TIME-VARYING VOLATILITY OF STOCK RETURNS IN THE MSM: ARCH AND GARCH EFFECTS[1]

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Abstract

The Muscat Securities Market (MSM) was established in 1989 with 71 listed companies with an equity capital of about US$700 million. There has been an explosive growth of the market index in 1997reaching more than 500 points. In September 1998, the MSM Index dropped to 280 points. Despite the government subsequent reform measures with significant investments in modernizing the trading systems & institutional infrastructure, the MSM has not yet recovered from its 1998 crash. The negative growth of the MSM index, –16% and –27% reported in year 2000 and 2001 respectively. The S&P/IFCG Oman Index fell 10.2% in the last quarter of 2002, while the local MSM Index lost 9.9. This paper applies the family of ARCH models to examine the volatility of the MSM. Empirical results show that GARCH(1,1) model can adequately describe stock market behavior of the MSM which is much smaller and thinner than other developed stock markets. The coefficient of ARCH(1) indicates that the current period variances are higher if the past period had large disturbances**.** Estimation results of the asymmetric ARCH models, TARCH and EGARCH show that the impact of news is asymmetric and is confirmed by TARCH parameter estimates, indicating an existence of the leverage effect in future returns of the stock. The estimate of the asymmetric ARCH also indicates that the long run component converges very rapidly to the steady state, and the short run volatility component appears to be trivial. This result has been further confirmed by forecasting the mean and the conditional variance from the component model. The Quantile graph shows it was primarily a few large outliers that departed the market from its normality.

I. Introduction

A significant amount of empirical research has been conducted to investigate the behavior of asset return volatility over time. Attempts to explain this volatility in stock markets have focused in recent research on the issue of modeling time-varying volatility and the implied stochastic prices for expected returns. Measuring volatility of asset prices or returns has remerged as a major field of research against the background of financial deregulation and financial innovation. Conventional time series and regression models assume a constant variance of the stochastic term. Various authors have argued that variances of securities' prices or returns are not homoskedastic but exhibit heteroskedascity over time. They have observed that large changes tend to be followed by large changes in either direction, and so volatility must be highly predictable after large changes. This phenomenon of securities' volatility has important implications for security pricing and risk management. Among the most popular techniques currently used to capture the clustering effect and to forecast future volatility, belong to the family of Autoregressive Conditional Heteroskedastic (ARCH)

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models. Engle (1982) introduced ARCH model that permits a changing conditional variance. This model was subsequently extended by Bollerslev (1986) as GARCH process that allows for more flexible structure in the model. In time series analysis the objective often is to forecast future values of the variable. The ARCH models are designed to model and forecast the variance of the dependent variable. There are several reasons that we may need to forecast volatility. First, we may need to deal with volatility to understand the risk of holding a stock. Second, forecast confidence intervals may be time varying so that more accurate intervals can be obtained by modeling the variance of the errors. Third, more efficient estimators can be obtained if heteroskedasticity in the errors is handled appropriately.

The original ARCH and GARCH models were developed within the context of studies of inflation rate volatility. In foreign exchange markets, Abuaf and Jorian (1990) have applied the approach to gain a better understanding of, and support for, purchasing power parity. Baldauf and Santoni (1991) use an ARCH model to examine volatility associated with the introduction of program trading between cash and futures markets. However, these models and their extensions have now become common in finance, especially in studies of volatility in stock returns. Lamoureux and Lastrapes (1990) employ a GARCH model to examine the impact of information flow on the volatility of stocks. Schwert and Seguin (1990) consider that hetroskedasticity is a pervasive phenomenon in stock returns. Bera et al. (1988) developed an ARCH process for estimating beta in the market model, while Boudurtha and Mark (1991) examine a generalized methods of moments to overcome estimation problems in an ARCH model when evaluating betas.[2] Bottazzi and Corradi (1991) have successfully incorporated tests of heteroskedasticity in the study of the volatility in the Italian stock market. Poon and Taylor (1992) have also incorporated an ARCH model in their study of the U.K. Stock market. Errunza et al (1994), Bekaert and Harvey (1995), and Aggarwal, Inclan, and Leal (1995), among others, are examples of ARCH modeling in emerging markets. It has been argued by them that changes in regime followed by policy changes and other events yield a time series of returns that presents sudden changes in the variance. Leal and Bocater (1996) investigates the role of outliers in equity returns series in Argentina , Brazil, Chile, and Mexico. After removing the outliers they did not find ARCH effects in the series. They argued that the clean series could be modeled by the standard Box-Jenkins ARIMA process. They claim that ARCH effects in these markets were due to the presence of the outliers; otherwise, the variance of the time series was not changing though time according to a standard AHCH model. They identified the outliers related to major economic events such as the freezing of financial assets, economic liberalization plans, or debt related problems. A study by Ratner and Leal (1996) examines the equity market overreaction in the ten largest emerging stock markets in Latin America and Asia. They use daily data from January 1982 through April 1995. Their statistical results show no market over-reaction in a majority of the cases. However, their logit analysis shows that movements in Japanese, U.S. and World indexes explain some of the large one-day movements in the emerging Asian markets. There is evidence that shifts in regime or other events may cause sudden changes in the conditional variance that are not consistent with the type of modeling generally used in the variance equation in ARCH models.[3] There is also empirical evidence for emerging markets the sudden changes in the variance do occur.[4] This is not surprising given the changing nature of these markets and their recent opening to outside investors.

King et al. (1994) uses data on 16 national stock markets to estimate a multivariate factor

[2] For more comprehensive coverage of the literature on ARCH models in finance see Bollerslev, Chou, and Kroner (1992).

[3] See Inclan and Tiao, 1994; Bekaert, 1995; Bekaert and Harvey, 1995.

