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Empirical Study of Volatility Clustering in Stock Prices of IT Index

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Abstract

The volatility in the stock market creates the opportunity for the investor and their uncertainties also cause the risk for the investor. Keeping this in mind this paper has looked in to the volatility and with specific reference to IT Index in Indian stock market. For this purpose we have used the closing price of the BSE-IT Index for estimation of volatility using GARCH are from 1-04-05 to 31-03-2013.This paper tries to find out if there is volatility clustering in the BSE IT (Information Technology) index in the stock market using the ARCH/GARCH Model to indicate the volatility in the stock market. The closing prices considered. After fitting the GARCH model in the data, analysis on the findings will be done. Following which the concluding part of the paper, in which the limitations of this model along with further suggestions will be elucidated. It was found that GARCH 1,1 has proved the time varying volatility in the IT sector.

Keywords: BSE, Clustering, GARCH, Stock Market, Volatility

1. Introduction

The Indian IT sector is the major sector which has played an important role in the growth and decline of Indian stock market. The BSE IT index is the true representative of the Indian stock market. The stock market is exposed to a high degree of volatility; prices fluctuate within minutes and are determined by the demand and supply of stocks at a given time. In addition the international trading and investment exposure has made it imperative to better operational efficiency. With the view to improve, discipline and bring greater transparency in this sector, constant efforts are being made and to a certain extent improvements have been made. Due to previous trends, informed investors realise that the nature of the stock market is volatile. Volatility is the most important variable in valuating derivative instruments. It has central role in risk management, asset valuation and investment in general. Actually modern risk management practices rely on volatility of asset and correlation of assets. However, it must be borne in mind that volatility is not the same thing as risk. Risk management and correct hedging are hugely important and valuable businesses and misconceptions can have disastrous effects. Therefore since volatility has such a wide scope, it may be beneficial for an investor to study it. The IT and IT enabled services industry in India has recorded a growth rate of 22.4% in the last fiscal year. Out of this figure, the domestic IT market in India accounted for 900 billion rupees. Volatility in the stock market may be attributed to several reasons. Many technical experts are confidently assuring them that the stock markets will go to higher levels in a short period of time. Due increasing volatility, analysis of stock market trends has become increasingly important.

2. Information Technology Sector

2.1 Review of Literature

Gertler and Hubbard[1] revealed that business investment spending is also influenced by stock return Volatility. Schwert[4] characterized the changes in Stock Market Volatility through time. The Stock Volatility increased by a factor of two or three during this period compared with the usual level of the series. There is no other series that experienced the similar behavior. The relationship between Stock Volatility and several measures of corporate profitability was also analysed. Akgiray[2] discovered that daily series exhibited much higher degrees of statistical dependence than that had been reported in previous studies. Schwert[5] explained that volatility measured by the standard deviation of rates of return to a broad Stock Market index such as the Standard and Poor's 500. Bailey and Chang[3] found that investors tend to change with risk premium return of their portfolios with regard to changing macroeconomic fundamental like inflation, interest rate, exchange rate and industrial production, which evolve the long-term trend of volatility. Sias and Starks[4] associate the day of the week effects in explaining the volatility. Some researchers relate interest rate and inflation with fluctuations in the stock market. Bekaert[6] observes that in segmented capital markets, Volatility is a critical input in the cost of capital. Volatility can also be used as a decision making criterion. Chowan and Shukla have tried to analyse the following questions like, has the Stock Market Volatility increased? Has the Indian Stock Market developed into a speculative bubble due to the emergence of New Economy stocks? Why is this Volatility pronounced? They tried

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to unearth the rationale for those weird movements. Poon et al.[8], Volatility has a wide sphere of influence including investment, security valuation, risk management and policy making. They also put emphasis on the importance of Volatility forecasting in various things such as options pricing, financial risk management etc. Karmakar[9] measured the Volatility of daily stock return in the Indian Stock Market over the period of 1961 to 2005. Using GARCH model, he found strong evidence of' time varying Volatility. Parikh[6] had thrown flash that effect of the events on the markets are basically short lived, unless if it has the long-term implications. Joshi and Pandya[10], observed that Volatility in the stock market has important bearing on earnings of individuals investors and the efficiency of stock market. The relatively small value of error coefficient of GARCH (1, 1) implied that large market surprises induced relatively small revisions in future volatility. Chou[7], have found on the estimation using GARCH the analysis implied a deep drop in stock price. Therefore identification of sources of uncertainty was important. More serious attention should be paid towards takeovers and computer programmed trading as they cause sizable disturbances. Marko Rinaten[8] conducted a research on implied volatility measures; those can be interpreted as the market's perception on the future volatility of the underlying asset. Implied volatility seems even to bare eye present higher memory thus suggesting that higher order GARCH model would be suitable. However with only rolling n day measure as volatility proxy is inadequate to perform reliably more deep going analysis, and it was not in the original scope of this paper which was only meant to learn and test out the procedures related to volatility forecasting with ARCH/GARCH models.

