Modeling Stock Market Volatility in Emerging Markets: Evidence from India

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ABSTRACT

This study models the volatility present in the inter day returns in the stock of the two major national indices of India. Sensitive Index or Sensex related to Bombay Stock Exchange (BSE) and Nifty associated with National Stock Exchange (NSE). The objective is to model the phenomena of volatility clustering and persistence of shock using asymmetric GARCH family of models. Research showed that EGARCH model successfully models the Sensex (BSE) data whereas it is GJR-GARCH which was able to explain conditional variance in the returns from Nifty (NSE).

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1.0 THEORETICAL BACKGROUND

An efficient market is one which fully and instantaneously reflects all available relevant information in the share price. According to Fama (1970), there are three forms of market efficiency based on the information dissemination. These forms – weak form, semi-strong form and strong form – have been tested in various equity markets, both in developed and emerging markets. However most of the studies have attended to the weak form of efficiency which proposes that current stock prices reflect all information contained in past stock prices. This implied that no investor can consistently earn abnormal returns from trading based on historical prices.

The weak form efficiency hypothesis has been tested in developed markets in abundance . For example, Fama (1965) did it for U.S., Dryden (1970) for U.K., Andersen and Bollerslev (1997) for 8 European markets. Conrad and Juttner (1973) for Germany, Jennergren and Korsvold (1975) for Norway and Sweden. Similarly some of the Asian markets were also taken under study, such as Lawrence (1986) for Malaysia and Singapore. These studies provided inconclusive results. The developed markets, e.g., U.S and some European markets were found to be weak form efficient. However, evidence from emerging markets indicated rejection of the weak form of hypothesis. Can we say that the returns in such markets followed predictable trends?

Besides efficiency, it is the volatility prevailing in the market which influences the return distributions. The issue of volatility has gain prominence in the emerging markets like India as they move towards a trading scenario which aims to restrict the return distribution within resistance level. [INSERT Table #1 about here]

Volatility of returns in India became more prominent due to some crisis which challenged the trust and "interest" of the smaller investors and raised some microstructure issues. [INSERT TABLE#2 about here]. The author tried to address this issue in this study.

Volatility, to describe without a specific implied metric, is the variability of the random (unforeseen) component of a time series. It can be used to measure specific risk of a single instrument or the risk associated with an entire portfolio of instruments. Stock return volatility measures the random variability of the stock returns. More specifically, it is the standard deviation of daily equity returns around the mean value and the stock market volatility is the return volatility of the aggregate market portfolio.

The seminal work of Engle (1982) where he introduced the concept of Autoregressive Conditional Heteroscedasticity (ARCH) became a very powerful tool in the modeling of financial data in general and stock returns in particular. Compared to conventional time series models, ARCH models allowed the conditional variances to change through time as functions of past errors. First approach was to improve the univariate ARCH model with an alternative specification of the variance function. One improvement was introduced by Bollerslev (1986) where the Generalized Autoregressive Conditional Heteroscedasticity (GARCH) process was presented. Further, the Integrated GARCH (IGARCH) Engle and Bollerslev (1994) and the exponential GARCH (EGARCH) Nelson (1991) were prominent one where re-specification of variance equation was studied.

However, the magnitude of empirical research on stock return volatility in emerging markets like India was not abundant. While Roy and Karmakar (1995) focused on the measurement of the average level of sample standard deviation to examine whether volatility has increased , Goyal (1995) used conditional volatility estimates, as suggested by Schwert (1989), to identify the trend in volatility. He also studied the impact of carry forward system on the level of volatility. ARCH/GARCH models have been used by Thomas (1995, 1998), Pattanaik & Chatterjee (2000) to model the volatility in Indian financial market.

The research objective of this paper was to understand the return data (inter day) of securities & see if asymmetric GARCH models can explain persistence of shock and volatility.

