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MODELLING VOLATILITY OF DAILY STOCK RETURNS:
EVIDENCE FROM NSE LISTED COMPUTER SOFTWARE & MULTIMEDIA SCRIPTS

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ABSTRACT

Volatility of a financial time series has become a fertile area for research during last decades. Global financial meltdowns have massive shock on different sectors as well as on scripts returns. The objective of this paper is to study empirically the volatility pattern of NSE listed computer software and multimedia scripts. This study applies ARCH, GARCH, E-GARCH models provides the evidence of the persistence of time varying asymmetric volatility. Main findings suggest that time varying volatility behaviour of Indian stock market may be due to recent global financial meltdown which is originated from US sub-prime crisis. Also effect captured by different models show that negative shocks have significant effect on conditional volatility.

Keywords: *Time Series, Asymmetric Volatility, Conditional Volatility, Financial Meltdown.*

JEL Classification: *C32, C53, G28.*

Introduction

The prediction and modelling of stock market volatility has become significant in these recent years in the field of finance, and is considered point of interest for academicians and finance professionals. It refers to the uncertainty or more specifically the risk of changes in security's value. Volatility is considered as variability of return of asset pricing. A special feature of stock market volatility is that it is not directly observable. For example, consider the daily log returns of stock. More specifically daily volatility is unobservable from the return data because there is only one observation in a trading day. Over the last decades, modelling volatility of a financial time series has become an important part and it has gained attention from academicians, researchers and others stakeholders.

The research objective of this paper was to understand the return data (daily) of scripts in software & multimedia sector & see if asymmetric GARCH models can explain persistence of shock and volatility.

Conceptual Overview of Volatility

Volatility is useful for superior returns. Higher volatility causes higher risk. Estimation of stock price returns is important for several reasons- (i) Investment decision; (ii) Assets pricing; (iii) Expected returns and (iv) Risk of various assets etc. Various linear and non-linear methods by which stock returns volatility can be modeled. Volatility has several feathers that are commonly seen in asset returns.

- **Leptokurtic Distribution:** In general leptokurtic distribution has a kurtosis value higher than that of standard normal distribution and this characteristic is common in observed price, rate and return based time series data.
- **Volatility Clustering:** High and small values in a log-return sample tend to occur in a cluster which indicates that there is dependence in the tails. This attribute is also called volatility clustering.

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- **Leverage Effects:** Variability in stock prices tend to be negatively correlated with changes in volatility. Alternatively we can say that volatility is higher after negative shocks than after positive shocks of same magnitude.
- **Long Memory:** Sample autocorrelation of the data are small whereas the sample autocorrelations of the absolute and squared values are significantly different from zero even for higher lags.
- **Co-movements in Volatility:** when we analyze time series attributes from different markets, one observes that big movements in one financial time series is matched by big movements in another time series from a different market.

As we have worked on daily closing prices which have been converted stock return using following formula

$$r_t = [(P_t - P t-1)/ P_t] *100$$

Where r_t indicates daily return, P_t is the price of the security on day t and $P t-1$ is the price of the security on day $t-1$. This measure of return takes into account only apperception / depreciation in the share price and share price are taken after adjusting dividend yield and inflation.

A Survey of Literature and Research Gap

Several studies on modelling volatility of daily stock returns and on related areas both by foreign as well as by Indian researchers could be cited. A few of them are enumerated here:

Ali (2016) in his research paper '*Stock market volatility and returns: A study of NSE & BSE in India*' investigated relationship between returns and volatility, volatility clustering, leverage effect and persistence of volatility for the Indian stock market. This study finds that there exists a significant presence of volatility clustering and degree of volatility in daily return series and existence of leverage effect indicating that negative shocks or bad news have more impact on volatility than the positive shocks or good news this study also exhibits that the relation between returns and volatility at the return series were statistically insignificant;