[4] See also,Aggarwal, Inclan, and Leal, 1995.

model in order to investigate whether time-varying volatility of returns is induced by changing volatility in the underlying factors. They try to identify those factors that are responsible for changes over time in stock market volatility. Unanticipated returns are assumed to depend both on the innovations in observable economic variables and the on unobservable factors. They find that only a small proportion of the covariance between national stock markets and their time-variation can be accounted for by observable economic variables. Changes in correlations between markets are driven primarily by movements in unobservable variables. They also find that idiosyncratic risk is significantly priced, and that the price of risk is not common across countries. It is now well documented that asset returns exhibit volatility clustering which implies that the volatility of asset returns is not constant but is time-varying. Some of the evidence is given by Baillie and Bollerslev (1989) and Pagan and Schwert (1990). The considerable evidence on the time-varying behavior of asset return volatility has led to renewed interest in finding the causes of volatility movements. In the equity market, for example, financial leverage suggested by Black (1976) to cause changes in volatility. Others like Officer (1973) and Schwert (1989) found movements in volatility to be related to macroeconomic variables. Many studies have also documented that volatility of asset returns increases significantly around the time information is released to the market. In fact the close association between the volatility movements and information flows is considered in models developed by Clark (1973) and Ross (1989). Using volume as a proxy for information arrival, Schwert (1989) and Lamoureux and Lastrapes (1990) found evidence consistent with these models. Further support for these models is given by the empirical studies of Patel and Wilson (1979) and Harvey and Huang (1991) where both studies found that the volatility of asset returns is higher around the time information announcements.

A further phenomenon on the distributional properties of the asset returns any also be explained by the arrival process of information to financial markets. Many studies have found that unconditional distribution of returns are typically fat-tailed or letokurtic. Examples of these studies include those by Hsieh (1989) and Baillie and Bollerslev (1989). Baillie and Bollerslev (1991) and Bollerslev, Chau, and Kroner (1992) suggested such distributional properties of asset returns may be explained partly by information arriving in clusters to financial markets. As a result, the degree of leptokurtosis in the distribution of returns may be reduced if we can determine and account for any known timing in the announcement of news. Lastrapes (1989) provided some results consistent with this hypothesis. Bollerslev (1987), Schwert (1989), and Islam and Landeck (1996), among others, studied the observed behavior and movement of many high frequency financial speculative price variables that change over time, and found that statistical distribution of returns is skewed and leptokurtic. Moreover, their studies show that volatility is negatively correlated with past returns. Hamao et al. (1990) examine the short-run interdependence of prices and price volatility across three major international stock markets. They use the daily opening and closing prices from April 1985 to March 1988 of major stock indexes for the New York, London and Tokyo. Applying the ARCH family of statistical models to explore these pricing relationships, their study shows the evidence of one way price volatility spillovers from New York to Tokyo, London to Tokyo, and New York to London. Claessens and Dasgupta (1994) have focused on analyzing the behavior of returns in emerging stock markets. Their study support high and positively skewed stock returns in those markets.

Historically, most tests were conducted on the markets in developed industrial countries. Over the past few years, there has been a growing interest in emerging markets. With respect to Arab countries, a few studies have been undertaken to date. Bekaert and Harvey (1997) argue that high fluctuations in volatility that increase uncertainty of capital asset returns and payoff risks may raise the costs of capital and delay investment decisions, thus leading to lower levels of growth and inflation. Their study also shows that Egyptian stock returns are characterized by high volatility. Moursi (1999) examined the behavior of stock returns and market volatility in Egypt by using the GARCH model. His investigation shows that market volatility is considerably affected by past shocks associated with the arrival of news. Moreover, he argues that volatility is also affected by the past conditional prediction of returns, and that relative high variance in stock return volatility, especially in new emerging markets, can have negative effects on the level of investment. Dahel (1999) focuses on the issue of volatility of returns in a study that also includes emerging and developed markets, and finds that Arab markets exhibit the lowest level of volatility and the emerging markets the highest.

While the behavior of other securities markets has been examined extensively, little attention has been paid towards an extensive analysis of the volatility of the emerging stock markets of GCC countries, especially Oman. At this point in time there is no evidence of studies of the emerging stock market of Oman that attempt to model the time-varying properties of volatility along the lines of Engle (1982) and Bollerslev (1986). These models are applied to the variance of the rate of return implicit in the time series of stock prices in the emerging stock market in Oman, known as the Muscat Security Market (MSM), by using high frequency daily stock prices from 1997 to 2000. The recent statistics shows that the flow of investment has been increasing in Oman. In response to its stable macroeconomic factors and capital market liberalization, the MSM is now receiving increasing attention from investors from other GCC countries. This study thus examines the time-varying volatility by applying the family of ARCH (GARCH, TARCH and EGARCH) model in order to investigate volatility of the market.

Data and the Variable:

The data include 628 daily observations for Muscat stock market general price indices (MSM INDEX) covering the period from the February 15, 1997 through June 19, 2000. The data are obtained from the Capital Market Authority of the MSM and the Standard & Poor's Emerging Market Data Base (EMDB) databases. Stock dividends are not included because the wealth effect is not considered. The MSM Index returns are calculated using the continuously compounding formula in natural logarithms as

$$\mathbf{R_t = \ln (P_t/P_{t-1})}$$

where $\mathbf{P_t}$ is the General Price Index of MSM at time t, $\mathbf{R_t}$ is the return of MSM price index (RMSM), and **ln** is the natural logarithm.

The remainder of this paper is organized as follows. Section II discusses the Trends of the MSM. Section III discusses the methodology. The empirical results are discussed in section IV, while section V concludes the paper.

II. Trends of the Market:

The Muscat Securities Market (MSM) was established in 1989 with 71 listed joint stock companies with an equity capital of US$702 million. The members of the MSM include public corporations, listed companies, intermediaries and the Central bank of Oman. In 1999 a new capital market law was introduced to establish the Capital Market Authority (CMA) to regulate the new issuance and trading of securities on the MSM. The MSM Index includes four sectors: Banking, Investment, Industrial, and Services, each one with its own index. The banking sector captures about 45% of the market volume. Trading in the investment sector accounts for about 19% of the market volume and trading in the industrial sector accounts for 13% of the market volume, while trading in the service sector is about 23% of the market volume. Listing with the market requires that listing companies must have a capital of $5.2 million and have at least 100 shareholders. There is no capital gains tax, no withholding tax and no tax on dividends. In 1996, amendments were made to the Companies Tax Law aimed at encouraging Oman joint stock companies to allow non-Omani shareholders. Corporate taxation stands at 12% of the net income. At present, the MSM has five indices—General, Services, Investment, Banks and Industry.