2.0 RESEARCH DESIGN

The study spanned the period from March 1995 through March 2005. reason being major changes were brought about in the structure and functioning of the Indian stock market during those years. The sample population of the study consists of the daily returns of the two most prominent domestic indices, viz., Sensex and Nifty. These market indices were fairly representative of the various industry sectors.

The daily stock price data on Sensex and Nifty were downloaded from PROWESS, the online database maintained by the Centre for Monitoring of Indian Economy (CMIE). Daily opening, high, low and closing prices of the two indices were considered for the period of study. These equity prices were adjusted for bonus and right issues.

The daily stock prices were converted to daily returns. Logarithmic difference of prices of two successive periods was used to determine the rate of return.

3.0 Methodology

Ordinary regression model assumed homoscedisticity (errors have same variance through out). If the error variance was not a constant, the data were said to be heteroscedastic. Heteroscedasticity in stock returns are well documented (Fama, 1965; Bollerslev, 1986). Studies found that the stock returns were characterized by - auto correlation in the returns, serial correlation in the square of return values indicating volatility clustering, negative asymmetry in the distribution of returns and Leptokurtosis in the distribution of returns (thicker tails compared to a normal distribution).

The ARCH and the GARCH family of models assumed conditional heteroscedasticity with homoscedastic unconditional error standard deviation. That is, the changes in variance were a function of preceding errors and represent temporary and random departures from a constant unconditional variance .The advantage of ARCH/GARCH family of models was that it captures the tendency in financial data for volatility clustering.

The mean return was modeled as an AR (Auto Regressive) (p) process. This required testing for stationarity of the series to imply that mean and covariance of the return distribution were time independent. This was done using the unit root test. Then an AR model was fitted to the data generating process as suggested by Box and Jenkins (1976). Finally, the conditional variance was modeled as a symmetrical or asymmetrical GARCH process.

4.0 TESTS, RESULTS AND ANALYSIS

4.1 Diagnostic Tests

A visual examination of the plot of daily returns on Sensex [INSERT figure #1 about here] showed that returns continuously fluctuated about the mean value that was close to zero. The return movements were both in positive and negative territory. Larger fluctuations tend to cluster together and were separated by periods of relative calm. This was in accordance with Fama's (1965) observation of "volatility clustering".

Descriptive statistics [INSET Table #3 about here] for both Sensex and Nifty returns showed skewness statistic of daily returns different from zero which indicated that the return distribution was asymmetric. Furthermore, relatively large excess kurtosis suggested that the underlying data was leptokurtic (heavily tailed and sharp peaked) . The Jarque – Bera statistic calculated to test the null hypothesis of normality rejected the normality assumption.

Both the indices appeared to have strong autocorrelations in one-day lag returns with significant coefficient. Also, the autocorrelation in the squared daily returns suggested presence of clustering. The results rejected the independence assumption for the time series of given data set. Stationary of the return series were tested by conducting both Dickey-Fuller and Phillip-Peron tests. The results of both the test confirmed that the series are stationary. [INSERT Table #4 about here].

4.2 Application of Box-Jenkins Methodology

For both the indices the autocorrelation function (ACF) and partial autocorrelation function (PACF) were determined. Ljung-Box-Pierce Q statistic was highly significant [refer Table #3] which confirmed the presence of first order correlation in the series. The existence of a leptokurtic distribution, presence of volatility clustering and changing conditional variance suggested an ARCH or GARCH process, which was confirmed by computing the value of Lagrange Multiplier (LM).