Volatility is an area of research for many academicians, and most of the studies have been conducted on the major stock indices like NIFTY and SENSEX. While the studies conducted on the volatility of the sectoral indices are very few, therefore the present study seeks to analyse the volatility of the IT sector volatility based BSE IT Index.

2.2 Objective

The objective behind this paper is to check for volatility in the BSE-IT (Information Technology) index, through ARCH/GARCH (Generalised Auto Regressive Conditional Heteroskedasticity) model. The aim is to theorize the statistical results to understand the behaviour of this stock market index.

2.3 Scope and Coverage

The study of volatility using ARCH/GARCH has a very wide scope. Understanding volatility is very important. In this paper volatility has been studied in the closing prices of the previous years from (2005–2013) using the ARCH/GARCH model. However this model can also be used in volatility forecasting. Volatility also has a pronounced role in modern finance as it is used in multiple risk management solutions.

2.4 Data Research and Methodology

The data considered for estimation of volatility using ARCH/GARCH is the closing price of BSEIT index from 1–04–05 to 31–08–2013.

2.4.1 The GARCH Model

The GARCH is a time-series technique that allows users to model the serial dependence of volatility. GARCH modelling builds on advances in the understanding and modelling of volatility in the last decade. It takes into account excess kurtosis and volatility clustering, two important characteristics of financial time series. It provides accurate forecasts of variances and covariance's of asset returns through its ability to model time-varying conditional variances. Therefore, GARCH models can be applied to such diverse fields term structure of interest rates, Portfolio management and asset allocation, Option pricing, Foreign exchange, Risk management

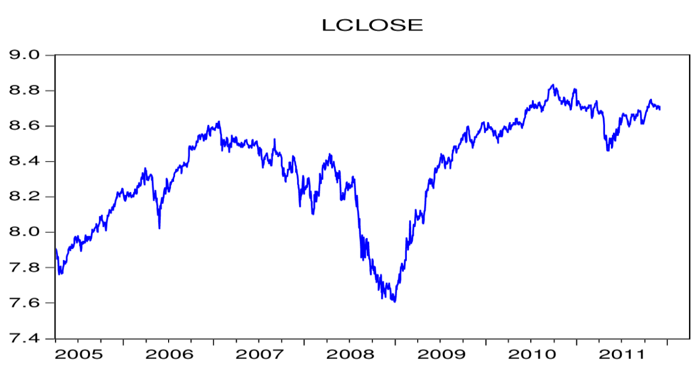
2.4.2 Unit Root Test (Stationarity Test)

A unit root test has been applied to check whether a series is stationary or not. Stationarity condition has been tested using Augmented Dickey Fuller (ADF) [Dickey and Fuller (1979, 1981), Gujarati (2003), Enders (1995)].

2.5 Empirical Estimation

As mentioned above volatility will be checked for the closing price of BSEIT index for the period of 1–4–05 to 31–3–13.The necessary tests along with analysis and interpretation have been conducted:

The Graph 1 shows that the closing prices of the IT index are fluctuating and not uniform in nature. In the Table 1, observed that since chi square value is zero, it implies that heteroskedasticity is

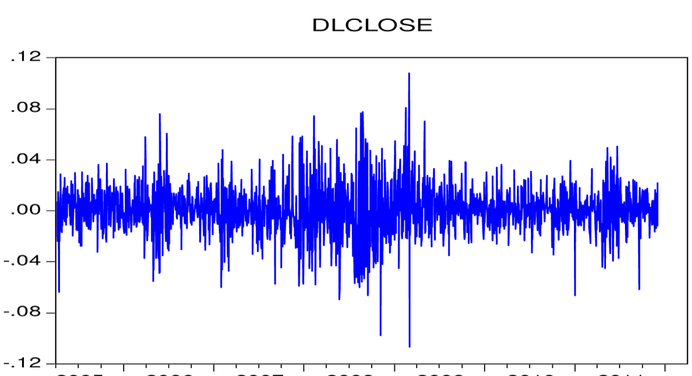


Graph 1. Line graph of L close.

