)}{0.1238^{***}} [|\varepsilon_{t-1}| / \sqrt{h_{t-1}}] - \underset{(-3.0538)}{0.0963^{***}} [\varepsilon_{t-1} / \sqrt{h_{t-1}}]$$

LogL = -1462.142

GARCH(1,1)(E&N)

$$h_t = \underset{(2.2977)}{0.0845^{**}} + \underset{(22.5159)}{0.8666^{***}} h_{t-1} + \underset{(3.3490)}{0.0909^{***}} (\varepsilon_{t-1})^2$$

LogL = -1475.106

GJR (E&N)

$$h_t = \underset{(2.7145)}{0.1083^{***}} + \underset{(19.6073)}{0.8465^{***}} h_{t-1} + \underset{(1.2649)}{0.0307} (\varepsilon_{t-1})^2 + \underset{(2.6531)}{0.1388^{***}} [D_{t-1} (\varepsilon_{t-1})^2]$$

LogL = -1465.265

EGARCH(1,1)(E&N)

$$\log(h_t) = \underset{(-2.2141)}{-0.0485^{**}} + \underset{(104.8132)}{0.9724^{***}} \log(h_{t-1}) + \underset{(2.7632)}{0.836^{***}} [|\varepsilon_{t-1}| / \sqrt{h_{t-1}}] - \underset{(-3.4189)}{0.0817^{***}} [\varepsilon_{t-1} / \sqrt{h_{t-1}}]$$

LogL = -1456.882

Diagnostic Test Results

Model	Ljung-Box (6)	Ljung-Box (12)	Ljung-Box (24)	Sign Bias	Negative Size Bias	Positive Size Bias	Joint Test
GARCH(1,1)	5.5717	8.3297	20.35	-0.067	-0.09	-0.235	0.09
GJR	9.1369*	11.354	21.887	-0.926	0.019	1.444	2.56
EGARCH(1,1)	14.417**	16.093	30.658	-1.027	-0.494	2.041**	5.98
GARCH(1,1)(E&N)	11.844*	13.047	21.981	0.536	-3.385***	1.336	18.79***
GJR(E&N)	8.8847	10.955	21.686	0.36	-2.822***	0.901	12.81***
EGARCH(1,1)(E&N)	15.739**	17.335	31.647	0.278	-2.78***	0.871	11.96***

*Significant at 90% confidence level **Significant at 95% confidence level
***Significant at 99% confidence level

TABLE 6

Estimation Results and Diagnostic Tests for the After-Float Subsample (Jul 2, 1997 to Dec 30, 1999)

This table reports the estimation and diagnostic test results of various volatility estimator models for the daily return of the SET index. Day-of-the-week and autocorrelation effects are removed using either the class of GARCH in mean procedure or Engle and Ng (1993)'s procedure (presented by E&N) in Table 3. The volatility estimation is performed by the method of quasi maximum likelihood using the BHHH numerical optimization algorithm.

h_t is the conditional variance on day *t*. ε_{t-1} is the unexpected return on day *t-1* after the day-of-the-week and autocorrelation effects are removed. The t-values are in parentheses. Ljung-Box(x) is the Ljung-Box statistics for x^{th}-order serial correlation.

Estimation Results

GARCH(1,1)

$$h_t = \underset{(3.1372)}{3.2633^{***}} + \underset{(1.4697)}{0.2640} h_{t-1} + \underset{(2.9262)}{0.2156^{***}} (\varepsilon_{t-1})^2$$

LogL = -1419.345

GJR

$$h_t = \underset{(3.8241)}{3.2194^{***}} + \underset{(2.0448)}{0.2770^{**}} h_{t-1} + \underset{(3.2589)}{0.3483^{***}} (\varepsilon_{t-1})^2 - \underset{(-2.1638)}{0.3008^{**}} [D_{t-1} (\varepsilon_{t-1})^2]$$

LogL = -1414.392

EGARCH(1,1)

$$\log(h_t) = \underset{(1.1679)}{0.5421} + \underset{(2.0139)}{0.5686^{**}} \log(h_{t-1}) + \underset{(2.1315)}{0.2802^{**}} [|\varepsilon_{t-1}|/\sqrt{h_{t-1}}] + \underset{(0.2401)}{0.0182} [\varepsilon_{t-1}/\sqrt{h_{t-1}}]$$

LogL = -1426.280

GARCH(1,1)(E&N)

$$h_t = \underset{(2.9159)}{2.6873^{***}} + \underset{(2.2444)}{0.3769^{**}} h_{t-1} + \underset{(2.5304)}{0.1926^{**}} (\varepsilon_{t-1})^2$$