5.0 MODELING VOLATILITY

5.1 Volatility Behavior

Preceding section revealed that the volatility of the indices might follow an ARCH process. However, we begin with a commonly used volatility estimator – the extreme value volatility estimator, as proposed by Garman and Klass (1980).[insert equation#1 about here] This estimator was based on the best analytic scale invariant estimator which made use of the intra day values - opening, closing, high and low. The Garman & Klass estimator values obtained for Sensex.(here, n=1) showed a change in volatility . [INSERT figure #2 about here]

5.2 Model Specifications

There was a significant presence of ARCH effect in the residuals of the fitted AR (1) return generating process. Also, the volatility estimators indicating graphically of volatility clustering led us to the next step of modeling. The conditional variance of the residual was modeled as an ARCH (Q) process with the mean return governed by AR(1) process. [INSERT Equiation #2 about here]. In all the cases, ARCH parameters were significant. The ARCH parameters were insignificant from ARCH (8) onwards in the case of Sensex and ARCH (6) for Nifty. The model was selected on the basis of highest log-likelihood values and minimum AIC (Akaike Information Criterion) and the SBC (Schewart's Information Criterion) values [shown in Table #5 and Table # 6 for Sensex]. We select AR(1) – ARCH (7) process for the Sensex and AR(1) – ARCH (5) for Nifty as the representative of the conditional volatility process.

The autocorrelation function (ACF) and the partial autocorrelation function (PACF) of the squared residual series were examined as a diagnostic on the appropriateness of the ARCH process. It was found that although the estimated ACF of the squared residual series seemed to decay as the lag increased, the PACF did not become zero after seven lags for Sensex and five lags for Nifty. Therefore, as far as the ACF and PACF are concerned, the data do not fully agree with a pure ARCH process.

We now fit the GARCH models to the daily return series. [INSET Equation # 3 about here]

We found all the parameters in the GARCH (1,1) model were significant. Also the model favored GARCH (1,1) process as it had a lower AIC and SBC criteria for a comparable log –likelihood function.[INSERT Table # 7 about here]. As for the stationarity of the variance process, it was observed that $\alpha_1+\beta_1$ is 0.9752 for Sensex and 0.9577 for Nifty respectively. This is less that unity indicated no violation of any stability condition. However, the sum was rather close to one which indicated a long persistence of shocks in volatility.

Lamoureux and Lastrapes (1990) had proposed a half life period of a shock to the variance. Half-life period is that period in which the shock diminishes to half of its original size. The half life for the GARCH (1, 1) process [INSET equation #4 about here] was 23.75 days for Sensex and 17.04 days for Nifty. It meant that any bad or good news did have a long lasting and significant impact on the volatility of the prices.

5.3 Asymmetrical Response to the Arrival of News

Schwert (1989) and Black (1976) had shown that the returns are negatively correlated with volatility. This implied that the returns were more volatile in response to bad news compared to the good news. Differential approach to the information is not captured in the symmetrical GARCH model. A separate modeling techniques need to be used to capture the asymmetric response as suggested by Engle, Ng and Rothschild (1990).

Estimating the GJR – GARCH and the EGARCH (exponential GARCH) and testing the significance of the asymmetric terms was considered to test the asymmetric effects.

5.4 The GJR-GARCH Model

The GJR- GARCH model was introduced by Glosten, Jagannathan, and Runkle (1993). The specification for the conditional variance is:[INSERT equation # 5 about here]

In this model the good and bad news had differential effects on the conditional variance. Good news have the influence of α, while the bad news have the influence of $(\alpha + \omega)$. If $\omega > 0$, we could say that the leverage effect exists while news is asymmetric when $\omega \neq 0$. The outcome of the model (refer Table #7) showed that the parameters in the variance equation was significant. The leverage term was highly significant both for Sensex (0.09515) and Nifty (0.0897). The assumption that positive and negative shocks have different impact on the volatility of daily returns was reinforced. The AIC and the SBC of this model was lower compared to the GARCH (1, 1) model and also had a higher log likelihood value.

5.5 The EGARCH Model

The EGARCH model was proposed by Nelson (1991). The specification for the conditional variance is:[INSERT equation #6 about here]

The left-hand-side of the equation has the log of the conditional variance hence the leverage effect is exponential rather than quadratic. Therefore, the forecast of the conditional variance were guaranteed to be non-negative. [refer Table #7 for EGARCH estimation]. We found all the coefficients were significant for both Sensex (0.052) and the Nifty (0.065). The leverage term was negative and statistically different from zero indicating the presence of leverage effect for the stock market returns during the sample period. The log –likelihood was higher and the AIC and the SBC were lower compared to GARCH (1, 1) model for both the indices.