The opening of the MSM to international investors was initiated by the government liberalization program. There are no taxes on foreign investors' capital gains or any other income accrued for investing in MSM. There are no limits on repatriation of funds with a stable freely convertible currency. Foreigners are free to buy and sell shares directly through the MSM but such transactions must be done through the local licensed brokerage companies. Foreign participation has increased to 33 non-Omani nationalities at the end of 1997. Before the crash in 1998, foreign investment was about one billion US dollars (11% of total market shares).[5]

From 1989 to 1994, the MSM general index increased about 46%. In 1995 and 1996, the market gained 8%, and 26%, respectively. In 1997, it jumped 141%, indicating the best performing market in the region. Although the market index reached to 510, however by the end of 1998 it fell to 228. In 1998 the aggregate earnings of listed companies declined by 53% compared with 1997 profits. On 22 October 2000, the index declined further to 187. Critiques have attributed the plunge of the market to speculation, over-valued prices, and the drastic fall in oil price combined with the impact of the Asian financial crisis. The behavior of the random walk of the market index is exhibited in Graph 1. However, the returns Rt, series of the MSM are stationary as exhibited in graph 2.

Insert Graphs 1 and 2 about here

III. Methodology

ARCH Models:

As described earlier that the ARCH models are introduced by Engle (1982), and subsequently generalized as GARCH (Generalized ARCH) by Bollerslev (1986). These models are widely used in various branches of econometrics, especially in financial time series analysis. Here we use ARCH to refer to both ARCH and GARCH models, except where there is a possibility of confusion. An ARCH model, requires to consider two distinct specifications—one for the conditional mean and one for the conditional variance.

[5] However 33% of the foreign holdings came from the UAE alone. The openness of MSM to foreign investors and its high level of transparency and the quality of corporate accounting were due to compliance of international accounting standards. The new listing requirement makes it obligatory for companies to allow non-GCC investors to own up to 49% of the company's shares.

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The GARCH (1, 1) Model

In the standard GARCH (1, 1) specification**:**

$$y_t = x_t \gamma + \varepsilon_t \tag{1}$$

$$\sigma_t^2 = \omega + \alpha \varepsilon_{t-1}^2 + \beta \sigma_{t-1}^2 \tag{2}$$

The mean equation (1) is written as a function of exogenous variables with an error term. Since σ_t^2 is the one-period ahead forecast variance based on past information, it is called the *conditional variance.* The conditional variance equation (2) is a function of three terms:
The mean ω; news about volatility from the previous period, measured as the lag of the squared residual from the mean equation ε_{t-1}^2 (the (ARCH term); and the last period's forecast variance σ_t^2 (the GARCH term). The (1,1) in GARCH(1,1) refers to the presence of a first-order GARCH term and a first-order ARCH term. An ordinary ARCH model is a special case of a GARCH specification in which there are no lagged forecast variances in the conditional variance equation.[6]

This specification is often interpreted in a financial context, where an agent or trader predicts this period's variance by forming a weighted average of a long term average (the constant), the forecasted variance from last period (the GARCH term), and information about volatility observed in the previous period (the ARCH term). If the asset return was unexpectedly high in either the upward or the downward direction, then the trader will increase the estimate of the variance for the next period. This model is also consistent with the volatility clustering often seen in stock returns data, where large changes in returns are likely to be followed by further large changes.

If we recursively substitute for the lagged variance on the right-hand side of equation (2), we can express the conditional variance as a weighted average of all of the lagged squared residuals:

$$\sigma_t^2 = \frac{\omega}{(1-\beta} + \alpha \sum_{j=1}^{\infty} \beta^{j-1} \varepsilon_{t-j}^2 \tag{2a}$$

We see that the GARCH (1,1) variance specification is analogous to the sample variance, but that it down-weights more distant lagged squared errors. The error in the squared returns is given by $v_t = \varepsilon_t^2 - \sigma_t^2$. Substituting for the variances in the variance equation and rearranging terms we can write our model in terms of the errors:

$$\varepsilon_T^2 = \omega + (\alpha + \beta)\varepsilon_{t-1}^2 + \upsilon_t - \beta \upsilon_{t-1} \tag{2b}$$

Thus, the squared errors follow a heteroskedastic ARMA (1,1) process. The autoregressive root which governs the persistence of volatility shocks is the sum of α and β. In many applied settings, this root is very close to unity so that shocks die out rather slowly.

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[6]ARCH models in Eviews are estimated by Maximum Likelihood method under the assumption that errors are conditionally normally distributed.

Equation (2) may be extended to allow for the inclusion of exogenous or predetermined regressors, z, in the variance equation:

$$\sigma_t^2 = \omega + \alpha\varepsilon_{t-1}^2 + \beta\sigma_{t-1}^2 + \pi z_t \tag{3}$$

Forecasted variances from this model are not guaranteed to be positive.[7]

The GARCH(p,q) Model

The higher order GARCH models, denoted GARCH (*p,q)*, can be estimated by choosing either p or q greater than 1, the representation of the GARCH*(p,q)* variance is

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

where p is the order of the GARCH terms and q is the order of the ARCH term.

The TARCH Model

The Threshold ARCH (TARCH) model was introduced independently by Zakoian (1990) and Glosten, Jaganathan, and Runkle (1993). The specification for the conditional variance is

$$\sigma_t^2 = \omega + \alpha\varepsilon_{t-1}^2 + \gamma\varepsilon_{t-1}^2 d_{t-1} + \beta\sigma_{t-1}^2 \tag{5}$$

where d_t=1 if $\epsilon_t > 0$, and 0 otherwise.

In this model, good news ($\epsilon_t > 0$), and bad news ($\epsilon_t < 0$), have differential effects on the conditional variance. Good news has an impact of α, while bad news has an impact of ($\alpha + \gamma$). If $\gamma > 0$ then there exists the *leverage effect*. If $\gamma \neq 0$, the news impact is asymmetric. The higher order specifications of the TARCH model is

$$\sigma_t^2 = \omega + \sum_{i-1}^{q}\alpha_i\varepsilon_{t-1}^2 + \gamma\varepsilon_{t-1}^2 d_{t-1} + \sum_{j=1}^{p}\beta_j\sigma_{t-j}^2 . \tag{5a}$$

The EGARCH Model

The Exponential GARCH (EGARCH) model was proposed by Nelson (1991). The specification for the conditional variance is

$$\log\left(\sigma_t^2\right) = \omega + \beta\log\left(\sigma_{t-1}^2\right) + \alpha\left|\frac{\varepsilon_{t-1}}{\alpha_{t-1}}\right| + \gamma\frac{\varepsilon_{t-1}}{\sigma_{t-1}} \tag{6}$$

[7] One may wish to introduce regressors in a form where they are always positive to minimize the possibility that a single, large negative value generates a negative forecasted value. For example, one may want to set $z_t = |x_t|$.