LogL = -1419.034

GJR (E&N)

$$h_t = \underset{(3.7790)}{3.2027^{***}} + \underset{(2.0454)}{0.2867^{**}} h_{t-1} + \underset{(3.2494)}{0.3320^{***}} (\varepsilon_{t-1})^2 - \underset{(-2.2131)}{0.2928^{**}} [D_{t-1} (\varepsilon_{t-1})^2]$$

LogL = -1413.416

EGARCH(1,1)(E&N)

$$\log(h_t) = \underset{(1.5860)}{0.5318} + \underset{(3.1839)}{0.5862^{***}} \log(h_{t-1}) + \underset{(2.3201)}{0.2543^{**}} [|\varepsilon_{t-1}|/\sqrt{h_{t-1}}] + \underset{(1.8020)}{0.1305^{*}} [\varepsilon_{t-1}/\sqrt{h_{t-1}}]$$

LogL = -1417.554

Diagnostic Test Results

Model	Ljung-Box (6)	Ljung-Box (12)	Ljung-Box (24)	Sign Bias	Negative Size Bias	Positive Size Bias	Joint Test
GARCH(1,1)	5.8627	11.944	23.462	-1.193	2.182**	1.562	6.13
GJR	4.1358	8.8867	19.568	0.232	0.551	-0.182	0.61
EGARCH(1,1)	7.2272	17.100	27.849	-1.488	1.854*	2.146**	6.13
GARCH(1,1)(E&N)	4.9986	12.533	23.334	-0.932	2.213**	1.4 78	6.74*
GJR(E&N)	4.1861	9.1013	18.83	0.27	0.542	-0.182	1.23
EGARCH(1,1)(E&N)	5.1241	9.8619	19.393	0.158	0.729	0.682	2.45

*Significant at 90% confidence level **Significant at 95% confidence level

***Significant at 99% confidence level

TABLE 7

Summary Statistics of the Conditional Variance Estimates

This table reports the summary statistics of the estimated conditional variance of the SET index daily return under various models. The data period is from January 4, 1994 to December 30, 1999. This data set is divided into two subperiods: the Before-Float period is from January 4, 1994 to June 30, 1997 and the After-Float period is from July 2, 1997 to December 30, 1999.

h_t GARCH, h_t GJR, h_t EGARCH, h_t GARCH(E&N), h_t GJR(E&N), h_t EARCH(E&N) are the conditional variances estimated from the GARCH-M, GJR-M, EGARCH-M, GARCH(1,1), GJR, and EGARCH(1,1) in Table 4 to 6. For the last three models, the estimation processes are from Engle and Ng (1993). Therefore, we put (E&N) after these models.

Total Sample (Jan 4, 1994 to Dec 30, 1999)						
	Mean	**Std. Dev.**	**Min**	**Max**	**Skewness**	**Kurtosis**
h_t**GARCH**	4.1518	3.5644	0.6646	29.7250	2.3649	11.3677
h_t**GJR**	4.1462	3.5696	0.6341	31.0329	2.4305	12.3288
h_t**EGARCH**	4.0223	3.0973	0.5170	24.4453	1.8515	8.1865
h_t**GARCH(E&N)**	4.1886	3.6481	0.6857	29.2546	2.2987	10.3591
h_t**GJR(E&N)**	4.1462	3.5439	0.6551	28.5201	2.2737	10.4976
h_t**EGARCH(E&N)**	4.0367	3.1709	0.5284	23.3752	1.9507	8.2182

Before-Float Subsample (Jan 4, 1994 to Jun 30, 1997)						
	Mean	**Std. Dev.**	**Min**	**Max**	**Skewness**	**Kurtosis**
h_t**GARCH**	2.1709	1.8219	1.0253	25.1727	5.3895	48.8085
h_t**GJR**	2.1786	1.8129	0.7779	18.4639	3.8496	24.5627
h_t**EGARCH**	2.0735	1.3461	0.5559	9.6441	2.0500	9.2702
h_t**GARCH(E&N)**	2.1565	1.7081	0.8087	15.1617	4.1846	25.1583
h_t**GJR(E&N)**	2.1576	1.9359	0.8138	19.7798	4.3219	27.9137
h_t**EGARCH(E&N)**	2.1402	1.7964	0.6403	15.1771	3.9992	23.7191

After-Float Subsample (July 2, 1997 to Dec 30, 1999)						
	Mean	**Std. Dev.**	**Min**	**Max**	**Skewness**	**Kurtosis**
h_t**GARCH**	6.3384	3.0407	4.4539	29.3529	4.0059	23.5352
h_t**GJR**	6.4744	4.4626	4.4610	47.6266	5.0029	34.7484
h_t**EGARCH**	6.0025	1.8937	3.8635	20.2757	2.9027	15.3467
h_t**GARCH(E&N)**	6.3460	3.0733	4.3560	32.5981	4.0296	24.1065
h_t**GJR(E&N)**	6.4708	4.4442	4.4976	50.1535	5.0626	36.0175
h_t**EGARCH(E&N)**	6.1520	2.6683	3.9443	28.6825	3.5269	20.7579