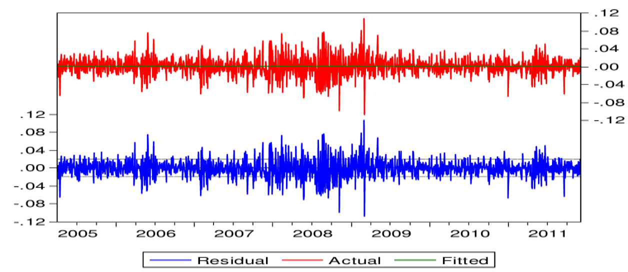
there, therefore this series is not stationary we will now examine stationarity with the help of correlogram and unit root tests. The Table 2 finds that the spikes in the ACF and PCF at some lags are sticking out of the bars so the series is not stationary. After examining the p value of LCLOSE in the above tests, we see that it is greater than alpha, the level of significance which is taken to be 10%. So we accept the null hypothesis that LCLOSE has a unit root. So LCLOSE is not stationary. Therefore, we shall take the first difference of the LCLOSE time series and then conduct unit root test and observe the Correlogram. Table 6 observed that spikes lie within the bars therefore LCLOSE is stationary. Furthermore, we superimpose the plots of our actual and simulated time series. The aforementioned rigorous analysis and statistical testing support the conclusions concerning the results. Volatility in the stock market has important bearing on earnings of individual investors and the efficiency of stock market in general for channelising resources for its productive uses. Present study attempts to get insight into behaviour of the volatility in Indian Stock Market. The model with large value of lag coefficient shows that the volatility in the both markets is highly persistent and is predictable. The relatively small value of error coefficient of GARCH (1, 1) implies that large market surprises induce relatively small revisions in future volatility. Table 9 explains that we can find that the p value of D(LCLOSE) is 0.00 is less than the level of significance so the null hypothesis is rejected. This means that D(LCLOSE) doesn't have a unit root. Hence, it is stationary. Now we shall generate a series on DLCOSE which is the first difference of LCLOSE.

The Graph 2 of the series Dlclose shows that there is very high volatility. There are very large and sudden variations. Table 10 explain chi square value of DLCLOSE is greater than level of significance so the Null Hypothesis (there is no Heteroskedasticity) is accepted. So the problem of Heteroskedasticity is solved. The series DLCLOSE is stationary. We will now fit the ARCH model till it fails. Since the p-value is greater than the level of significance, we can see that the ARCH model fails at (4,0). We will now fit the corresponding GARCH models. Only the models that fit the required criteria (p-value of resids and garch should be less than level of significance) have been shown. Table 5 found that P-value of GARCH term<level of significance so the Null Hypothesis (beta2, the coefficient of RESID(-1)^2 is zero) is rejected. So there is significant GARCH effect and volatility is present. Thus the GARCH effect at (1,1) can be observed in the Graph 3.

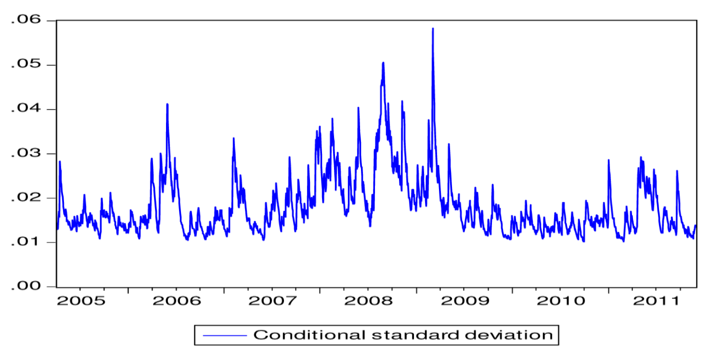
GARCH 2, 1 show that since all the spikes are within the bars, the model has been properly fitted (Table 11). GARCH 2,1 shows that since P-value is less than level of significance, we can see that GARCH effect is present (Table 12). GARCH 2,2 present that Since P-value is less than level of significance, we can see that