Banumathy et al. (2015) in the research paper '*Modelling stock market volatility: Evidence from India*' have studied volatility pattern of Indian stock market based on index data using both symmetric and asymmetric models. Volatility of NIFTY index return is tested and coefficient has the expected sign both EGARCH and TGARCH models. Study also argued that increased risk did not increase the returns;

Kumar & Singh (2014) in the research paper '*Volatility modeling, seasonality and risk return relationship in GARCH- in- mean framework: the case of Indian stock and commodity markets*' discussed the relationship of volatility, risk premium and seasonality in risk-return relation of the Indian stock and commodity markets. This study concluded that stock and commodity market returns showed persistence in the volatility and clustering and asymmetric properties and for symmetric conditional volatility structure GARCH (1, 1) is found to be more appropriate for NIFTY and some commodity products;

Padhi (2006) in the research paper '*Stock Market Volatility in India: A Case of Select Scripts*' investigated that market volatility at the individual script level and at the aggregate indices level to know how volatility changes whether volatilities shows the same trend or it varies across the selected sectors. She conducted LM test to confirm the presence of ARCH effect in the aggregate indices and exhibits time – varying heteroscedasticity. Different ARCH coefficients are found for different indices at different lag values. Five sectors showing the same trend for persistence characteristics;

Md. Shawkatul Islam et. al (2014) discussed about daily and monthly average of Dhaka Stock Exchange (DSE) general index about presence of volatility using GARCH model. It is found that volatility of DSE was highest at 2010. After 2010 DSE volatility is decreasing in Bangladesh stock exchange. This study concluded that the volatility of DSE return is decreasing over time.

Savadatti (2018) discuss about the different types volatility of the Bombay Stock Exchange (BSE) using the daily return series of the S&P BSE all index covering fifteen years using both symmetric and asymmetric GARCH models. Asymmetric GARCH model showed that enough evidence for the presence of leverage effect in the return series. Study results are helpful to the investors and other stake holders of the stock market during their investment decision.

Tripathy & Rahman (2013) mentioned that modeling and forecasting the variability of daily closing value data for both SENSEX and Shanghai Stock Exchange Composite Index. This study attempted to fit appropriate GARCH model to estimate the conditional market volatility for both BSE and Shanghai Stock Exchange respectively. Study concluded that there are significant ARCH effects in both the stock markets, and it is appropriate to use the GARCH model to estimate the process.

Most of the research on the stock market volatility in India based on broad indices and studies have been done for stock market of developed country as a whole. The reasons behind conducting this study are that stock market is an unavoidable issues, it is important to explore how volatility of individual script changes with respect to different time period and economic policies, incident etc and underlying different factors and shocks which can effect individual securities are observed less in recent past studies.

Research Methodology

- **Sample Design and Sources of Data**

This study is based on secondary data. We have considered the Capitaline corporate database with market capitalisation as a parameter to find out five companies such as Wipro, Infosys, Mphasis, HCL Technology and Zee entertainment based on judgemental sample technique method which are actively traded in NSE from 2001- 02 to 2015- 16. Presently, computer software and multimedia is a booming as well as vulnerable sector.

- **Period of Study**

To get a comprehensive view, our research study has been made for 15 years from 2001-02 to 2015-16 (Period I - 1.4.2001 to 31.3.2007 known as pre global financial meltdown period; Period II - 1.4.2007 to 31.3.2016 known as post global financial meltdown period and Period III- 1.4.2001 to 31.3.2016 known as overall time period). We have selected our the study periods based on the economic instable situations which were raised due to global financial crisis, instability in rupee value, US sub-prime crisis, negative growth etc.,

- **Statistical and Econometrics Tools**
  - **Descriptive Statistics:** In this paper we have used descriptive statistics to understand the basic features of data series and the mean value difference in our study. We have presented average value (mean), S.D., Variance, Kurtosis and Skewness.
  - **Test of Stationarity:** There is always need for testing whether the data are stationary or not and it is tested by unit root test, which is conducted by Augmented Dickey-Fuller (ADF) test and Philips – Perron (PP) Test.
  - **Test for Heteroscedasticity:** One of the most essential issues before applying the GARCH methodology is to first examine the residuals for the evidence of Heteroscedasticity. To test the presence of Heteroscedasticity in residual of the return series of daily adjusted closing price we have used ARCH test.