Figure 1

The News Impact Curves of the GARCH-M Model and the GJR Model for the Before-Float Subsample (Jan 4, 1994 to Jun 30, 1997)

The solid line represents the GJR news impact curve. The equation for the GJR news impact curve is from GJR equation in Table 5. By giving previous conditional variance, h_{t-1}, constant at 1; the equation for the GJR news impact curve can be expressed as follows:

$$h_t = 0.9482 + 0.0293(\varepsilon_{t-1})^2 + 0.1596\,[D_{t-1}\,(\varepsilon_{t-1})^2]$$

where D_{t-1} is a dummy variable whose value is 1 when ε_{t-1} is negative.

The dashed line represents the GARCH-M news impact curve. The equation for the GARCH-M news impact curve is from GARCH(1,1) equation in Table 5. By giving previous conditional variance, h_{t-1}, constant at 1; the equation for the GARCH-M news impact curve can be expressed as follows:

$$h_t = 0.9949 + 0.2585\,(\varepsilon_{t-1})^2$$

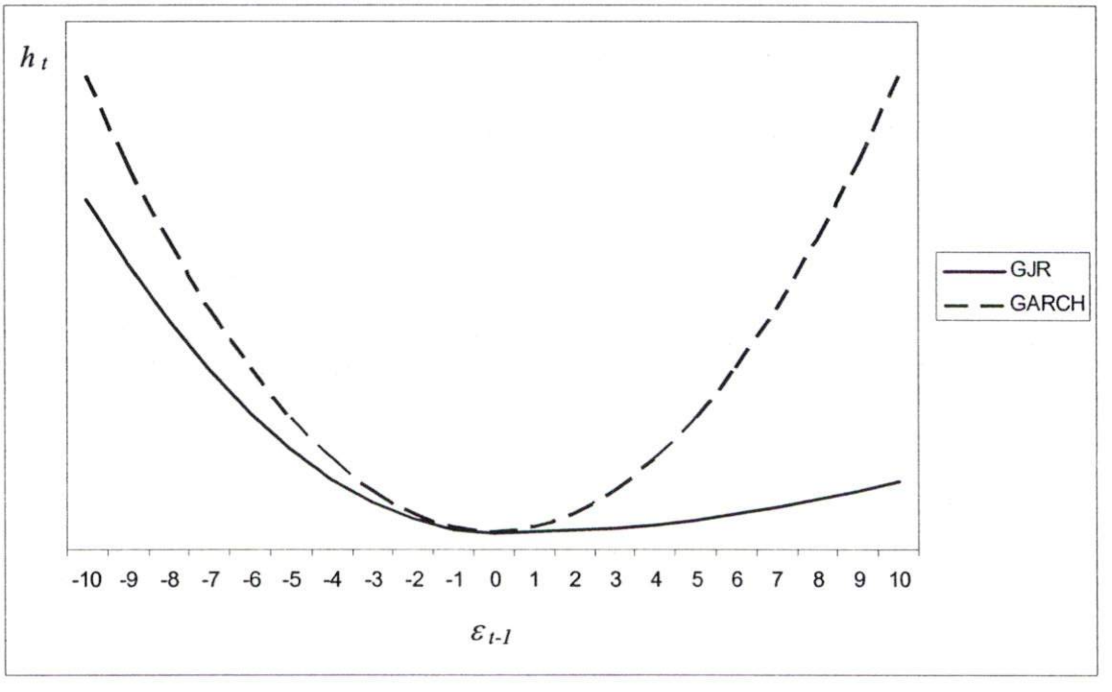

Figure 2

The News Impact Curves of the GARCH-M Model and the GJR Model for the After-Float Subsample (Jul 2, 1997 to Dec 30, 1999)

The solid line represents the GJR news impact curve. The equation for the GJR news impact curve is from GJR equation in Table 6. By giving previous conditional variance, h_{t-1}, constant at 1; the equation for the GJR news impact curve can be expressed as follows:

$$h_t = 3.4964 + 0.3483(\varepsilon_{t-1})^2 - 0.3008[D_{t-1}(\varepsilon_{t-1})^2]$$

where D_{t-1} is a dummy variable whose value is 1 when ε_{t-1} is negative.

The dashed line represents the GARCH-M news impact curve. The equation for the GARCH-M news impact curve is from GARCH(1,1) equation in Table 6. By giving previous conditional variance, h_{t-1}, constant at 1; the equation for the GARCH-M news impact curve can be expressed as follows:

$$h_t = 3.5273 + 0.2156(\varepsilon_{t-1})^2$$