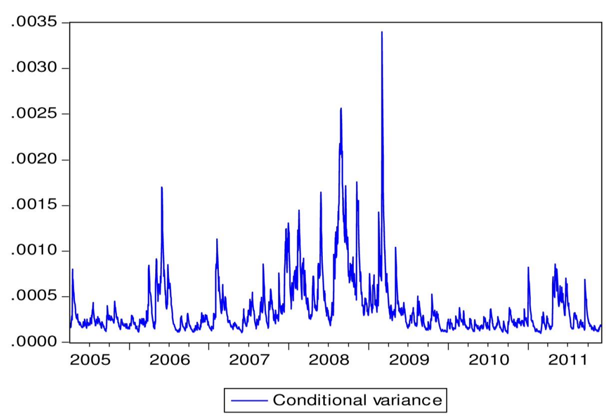
Graph 2. Line graph of Dlclose.



Graph 3. GARCH graph for conditional standard deviation.



Graph 4. GARCH graph for conditional variance.



Graph 5. GARCH graph for time varying volatility.

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GARCH effect is present (Graphs 4 and 5). Therefore we have fitted the GARCH model at (1,1), (2,1) and (2,2). We failed in fitting the model at (1,2), (2,3) and (3,1). In order to determine the best model out of the above, we will be taken the following parameters into consideration:

1) R^2 and adjusted R^2 should be maximum.
2) Akaike info criterion should be minimum.
3) Schwarz criterion should be minimum.
4) Durban Watson criterion should be closest to 2.

According the above criteria the GARCH (1,1) model is the best fit out of the above models.

3. Conclusion

It can be concluded that the BSE IT is a volatile index where time varying volatility is present as provided by the GARCH 1,1 and GARCH 2,1. After looking at the behaviour of the BSE-IT index and the volatility clustering associated with it one can come to the conclusion that volatility persists within this index. We observed that the GARCH effect was there when we fit the data within the model. However though we have completed our objective, there are a few limitations in this paper as well No focus has been given to the forecasting of future values using the GARCH model. Another drawback is not taking into consideration any other variables from the index whose impact may be of a certain degree of importance. Finally, due to the study of data only between April 2005 and March 2013 we were unable to note down and study the effects before and after these dates.

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Appendix for GARCH/ ARCH/UNIT ROOT TEST tables

Note: Only relevant tables are given here.

Table 1. Heteroskedasticity Test: ARCH

F-statistic	62.37867	Prob. F(1,1736)	0.0000
Obs*R-squared	60.28437	Prob. Chi-Square(1)	0.0000

Test Equation:

Dependent Variable: RESID^2

Method: Least Squares

Date: 11/08/13 Time: 11:00

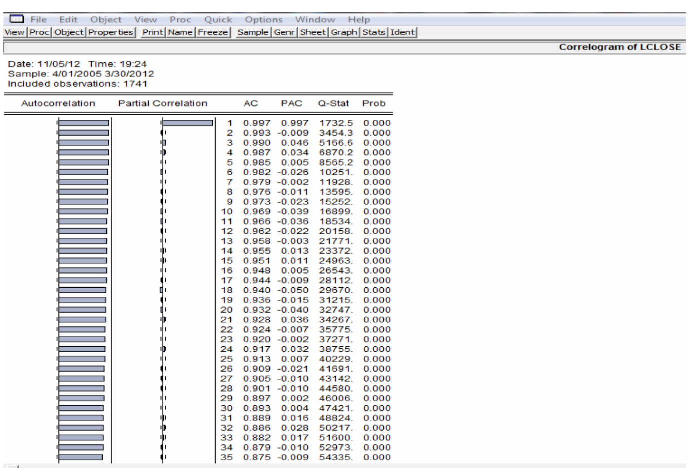
Sample (adjusted): 4/06/2005 3/30/2013

Included observations: 1738 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	4977.922	318.0004	15.65382	0.0000
RESID^2(-1)	0.186274	0.023585	7.898017	0.0000

R-squared	0.034686	Mean dependent var	6115.255
Adjusted R-squared	0.034130	S.D. dependent var	13027.08
S.E. of regression	11820.05	Akaike info criterion	21.59413
Sum squared resid	2.43E+11	Schwarz criterion	21.60042
Log likelihood	-18763.30	Hannan-Quinn criter.	21.59646
F-statistic	62.37867	Durbin-Watson stat	2.025141
Prob(F-statistic)	0.000000		

Table 2. Correlogram at level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Correlogram of LCLOSE

Date: 11/05/12 Time: 19:24
Sample: 4/01/2005 3/30/2012
Included observations: 1741