On the left-hand side of this model is the *log* of the conditional variance. This implies that the leverage effect is exponential, rather than quadratic, and that forecasts of the conditional variance are guaranteed to be nonnegative. The presence of leverage effects can be tested by the hypothesis that $\gamma > 0$. The impact is asymmetric if $\gamma \neq 0$. [8]

IV. **Empirical Results**

The simplest and most widely used ARCH modeling group in finance is GARCH (1,1) where today's variance depends on three factors: a constant (long term average), yesterday's news about volatility which taken to be the squared residual from yesterday (the ARCH term) and yesterday's forecast variance (the GARCH term). This specification makes sense in the stock market where investors predict today's variance by forming a weighted average of a long term average (or constant variance), the forecast from yesterday (GARCH term), and what was learned from yesterday's news (ARCH term). Table 1 reports the GARCH(1,1) estimates for return series R_t. The result shows only ARCH(1) has significant effect on the volatility of the market.[9] The ARCH(1) means that the model of the variance R_t involves only the most recent actual squared value. News about volatility from the previous day (the ARCH term) had significant impact on current the market volatility, but the previous day's forecast variance (the GARCH term) did not have a significant effect on today's volatility.

Insert Table 1 about here

The main output from ARCH estimation is divided into two sections; the upper part provides the standard output for the mean equation, while the lower part, labeled "Variance Equation" contains the coefficients, standard error, z-statistics and p-values for the coefficients of the variance equation. The ARCH parameters correspond to α and the GARCH parameters to β. The lower panel of the output presents the standard set of regression statistics using residuals from the mean equation.[10] In our estimation, the sum of the ARCH and GARCH coefficients ($\alpha + \beta$) is very close to 1, indicating that volatility shocks are quite persistent. This result is consistent with studies using high frequency data such as daily and weekly series.

Graph 3 displays the view of RMSM (R_t) residuals while Graph 4 displays the standardized residuals of return series R_t.

Insert Graphs 3 and 4 about here

We have performed several diagnostic tests for the standardized residuals of R_t series. Table 2 provides the results of correlogram (autocorrelations and partial autocorrelations) of the standardized residuals. This result could be used to test for the remaining serial correlation in the mean equation as well as to test the specification of the mean equation. If the mean equation is correctly specified, all Q-statistics should not be significant. In our case all Q-statistics are highly significant (p-value close to 0) that implies that the mean equation is not correctly specified.

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[8] There are two differences between the Eviews specification of the EGARCH model and the original Nelson model. First, Nelson assumes that the ε follows a generalized error distribution, while Eviews assumes normally distributed errors. Second, Nelson's specification for the log conditional variances differs slightly from the specification above.

[9] Although higher order GARCH (p,q) are estimated, there is no change in our conclusions.

[10] Note that R^2 is negative and is not meaningful here because there is no regressors in the mean equation.

Insert Table 2 about here

Table 3 displays descriptive statistics and a histogram of the standardized residuals. Here we use the J-B statistics to test whether the standardized residuals are normally distributed. If the J-B statistic is significant then the standardized residuals are not normally distributed. In our estimation, the residuals are highly leptokurtic and J-B statistic decisively rejects the hypothesis of normal distribution.

Insert Table 3 about here

An alternative way to check the distribution of the residuals is to plot the Quantiles. Thus we plotted the Quantile graph against Quantiles of the normal distribution and are displayed in graph 5. If the residuals are normally distributed, the QQ-plots should lie on the straight line. The plot shows that it is primarily a few large outliers that are driving the departure from its normality.

Insert Graph 5 about here

Table 4 provides the results of ARCH LM test that carries out Lagrangian multiplier tests to check whether the standardized residuals exhibit additional ARCH (Engle 1982).[11] If the variance equation is correctly specified, there should be no ARCH left in the standardized residuals. The ARCH LM test statistic is computed from an auxiliary test regression. To test the null hypothesis (H_0) that there is no ARCH up to order q in the residuals, we run regression on the squared residuals on the constant and lagged squared residuals up to order q. Table 4 reports two test statistics from this test regression. The upper part shows the F-statistic which is an omitted variable test for the joint significance of all lagged squared residuals.[12] We cannot reject the H_0 implying that there is no additional ARCH effect in the residuals equation.

Insert Table 4 about here

Table 5 reports ARCH-in-Mean (ARCH-M) model (Engle, Lilien, Robins, 1987) for R_t by inducing the conditional variance into the mean equation. This model is often used in financial applications where the expected return on an asset is related to the expected asset risk. The estimated coefficient on the expected risk is a measure of the risk-return tradeoff.

Insert Table 5 about here

As discussed earlier for stocks, it is often observed that downward movements in the market are followed by higher volatilities than upward movements of the same magnitude. To account for this phenomenon, Engle and Ng (1993) describe a News Impact curve with asymmetric response to good and bad news. Here we estimate two models that allow for asymmetric shocks to volatility: Threshold ARCH (TARCH) model, introduced by Zakonian

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[11] This particular specification of heteroscedasticity was motivated by the observation that in many financial time series, the magnitude of the residuals appear to be related to the magnitude of recent residuals. ARCH in itself does not invalidate standard least squares (LS) inference. However, ignoring ARCH effects nay result in loss of efficiency.

[12] The Obs*R-squared statistic is Engle's LM statistic, computed as the number of observations times the R^2 from the test regression. The exact finite sample distribution of the F-statistic under H_0 is not known but the LM test statistic is asymptotically distributed χ^2 (q) under quite general conditions. Note ARCH LM test is available for equations estimated by LS, 2SLS as well as non-linear LS.

(1990) and Glosten, Jaganathan, and Runkle (1993), and the exponential GARCH (EGARCH) model proposed by Nelson (1991).

Table 6 reports the estimation of TARCH and EGARCH models in Panel A and Panel B, respectively.

Insert Table 6 about here

The TARCH (1,1) model fitted to the daily return series R_t shows the leverage effect term, γ, represented by (RESID < 0)*ARCH(1) in the output, is significantly negative, implying the news impact is asymmetric. Since the estimated coefficients of both α and γ statistically significant, it appears that bad news has an impact on the conditional variance. We use the quasi-likelihood robust standard errors since the residuals are highly leptokurtic.[13] The leverage effect term**,** γ, denoted by RES/SQU[GARCH](1) in the estimation in Panel B of Table 6, is positive and is highly statistically significant, indicating the existence of the leverage effect in future stock returns during the sample period.

The estimation results of fitting the asymmetric component model to the stock returns are shown in Table 7. The coefficients labeled "Perm:" are the coefficients for the permanent equation and those labeled "Trans:" correspond to the transitory equation. The estimate of the persistence in the long-run component, ρ = 0.315, and is statistically significant, indicating that the long-run component converges rapidly to the steady state. The short run volatility component is found to be significant.