The GJR-GARCH model and the EGARCH model outperformed the GARCH class of models. However, when we compared the asymmetric models, we found that, for Sensex, the EGARCH model was a better fit. This was in accordance with the lowest AIC and the SBC and the highest log –likelihood value. The improvement in model fitting signifies that returns respond differently to the arrival of negative and positive shocks unlike the vanilla GARCH model.

6.0 CONCLUSION

The volatility of the Indian stock market exhibited characteristics similar to those found earlier in many of the major developed and emerging stock markets, viz., autocorrelation and negative symmetry in daily returns. It was shown that asymmetrical GARCH models outperform the OLS models and the Vanilla GARCH models. While it was the EGARCH model which provided a better fit for the Sensex data, GJR-GARCH model showed better acceptance in case of Nifty. A significant half life for both the indices indicated the persistence of shock in the system. Persistence of shock could explain the time varying risk premium. If the shock was short term in nature, then the investor would restrain from making any changes in their discounting factor while obtaining the present discounted value of the stock and hence its price.

APPENDIX

TABLE # 1

Date/month/year	Landmark(s)
03-Nov-94	Electronic trading incorporated in NSE
13-Dec-94	Ban on "badla"in Indian market
Mar/Jul 1995	Electronic trading commences in BSE
17-Jun-95	Circuit filter system adopted by NSE
05-Oct-95	Ban on "badla" revised
Apr /Nov 1996	NSCC & NSDL (Depositories) commences their operation
1999	Securities Law amended to enable derivatives trading
Dec-99	Rolling settlements system introduced
12-Jun-00	Start of equity index futures trading
04-Jul-01	equity index options trading commences
02-Jul-01	Carry forward trade was abolished

TABLE #2

Year	Events **(**stock market crisis**)**	Amount involved(INR)
1992	Harshad Mehta **:** the market went up by 143% between Sept 91 & Apr 92	**54** Billion
1994	M.S.Shoes**:** **(**Pawan Sachdeva**)** manipulated the share prices before a Rights issue	**170** Million
1995	Sesa Goa , Rupangi Impex & Magan Industries Ltd	**61.8** Million
1997	CRB Group **:** C.R**.** Bhansali	**7** Billion
1998	involving BPL, Videocon,Sterlite stocks	Rs**.** **0.77** Billion
2001	Ketan Parekh **(**K10 stocks**)**	Rs**.** **1** Billion

TABLE #3 : DESCRIPTIVE STATISTICS OF DAILY RETURNS

Statistics	Sensex(BSE)	Nifty(NSE)
Observation period	Mar95/MAY04	MAR95/May04
# observations(T)	2134	2134
Mean	0.00348	0.00012
StandardDeviation	0.017298	0.016963
Skewness	0.1236	0.43147
Excess Kurtosis	2.8353	3.973548
Jarque Bera statistics	621.7(2tailedp=0.00)	1470. 126(2tailedp=0.00)
Q(1)[a]	26.42(2tailedp=0.00)	6.37(2tailedp=0.00)
$Q^2(1)$[b]	117.26(2tailedp=0.00)	65.48(2tailedp=0.001)
ARCH LM statistic(atlag=1)	129.35	117.64
ACF[d]atlag=1forreturns	0.11(Asymptoticbound=0.042)	0.078(Asymptoticbound=0.042)
ACFatlag=1forsquaredreturns	0.27(Asymptoticb ound=0.042)	0.168(Asymptoticbound=0.042)

Notes

a. Q(K)is the LjungBox statistic identifying the presenceoffirstorderautocorrelationinthe returns.nullhypothesis:noautocorrelation.Dist ributedaschisquare(K).
b. Q^2(K)istheLjungBoxstatisticidentifyingthepres enceoffirstorderautocorrelationinthe squaredreturns.nullhypothesis:noautocorrelati on,distributedaschisquare(K).
c. ARCHLMstatisticistheLagrangeMultipliertes tstatisticforthepresenceofARCH.Null hypothesis:noheteroscedasticity,distributedasa chisquare(K).Criticalvalueat1per centlevelofsignificanceis6.63at1degreeoff reedom.Valuesforotherhigherlagare alsosignificant.
d. ACFisautocorrelationfunctionforreturnsand squaredreturnsresp.