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.997	0.997	1732.5	0.000
		2	0.993	-0.009	3454.3	0.000
		3	0.990	0.046	5166.6	0.000
		4	0.987	0.034	6870.2	0.000
		5	0.985	0.005	8565.2	0.000
		6	0.982	-0.026	10251.	0.000
		7	0.979	-0.002	11928.	0.000
		8	0.976	-0.011	13595.	0.000
		9	0.973	-0.023	15252.	0.000
		10	0.969	-0.039	16899.	0.000
		11	0.966	-0.036	18534.	0.000
		12	0.962	-0.022	20158.	0.000
		13	0.958	-0.003	21771.	0.000
		14	0.955	0.013	23372.	0.000
		15	0.951	0.011	24963.	0.000
		16	0.948	0.005	26543.	0.000
		17	0.944	-0.009	28112.	0.000
		18	0.940	-0.050	29670.	0.000
		19	0.936	-0.015	31215.	0.000
		20	0.932	-0.040	32747.	0.000
		21	0.928	0.036	34267.	0.000
		22	0.924	-0.007	35775.	0.000
		23	0.920	-0.002	37271.	0.000
		24	0.917	0.032	38755.	0.000
		25	0.913	0.007	40229.	0.000
		26	0.909	-0.021	41691.	0.000
		27	0.905	-0.010	43142.	0.000
		28	0.901	-0.010	44580.	0.000
		29	0.897	0.002	46006.	0.000
		30	0.893	0.004	47421.	0.000
		31	0.889	0.016	48824.	0.000
		32	0.886	0.028	50217.	0.000
		33	0.882	0.017	51600.	0.000
		34	0.879	-0.010	52973.	0.000
		35	0.875	-0.009	54335.	0.000

Table 3. Unit root test of LCLOSE at level(intercept)

Null Hypothesis: LCLOSE has a unit root

Exogenous: Constant

Lag Length: 0 (Automatic based on SIC, MAXLAG=24)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-1.560279	0.5028
Test critical values:	1% level	-3.433905	
	5% level	-2.862997	
	10% level	-2.567593	

Augmented Dickey-Fuller Test Equation

Dependent Variable: D(LCLOSE)

Method: Least Squares

Date: 11/03/13 Time: 22:00

Sample (adjusted): 4/04/2005 13/02/2011

Included observations: 1740 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
LCLOSE(-1)	-0.002479	0.001589	-1.560279	0.1189
C	0.021190	0.013292	1.594142	0.1111

R-squared	0.001399	Mean dependent var	0.000463
Adjusted R-squared	0.000824	S.D. dependent var	0.019325
S.E. of regression	0.019317	Akaike info criterion	-5.054481
Sum squared resid	0.648550	Schwarz criterion	-5.048204
Log likelihood	4399.399	Hannan-Quinn criter.	-5.052160
F-statistic	2.434472	Durbin-Watson stat	1.957282
Prob (F-statistic)	0.118876		

Table 4. Unit root test of LCLOSE at level(trend and intercept)

Null Hypothesis: LCLOSE has a unit root

Exogenous: Constant, Linear Trend

Lag Length: 0 (Automatic based on SIC, MAXLAG=24)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-1.747481	0.7296
Test critical values:	1% level	-3.963326	
	5% level	-3.413394	
	10% level	-3.138140	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation

Dependent Variable: D(LCLOSE)

Method: Least Squares

Date: 11/11/13 Time: 23:15

Sample (adjusted): 4/04/2005 3/30/2013

Included observations: 1740 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
LCLOSE(-1)	-0.003387	0.001938	-1.747481	0.0807
C	0.027985	0.015675	1.785365	0.0744
@TREND (4/01/2005)	9.20E-07	1.13E-06	0.818185	0.4134
R-squared	0.001783	Mean dependent var		0.000463
Adjusted R-squared	0.000634	S.D. dependent var		0.019325
S.E. of regression	0.019319	Akaike info criterion		-5.053717
Sum squared resid	0.648300	Schwarz criterion		-5.044301
Log likelihood	4399.734	Hannan-Quinn criter.		-5.050235
F-statistic	1.551718	Durbin-Watson stat		1.956259
Prob(F-statistic)	0.213177			

Table 5. Unit root test of LCLOSE at first difference (intercept)