Insert Table 7 about here

After setting the asymmetric effect to its mean, we have checked the joint hypothesis that ($\alpha + 0.5\gamma + \beta = 0$), by Wald coefficient restrictions test. The result is given in Table 8.

Insert Table 8 about here

The Table 8 reports the F-statistic and a χ^2 - statistic with associated p-values. The χ^2 - statistic is equal to the F-statistic times the number of restrictions under test. In our case, there is only one restriction and so the two test statistics are identical with p-values of both statistics indicating that we can decisively reject the H_0 hypothesis**.**

V. Summary and Conclusions

This study examines the volatility behavior of the MSM stock returns using daily data from February 17, 1997 through July 14, 1999. This volatility behavior is investigated by applying the tests of various ARCH models. We find that GARCH(1,1) model can adequately describe stock market behavior of the MSM which is much smaller and thinner than other developed stock markets. The coefficient of ARCH(1) indicates that current period variance is higher if past period had large disturbances. However, the coefficient of GARCH(1) indicates that the effect does not persist for longer time, and there is strong evidence of conditional heteroscedasticity. For diagnostic checking of the estimated ARCH model, we applied several tests on the standardized residuals of the stock returns. All residual tests

[13] When forecasting with this model, EViews assumes that the distribution of the residuals is symmetric so that d = 1 half of the time. Since we cannot identify when this occurs, we arbitrarily set d = 0.5 for all observations.

confirm that series are not normally distributed and show leptokurtic. Estimation results of the asymmetric ARCH models (TARCH and EGARCH) show that the news impact is asymmetric (confirmed by TARCH parameter estimates) and there is an existence of the leverage effect in future returns of the stock during the sample period. The estimate of the asymmetric ARCH indicates that the long run component converges very rapidly to the steady state and the short run volatility component appears to be zero. This result is also confirmed by forecasting the mean and the conditional variance from the component model. The Wald coefficient restrictions test rejects the null hypothesis of parameter restrictions. There are a few large outliers in 1997 and in early 1998 because of bullish market activities and its subsequent crash. This is clearly observed in histograms and residuals tests, indicating the residuals are highly leptokurtic and the Jarque-Bera test decisively rejects the normal distribution. This result is also consistent with the Quantile graph, plotting the residual series against quantiles of the normal distribution. The Quantile graph shows it is primarily a few large outliers that are driving the market from its normality.

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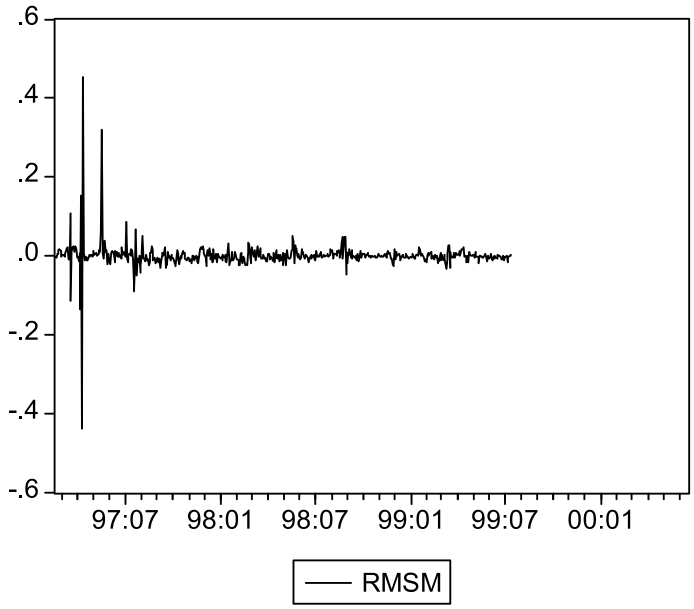
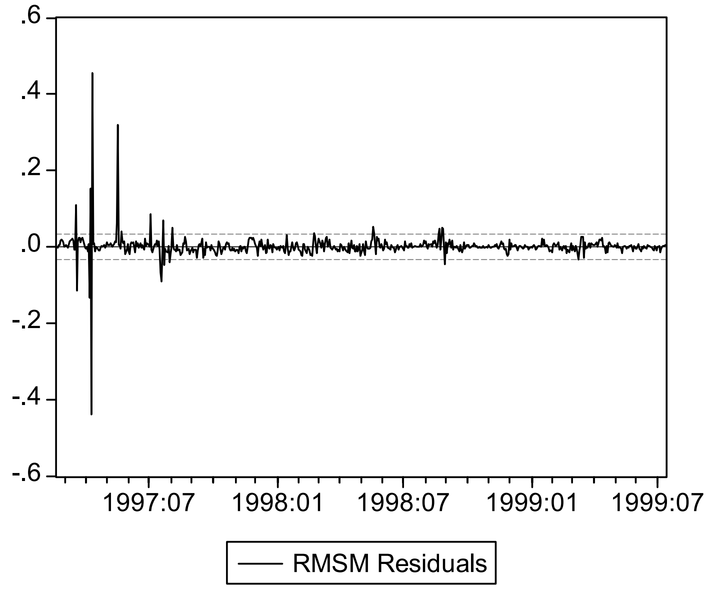
Graph 1: MSM Price Index