Table # 4:UNIT ROOT TESTING FOR DAILY RETURNS

AugmentedDickeyFullerTests			numberoflags=42
NullHypothesis	TestStatistic		MacKinnonAsymptoticcriticalvalue
	Sensex	Nifty	@10%C.I.
constant=0	7.926	6.566	1.6157
intercept=0 constant=0	7.927	6.566	2.59
trendcoeff.=0 intercept=0 constant=0	7.012	6.334	3.22
PhillipPerronTests			Truncatedlags=6(Nifty)&7 (Sensex)
NullHypothesis	TestStatistic		MacKinnonAsymptoticcriticalvalue
	Sensex	Nifty	@10%C.I.
intercept=0 constant=0	47.56	39.396	2.59
trendcoeff.=0 intercept=0 constant=0	39.97	36.737	3.22

Table # 5: Information criteria for BSE Sensex Return AR (p) – ARCH (q) models AIC

p/q	0	1	2	3	4	5	6	7
0	-5.316	-5.3145	-5.313	-5.3114	-5.3099	-5.3083	-5.3068	-5.3053
1	-5.205	-5.2273	-5.2496	-5.2719	-5.2942	-5.3166	-5.3389	-5.3612
2	-5.225	-5.2531	-5.2325	-5.2356	-5.2387	-5.2418	-5.2449	-5.2148
3	-5.2449	-5.2789	-5.2317	-5.1844	-5.2915	-5.2561	-5.2207	-5.1854
4	-5.2649	-5.3047	-5.22	-5.1432	-5.3442	-5.2704	-5.1966	-5.1227
5	-5.2849	-5.2781	-5.2713	-5.2645	-5.2576	-5.2508	-5.2144	-5.2372

Table #6 :Information criteria for BSE Sensex Return AR (p) – ARCH (q) models								
SBIC								
p/q	0	1	2	3	4	5	6	7
0	-5.1447	-5.1269	-5.1261	-5.1278	-5.126	-5.125	-5.1452	-5.3214
1	-5.1536	-5.1358	-5.1305	-5.1353	-5.1402	-5.145	-5.1254	-5.3415
2	-5.1504	-5.1447	-5.1349	-5.1429	-5.1543	-5.165	-5.1756	-5.3417
3	-5.1553	-5.1536	-5.1393	-5.1504	-5.1685	-5.185	-5.2015	-5.3124
4	-5.1581	-5.1625	-5.1437	-5.1579	-5.1826	-5.205	-5.2273	-5.313
5	-5.1609	-5.1714	-5.1481	-5.1655	-5.1968	-5.225	-5.2531	-5.3136

COEFFCIENTS OF SYMMETRIC AND ASYMMETRIC GARCH MODELS – SENSEX & NIFTY

	BSE-SENSEX			NSE-NIFTY		
	GARCH(1,1)	EGARCH(1,1)	GJRGARCH(1,1)	GARCH(1,1)	EGARCH(1,1)	GJRGARCH(1,1)
C	0.000648(0.000)	0.0521(0.000)	0.0551(0.000)	0.000 751(0.000)	0.0825	0.0957
α0	0.00000064(0.008)	0.1798	0.1605	0.00000314(0.00 02)	0.1189	0.1868
α1	0.062409(0.000)	0.2965	0.1527	0.055409(0.000)	0. 05447	0.06483
β1	0.912815(0.000)	0.9217	0.7988	0.902315(0.000)	0. 9328	0.8326
β1+α1	0.975224			0.95772		
		0.052			0.065	
[(Res<0)*ARCH(1)]			0.09515			0.089743
Loglikelihood	5785.784	5682.246	5589.231	5785.78 4	5458.357	5684.216
AIC	5.54127	5.5621	5.5528	5.54127	5.4781	5.65 79
SBIC	5.538487	5.5633	5.5488	5.538487	5.4958	5 .5962