Null Hypothesis: D(LCLOSE) has a unit root

Exogenous: Constant

Lag Length: 1 (Automatic based on SIC, MAXLAG=24)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-31.72531	0.0000
Test critical values:	1% level	-3.433910	
	5% level	-2.862999	
	10% level	-2.567594	

Augmented Dickey-Fuller Test Equation

Dependent Variable: D(LCLOSE,2)

Method: Least Squares

Date: 11/03/13 Time: 22:09

Sample (adjusted): 4/06/2005 13/02/2011

Included observations: 1738 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(LCLOSE(-1))	-1.062711	0.033497	-31.72531	0.0000
D(LCLOSE(-1),2)	0.084351	0.023932	3.524561	0.0004
C	0.000498	0.000463	1.075846	0.2821
R-squared	0.493511	Mean dependent var		1.64E-05
Adjusted R-squared	0.492927	S.D. dependent var		0.027067
S.E. of regression	0.019274	Akaike info criterion		-5.058408
Sum squared resid	0.644521	Schwarz criterion		-5.048983
Log likelihood	4398.757	Hannan-Quinn criter.		-5.054923
F-statistic	845.2727	Durbin-Watson stat		2.007839
Prob(F-statistic)	0.000000			

Table 6. Heteroskedasticity Test: ARCH

F-statistic	0.470662	Prob. F(1,1737)	0.4928
Obs*R-squared	0.471076	Prob. Chi-Square(1)	0.4925

Test Equation:
Dependent Variable: WGT_RESID^2
Method: Least Squares
Date: 11/13/13 Time: 14:51
Sample (adjusted): 4/05/2005 3/30/2013
Included observations: 1739 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.984962	0.050355	19.56027	0.0000
WGT_RESID^2(-1)	0.016460	0.023992	0.686048	0.4928

R-squared	0.000271	Mean dependent var	1.001424
Adjusted R-squared	-0.000305	S.D. dependent var	1.845831
S.E. of regression	1.846113	Akaike info criterion	4.065190
Sum squared resid	5919.921	Schwarz criterion	4.071471
Log likelihood	-3532.683	Hannan-Quinn criter.	4.067513
F-statistic	0.470662	Durbin-Watson stat	1.999519
Prob (F-statistic)	0.492774		

Table 7. ARCH (1,0)

Dependent Variable: D(LCLOSE)
Method: ML - ARCH (Marquardt) - Normal distribution
Date: 11/13/13 Time: 15:52
Sample (adjusted): 4/04/2005 3/30/2013
Included observations: 1740 after adjustments
Convergence achieved after 7 iterations
Presample variance: backcast (parameter = 0.7)
GARCH = C(2) + C(3)*RESID(-1)^2

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.000988	0.000416	2.376424	0.0175
	Variance Equation			
C	0.000263	8.06E-06	32.61008	0.0000
RESID(-1)^2	0.297770	0.032327	9.211302	0.0000

R-squared	-0.000740	Mean dependent var	0.000463
Adjusted R-squared	-0.001893	S.D. dependent var	0.019325
S.E. of regression	0.019344	Akaike info criterion	-5.143574
Sum squared resid	0.649939	Schwarz criterion	-5.134157
Log likelihood	4477.909	Hannan-Quinn criter.	-5.140092
Durbin-Watson stat	1.957943		

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Table 8. ARCH (2,0)

Dependent Variable: D(LCLOSE)
Method: ML - ARCH (Marquardt) - Normal distribution
Date: 11/13/13 Time: 15:53
Sample (adjusted): 4/04/2005 3/30/2013
Included observations: 1740 after adjustments
Convergence achieved after 7 iterations
Presample variance: backcast (parameter = 0.7)
GARCH = C(2) + C(3)*RESID(-1)^2 + C(4)*RESID(-2)^2

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.001176	0.000360	3.265006	0.0011
	Variance Equation			
C	0.000191	9.11E-06	20.95882	0.0000
RESID(-1)^2	0.274295	0.028839	9.511321	0.0000
RESID(-2)^2	0.245465	0.030841	7.959009	0.0000
R-squared	-0.001364	Mean dependent var		0.000463
Adjusted R-squared	-0.003094	S.D. dependent var		0.019325
S.E. of regression	0.019355	Akaike info criterion		-5.196699
Sum squared resid	0.650344	Schwarz criterion		-5.184143
Log likelihood	4525.138	Hannan-Quinn criter.		-5.192056
Durbin-Watson stat	1.956724			

Table 9. GARCH (1,1)