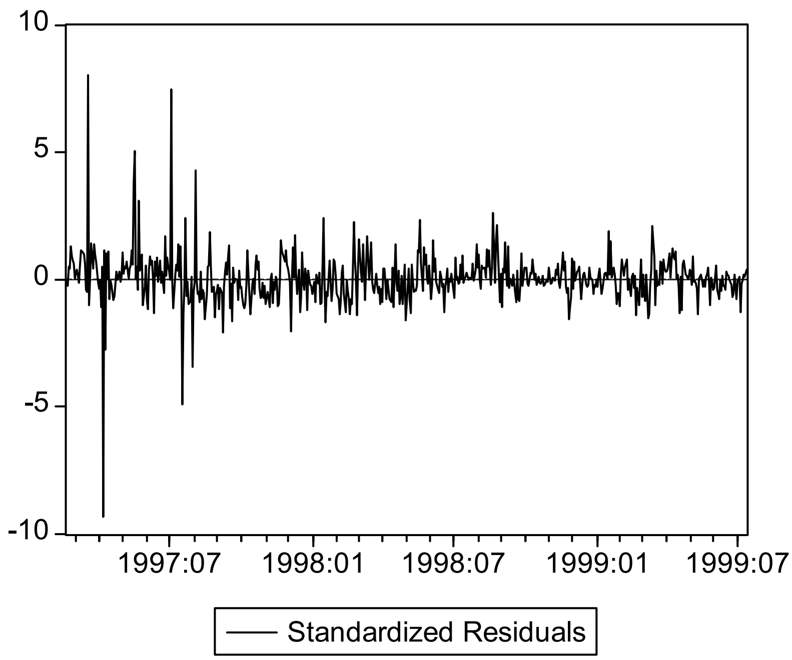
Graph 2: MSM Return Index



Graph 3: Residuals of Return Series



Graph 4: Standardized Residuals of Return Series



Graph 5 Quantiles of MSM Return Series

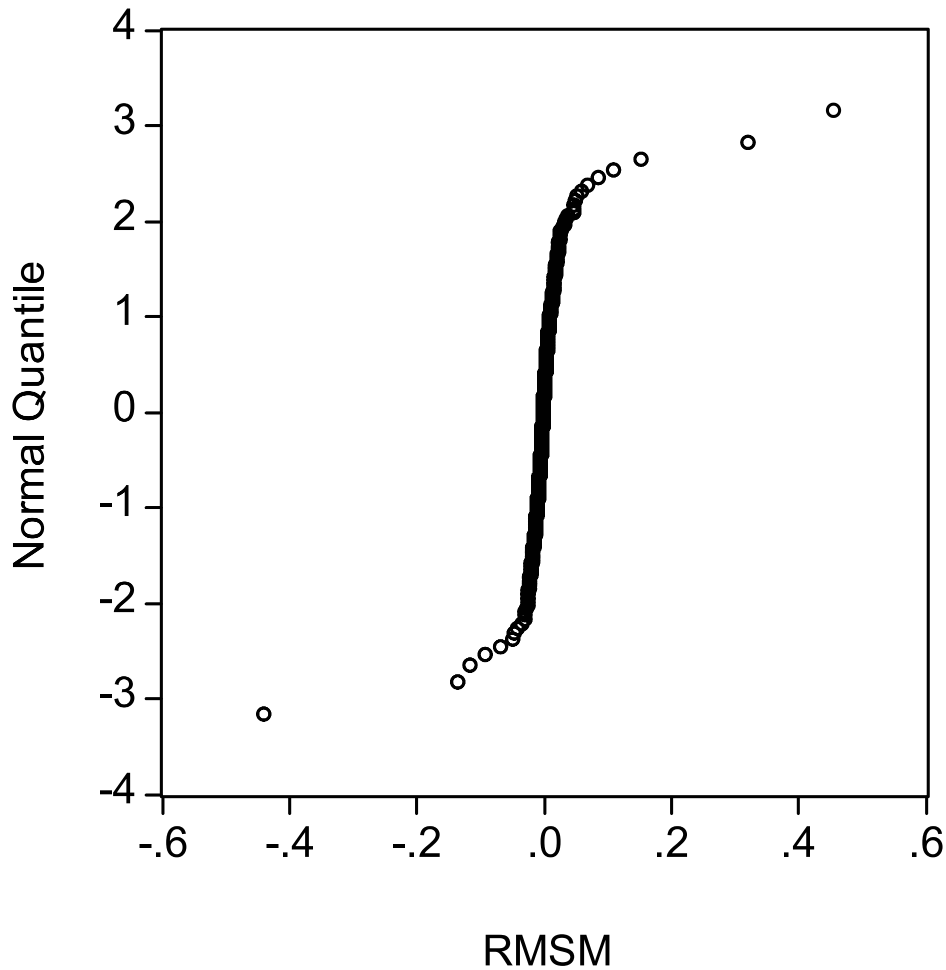


TABLE 1 : ARCH Estimation for Returns (RMSM)

GARCH (1,1)

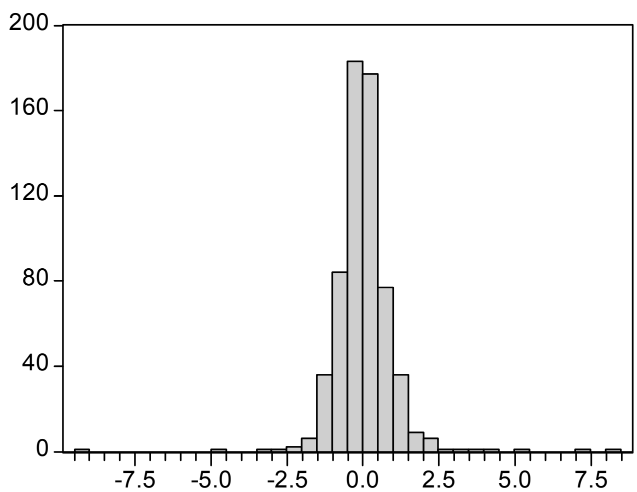
Dependent Variable: RMSM				
Method: ML - ARCH (Marquardt)				
Sample(adjusted): 2/18/1997 7/14/1999				
Included observations: 627 after adjusting endpoints				
Convergence achieved after 375 iterations				
Variance backcast: ON				
	Coefficient	Std. Error	z-Statistic	Prob.
C	-0.001401	0.000190	-7.381330	0.0000
	Variance Equation			
C =ω	0.000135	3.75E-06	35.99449	0.0000
ARCH(1) = α	1.043368	0.064963	16.06100	0.0000
GARCH(1) = β	-0.000551	0.002156	-0.255513	0.7983
R-squared	-0.001554	Mean dependent var		-9.72E-05
Adjusted R-squared	-0.006377	S.D. dependent var		0.033085
S.E. of regression	0.033190	Akaike info criterion		-5.489412
Sum squared resid	0.686296	Schwarz criterion		-5.461081
Log likelihood	1724.931	Durbin-Watson stat		2.719738
GARCH (2,2) Model Dependent Variable: RMSM				
Method: ML - ARCH (Marquardt)				
Date: 06/03/03 Time: 08:17				
Sample(adjusted): 2/18/1997 7/14/1999				
Included observations: 627 after adjusting endpoints				
Convergence achieved after 17 iterations				
Variance backcast: ON				
	Coefficient	Std. Error	z-Statistic	Prob.
C	-0.001969	0.001911	-1.030046	0.3030
	Variance Equation			
C = ω	0.000520	0.000115	4.519524	0.0000
ARCH(1) = α_1	0.166234	0.014991	11.08873	0.0000
ARCH(2)= α_2	0.024681	0.054384	0.453824	0.6500
GARCH(1) = β_1	0.352862	0.204090	1.728955	0.0838
GARCH(2)= β_2	-0.085256	0.052489	-1.624262	0.1043
R-squared	-0.003205	Mean dependent var		-9.72E-05
Adjusted R-squared	-0.011282	S.D. dependent var		0.033085
S.E. of regression	0.033271	Akaike info criterion		-4.816009
Sum squared resid	0.687427	Schwarz criterion		-4.773512
Log likelihood	1515.819	Durbin-Watson stat		2.715264