(p) = where, p is the probability value

TABLE # 7

FIGURES AND GRAPHS

FIGURE # 1

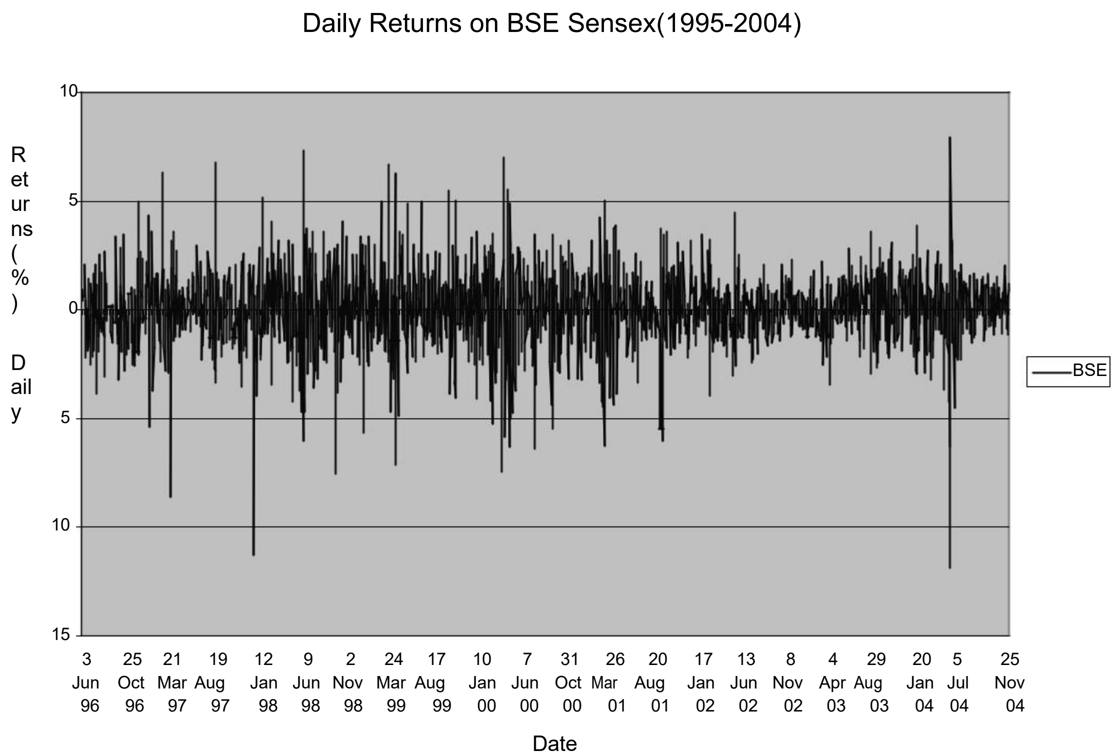
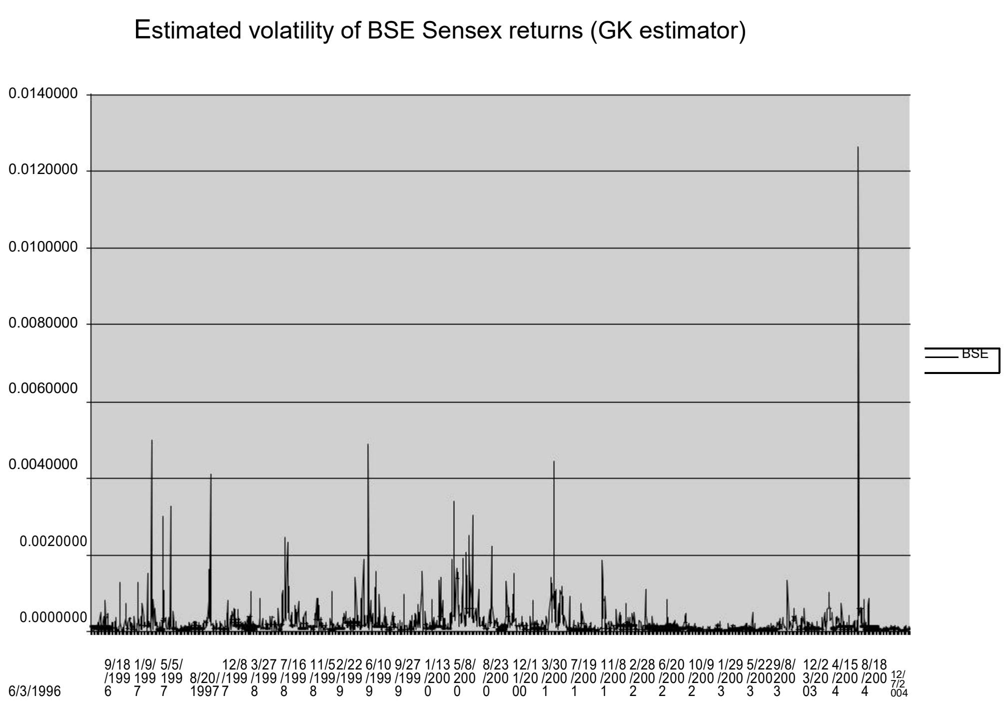