Dependent Variable: DLCLOSE
Method: ML - ARCH (Marquardt) - Normal distribution
Date: 11/03/13 Time: 22:28
Sample (adjusted): 4/04/2005 13/02/2011
Included observations: 1740 after adjustments
Convergence achieved after 9 iterations
Presample variance: backcast (parameter = 0.7)
GARCH = C(2) + C(3)*RESID(-1)^2 + C(4)*GARCH(-1)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.001340	0.000361	3.432397	0.0006
	Variance Equation			
C	1.44E-05	2.52E-06	5.707458	0.0000
RESID(-1)^2	0.138932	0.017693	7.852315	0.0000
R-squared	-0.001621	Mean dependent var		0.000463
Adjusted R-squared	-0.003351	S.D. dependent var		0.019325
S.E. of regression	0.019358	Akaike info criterion		-5.275220
Sum squared resid	0.650510	Schwarz criterion		-5.262664
Log likelihood	4593.441	Hannan-Quinn criter.		-5.270577
Durbin-Watson stat	1.956223			

Table 10. Correlogram Q-statistics

Date: 11/12/12 Time: 16:08
Sample: 4/04/2005 3/30/2012
Included observations: 1740

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.041	0.041	2.8938	0.089
		2	-0.043	-0.044	6.0734	0.048
		3	-0.031	-0.027	7.7069	0.052
		4	0.006	0.006	7.7679	0.100
		5	-0.008	-0.011	7.8757	0.163
		6	-0.018	-0.018	8.4696	0.206
		7	0.001	0.002	8.4701	0.293
		8	-0.003	-0.005	8.4879	0.387
		9	0.009	0.009	8.6456	0.471
		10	0.034	0.033	10.628	0.387

Table 11. GARCH (2, 1)

Dependent Variable: D(LCLOSE)

Method: ML - ARCH (Marquardt) - Normal distribution

Date: 11/13/13 Time: 16:16

Sample (adjusted): 4/04/2005 3/30/2013

Included observations: 1740 after adjustments

Convergence achieved after 10 iterations

Presample variance: backcast (parameter = 0.7)

GARCH = C(2) + C(3)*RESID(-1)^2 + C(4)*RESID(-2)^2 + C(5)*GARCH(-1)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.001315	0.000362	3.356416	0.0008
	Variance Equation			
C	1.04E-05	2.32E-06	4.504452	0.0000
RESID(-1)^2	0.169010	0.027300	6.190837	0.0000
RESID(-2)^2	-0.060303	0.028165	-2.141023	0.0323
GARCH(-1)	0.864147	0.019644	43.99135	0.0000
R-squared	-0.001516	Mean dependent var		0.000463
Adjusted R-squared	-0.003825	S.D. dependent var		0.019325
S.E. of regression	0.019362	Akaike info criterion		-5.275253
Sum squared resid	0.650443	Schwarz criterion		-5.259558
Log likelihood	4594.470	Hannan-Quinn criter.		-5.269449
Durbin-Watson stat	1.956427			

Table 12. GARCH (2, 2)

Dependent Variable: D(LCLOSE)

Method: ML - ARCH (Marquardt) - Normal distribution

Date: 11/13/13 Time: 16:19

Sample (adjusted): 4/04/2005 3/30/2013

Included observations: 1740 after adjustments

Convergence achieved after 11 iterations

Presample variance: backcast (parameter = 0.7)

GARCH = C(2) + C(3)*RESID(-1)^2 + C(4)*RESID(-2)^2 + C(5)*GARCH(-1) + C(6)*GARCH(-2)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.001390	0.000362	3.566971	0.0004
	Variance Equation			
C	5.82E-07	3.39E-07	1.719979	0.0854
RESID(-1)^2	0.160953	0.024037	6.695984	0.0000
RESID(-2)^2	-0.152869	0.022782	-6.710016	0.0000
GARCH(-1)	1.677141	0.062875	26.67438	0.0000
GARCH(-2)	-0.686809	0.058684	-11.70349	0.0000
R-squared	-0.001833	Mean dependent var		0.000463
Adjusted R-squared	-0.004722	S.D. dependent var		0.019325
S.E. of regression	0.019371	Akaike info criterion		-5.277564
Sum squared resid	0.650649	Schwarz criterion		-5.258730
Log likelihood	4597.480	Hannan-Quinn criter.		-5.270600
Durbin-Watson stat	1.955807			