TABLE 2: Residual Tests/Correlogram-Q-statistic
Number of lags: 36 days

<table>
<tr><td colspan="7">Sample: 2/18/1997 7/14/1999</td></tr>
<tr><td colspan="7">Included observations: 627</td></tr>
<tr><td>Autocorrelation</td><td>Partial Correlation</td><td></td><td>AC</td><td>PAC</td><td>Q-Stat</td><td>Prob</td></tr>
<tr><td>.|* |</td><td>.|* |</td><td>1</td><td>0.129</td><td>0.129</td><td>10.543</td><td>0.001</td></tr>
<tr><td>.|* |</td><td>.|* |</td><td>2</td><td>0.097</td><td>0.081</td><td>16.423</td><td>0.000</td></tr>
<tr><td>.|. |</td><td>.|. |</td><td>3</td><td>0.022</td><td>0.000</td><td>16.719</td><td>0.001</td></tr>
<tr><td>.|* |</td><td>.|* |</td><td>4</td><td>0.084</td><td>0.075</td><td>21.137</td><td>0.000</td></tr>
<tr><td>.|. |</td><td>.|. |</td><td>5</td><td>0.040</td><td>0.020</td><td>22.154</td><td>0.000</td></tr>
<tr><td>.|* |</td><td>.|. |</td><td>6</td><td>0.079</td><td>0.061</td><td>26.154</td><td>0.000</td></tr>
<tr><td>.|* |</td><td>.|. |</td><td>7</td><td>0.070</td><td>0.050</td><td>29.257</td><td>0.000</td></tr>
<tr><td>.|. |</td><td>.|. |</td><td>8</td><td>0.024</td><td>-0.007</td><td>29.629</td><td>0.000</td></tr>
<tr><td>.|* |</td><td>.|* |</td><td>9</td><td>0.097</td><td>0.085</td><td>35.679</td><td>0.000</td></tr>
<tr><td>.|. |</td><td>.|. |</td><td>10</td><td>-0.021</td><td>-0.055</td><td>35.955</td><td>0.000</td></tr>
<tr><td>.|. |</td><td>.|. |</td><td>11</td><td>0.018</td><td>0.002</td><td>36.170</td><td>0.000</td></tr>
<tr><td>.|. |</td><td>.|. |</td><td>12</td><td>-0.027</td><td>-0.033</td><td>36.652</td><td>0.000</td></tr>
<tr><td>.|. |</td><td>.|. |</td><td>13</td><td>0.052</td><td>0.038</td><td>38.380</td><td>0.000</td></tr>
<tr><td>*|. |</td><td>*|. |</td><td>14</td><td>-0.100</td><td>-0.113</td><td>44.835</td><td>0.000</td></tr>
<tr><td>.|* |</td><td>.|* |</td><td>15</td><td>0.066</td><td>0.077</td><td>47.657</td><td>0.000</td></tr>
<tr><td>.|. |</td><td>.|. |</td><td>16</td><td>-0.050</td><td>-0.057</td><td>49.250</td><td>0.000</td></tr>
<tr><td>.|. |</td><td>.|. |</td><td>17</td><td>0.020</td><td>0.023</td><td>49.503</td><td>0.000</td></tr>
<tr><td>.|. |</td><td>.|. |</td><td>18</td><td>-0.024</td><td>-0.016</td><td>49.863</td><td>0.000</td></tr>
<tr><td>.|. |</td><td>.|. |</td><td>19</td><td>-0.040</td><td>-0.040</td><td>50.879</td><td>0.000</td></tr>
<tr><td>*|. |</td><td>.|. |</td><td>20</td><td>-0.059</td><td>-0.040</td><td>53.152</td><td>0.000</td></tr>
<tr><td>.|. |</td><td>.|. |</td><td>21</td><td>-0.021</td><td>0.006</td><td>53.432</td><td>0.000</td></tr>
<tr><td>.|. |</td><td>.|. |</td><td>22</td><td>0.019</td><td>0.018</td><td>53.674</td><td>0.000</td></tr>
<tr><td>.|. |</td><td>.|. |</td><td>23</td><td>-0.028</td><td>0.000</td><td>54.183</td><td>0.000</td></tr>
<tr><td>.|. |</td><td>.|. |</td><td>24</td><td>-0.034</td><td>-0.049</td><td>54.922</td><td>0.000</td></tr>
<tr><td>.|. |</td><td>.|. |</td><td>25</td><td>-0.055</td><td>-0.015</td><td>56.873</td><td>0.000</td></tr>
<tr><td>.|. |</td><td>.|. |</td><td>26</td><td>-0.001</td><td>0.004</td><td>56.874</td><td>0.000</td></tr>
<tr><td>.|. |</td><td>.|. |</td><td>27</td><td>-</td><td>0.030</td><td>56.886</td><td>0.001</td></tr>
</table>

			0.004			
.|. |	.|. |	28	0.005	-0.012	56.899	0.001
*|. |	.|. |	29	-0.063	-0.032	59.543	0.001
.|. |	.|. |	30	0.005	0.003	59.558	0.001
.|. |	.|. |	31	-0.057	-0.040	61.710	0.001
.|. |	.|. |	32	0.006	0.018	61.731	0.001
.|. |	.|. |	33	-0.030	-0.018	62.310	0.002
.|. |	.|. |	34	0.053	0.061	64.154	0.001
.|* |	.|* |	35	0.110	0.115	72.233	0.000
.|. |	.|. |	36	0.006	-0.026	72.260	0.000

TABLE 3: Residual Tests/Histogram-Normality Tests



Series: Standardized Residuals
Sample 2/18/1997 7/14/1999
Observations 627

Mean	0.041145
Median	-0.001783
Maximum	8.034369
Minimum	-9.338536
Std. Dev.	0.998870
Skewness	0.379179
Kurtosis	28.07385
Jarque-Bera	16439.76
Probability	0.000000