FIGURE # 2



Mathematical expressions

Equation # 1

$$\hat{\sigma}^2_{GK} = \frac{1}{n}\sum_{t=1}^{n}(0.511(\ln\frac{H_t}{L_t})^2 - 0.019(\ln(\frac{C_t}{O_t})\ln(\frac{H_tL_t}{O_t^2}) - 2\ln(\frac{H_t}{O_t})\ln(\frac{L_t}{O_t}))$$
$$-0.383(\ln\frac{C_t}{O_t})^2),\ n \geq 1.$$

Equation# 2

$$r_t = a_0 + a_1 r_{t-1} + \varepsilon_t$$

$$\varepsilon_t \mid \Psi_{t-1} \sim N(0, h_t),$$
$$h_t = a_o + \sum_{i=1}^{q} a_i e^2_{t-i},$$
with: $\alpha_o > 0$ and $\alpha_i \geq 0$, $i = 1, \ldots, q$,

Where, Ψ_{t-1} s the set of information available at time t-1

Equation # 3

$$\varepsilon_t \mid \Psi_{t-1} \sim N(0, h_t),$$
$$h_t = a_o + \sum_{i=1}^{q} a_i e^2_{t-i} + \sum_{j=1}^{p} \beta_j h_{t-j} .$$

Equation # 4 Half Life determination

$H_f = 1 – [\ln 2 / \ln (\alpha_1+\beta_1)]$

Equation # 5

$$h_t = \alpha_0 + \sum_{i=1}^{q} \alpha_i \varepsilon^2_{t-i} + \sum_{i=1}^{q} \omega_i I_{t-i} \varepsilon^2_{t-i} + \sum_{j=1}^{p} \beta_j h_{t-j},$$

$$\textbf{where: } I_{t-i} = \begin{cases} 1 & \varepsilon_{t-i} \leq 0 \\ 0 & \varepsilon_{t-i} > 0 \end{cases}$$

Equation # 6

$$\ln h_t = \alpha_0 + \sum_{i=1}^{q} \alpha_i \cdot [\theta z_{t-i} + \gamma(|z_{t-i}| - \sqrt{2/\pi})] + \sum_{j=1}^{p} \beta_j \cdot \ln(h_{t-j}),$$

where $z_t \sim$ IID (0,1).

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