TABLE 4: Residual Tests/ARCH - LM Test

ARCH Test:				
F-statistic	0.055668	Probability		0.813557
Obs*R-squared	0.055841	Probability		0.813194
Test Equation:				
Dependent Variable: STD_RESID^2				
Method: Least Squares				
Sample(adjusted): 2/19/1997 7/14/1999				
Included observations: 626 after adjusting endpoints				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.989990	0.211723	4.675866	0.0000
STD_RESID^2(-1)	0.009445	0.040030	0.235940	0.8136
R-squared	0.000089	Mean dependent var		0.999427
Adjusted R-squared	-0.001513	S.D. dependent var		5.197999
S.E. of regression	5.201930	Akaike info criterion		6.139126
Sum squared resid	16885.49	Schwarz criterion		6.153309
Log likelihood	-1919.547	F-statistic		0.055668
Durbin-Watson stat	2.000608	Prob(F-statistic)		0.813557

TABLE 5: The ARCH(4)-M model

RMSM				
Method: ML - ARCH (Marquardt)				
Sample(adjusted): 2/18/1997 7/14/1999				
Included observations: 627 after adjusting endpoints				
Failure to improve Likelihood after 13 iterations				
Variance backcast: ON				
	Coefficient	Std. Error	z-Statistic	Prob.
SQR(GARCH)	0.517811	0.139002	3.725210	0.0002
C	-0.014470	0.003744	-3.864778	0.0001
	Variance Equation			
$C = \omega$	0.000522	2.25E-05	23.21077	0.0000
$ARCH(1) = \alpha_1$	0.150508	0.009407	16.00014	0.0000
$ARCH(2) = \alpha_2$	0.042855	0.019704	2.174949	0.0296
$ARCH(3) = \alpha_3$	-0.005414	0.003190	-1.697058	0.0897
$ARCH(4) = \alpha_4$	-7.50E-05	0.002277	-0.032919	0.9737
R-squared	0.062508	Mean dependent var		-9.72E-05
Adjusted R-squared	0.053436	S.D. dependent var		0.033085
S.E. of regression	0.032189	Akaike info criterion		-4.964827
Sum squared resid	0.642399	Schwarz criterion		-4.915247
Log likelihood	1563.473	F-statistic		6.889851
Durbin-Watson stat	2.796338	Prob(F-statistic)		0.000000

TABLE 6 : Asymmetric ARCH Models

Panel A. TARCH Model

Dependent Variable: RMSM				
Method: ML - ARCH (Marquardt)				
Sample(adjusted): 2/18/1997 7/14/1999				
Included observations: 627 after adjusting endpoints				
Convergence achieved after 307 iterations				
Variance backcast: ON				
	Coefficient	Std. Error	z-Statistic	Prob.
C	-0.001075	0.000349	-3.081618	0.0021
	Variance Equation			
C = ω	0.000141	4.04E-06	34.95967	0.0000
ARCH(1) = α_1	1.388220	0.137236	10.11560	0.0000
(RESID<0)*ARCH (1)= γ	-0.914563	0.177296	-5.158401	0.0000
GARCH(1) = β	-0.000512	0.001445	-0.354277	0.7231
R-squared	-0.000876	Mean dependent var		-9.72E-05
Adjusted R-squared	-0.007312	S.D. dependent var		0.033085
S.E. of regression	0.033206	Akaike info criterion		-5.503859
Sum squared resid	0.685831	Schwarz criterion		-5.468444
Log likelihood	1730.460	Durbin-Watson stat		2.721582

Panel B: EGARCH Model

Dependent Variable: RMSM				
Method: ML - ARCH (Marquardt)				
Sample(adjusted): 2/18/1997 7/14/1999				
Included observations: 627 after adjusting endpoints				
Convergence achieved after 47 iterations				
Variance backcast: ON				
	Coefficient	Std. Error	z-Statistic	Prob.
C	-0.002107	0.000323	-6.522190	0.0000
	Variance Equation			
C = ω	-1.077599	0.058225	-18.50763	0.0000
|RES|/SQR[GARCH](1)=α	0.715404	0.028899	24.75549	0.0000
RES/SQR[GARCH](1)=γ	0.135148	0.024589	5.496186	0.0000
EGARCH(1)=β	0.928809	0.007941	116.9593	0.0000
R-squared	-0.003697	Mean dependent var		-9.72E-05
Adjusted R-squared	-0.010152	S.D. dependent var		0.033085
S.E. of regression	0.033253	Akaike info criterion		-5.639569
Sum squared resid	0.687765	Schwarz criterion		-5.604154
Log likelihood	1773.005	Durbin-Watson stat		2.713931

TABLE 7 : The Component ARCH Model (Asymmetric Component)

Dependent Variable: RMSM				
Method: ML - ARCH (Marquardt)				
Sample(adjusted): 2/18/1997 7/14/1999				
Included observations: 627 after adjusting endpoints				
Convergence achieved after 13 iterations				
Variance backcast: ON				
	Coefficient	Std. Error	z-Statistic	Prob.
C	-0.000196	0.000894	-0.218679	0.8269
	Variance Equation			
Perm: C	0.000475	1.88E-05	25.30372	0.0000
Perm: [Q-C]	0.314771	0.094846	3.318777	0.0009
Perm: [ARCH-GARCH]	0.053413	0.012480	4.279899	0.0000
Tran: [ARCH-Q]	0.150410	0.011764	12.78606	0.0000
Tran: (RES<0)*[ARCH-Q]	0.350385	0.040533	8.644390	0.0000
Tran: [GARCH-Q]	0.010180	0.004934	2.063368	0.0391
R-squared	-0.000009	Mean dependent var		-9.72E-05
Adjusted R-squared	-0.009686	S.D. dependent var		0.033085
S.E. of regression	0.033245	Akaike info criterion		-5.233769
Sum squared resid	0.685237	Schwarz criterion		-5.184189
Log likelihood	1647.787	Durbin-Watson stat		2.723941

TABLE 8: Coefficient Tests/Wald Coefficient Restrictions

Wald Test:			
Equation: Untitled			
Test Statistic	Value	df	Probability
F-statistic	189.3413	(1, 620)	0.0000
Chi-square	189.3413	1	0.0000
Null Hypothesis Summary:			
Normalized Restriction (= 0)		Value	Std. Err.
C(5) + 0.5*C(6) + C(7)		0.335782	0.024403
Restrictions are linear in coefficients.			

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