ARCH model: $\pm_t^2 = a_0 + \Sigma_{t=1}^{q} a_i \,\mathrm{U}_{t-1}^2$ (Where a_0 is mean and a_1 is conditional volatility and U$t-1$ is white noise representing residual of time series).

- **Volatility Measurement Technique:** We have used GARCH(1,1) model to measure the stock returns volatility of selected companies daily return series and modelling asymmetric volatility T-GARCH (1,1) was applied. Generalized ARCH processes in the sense that the squared volatility ($\pm_t^2$) of the concerned period is allowed to depend on previous squared volatilities, as well as previous squared values of the process.

  Mean equation: $r_t = « + \text{£}_t$

  Variance equation: $\pm_t = \mathrm{w} + \sim\text{£}_{t-1}^2 + \sim_{t-1}^2$

Volatility arising as a result of different price-sensitive information from the preceding periods can be measured as the lag of the squared residual from the mean equation (ARCH term). The estimate of β1 shows the persistence of volatility of a shock.

On the other hand, The Exponential GARCH (EGARCH) model is a GARCH variant that models the logarithm of the conditional variance process. In addition to modeling the logarithm, the EGARCH model has additional leverage terms to capture asymmetry in volatility clustering.

An EGARCH model can be written as:

$$\mathrm{Log}\,(\pm^2) = \mathrm{w} + \;.\ln(\pm^2_{t-1}) + ¥.\frac{\text{£}_{t-1}}{\sqrt{\pm^2_{t-1}}} + \pm\frac{\text{£}_{t-1}}{\sqrt{\pm_{t-1}^{-2}}}$$

Where the persistence of the GARCH is effect and ¥ represents the leverage effect and ± represents ARCH effect.

Results and Discussion

To assess the distributional properties of the daily adjusted closing price of stock returns various descriptive statistics are conducted. Select companies mean value are majority lower (Mphasis Ltd stock mean return & S.D. is highest .21% and 3.4%) in pre global financial meltdown period. Skewness has been found to be negative in case of three out of five stocks. Kurtosis of the overall period indicate high pickedness (Leptokurtic) which implies that the return series is fat tailed and does not follow a normal distribution and clearly indicate presence of volatility in this sector daily adjusted stock price return series. On the other hand, in post global financial meltdown period specific stocks in Computer Software and Multimedia sector mean value and S.D. are majority lower except in case of HCL Technology stock return where S.D. is highest (mean return .11% and S.D. 2.5%). Skewness has been found to be negative in case of two out of five stocks. Kurtosis of the this period indicate high pickedness (Leptokurtic) which implies that the return series is fat tailed and does not follow a normal distribution and clearly indicate presence of volatility. But in the overall time period, Mphasis Ltd stock return where S.D. is highest (mean return .12% and S.D. 3%). Skewness has been found to be negative in case of two stocks in overall time period. Kurtosis of the overall period indicate high pickedness (Leptokurtic) which implies that the return series is fat tailed and does not follow a normal distribution and clearly indicate presence of volatility in this sector daily adjusted stock price return series in Table 1.1 and 1.2.

To make a return series stationary if its mean and variance are constant and independent of time and the covariance depend only upon the distance between two time periods, but not on time periods. Augmented Dickey Fuller (ADF) test and Phillips-Perron (PP) tests are employed to infer the stationarity of the stock daily return series for the overall period which is represented in Table – 1.3. According to the unit root test result it states that stationarity exists in select five companies' stock price returns series.

Heteroscedasticity test is applied to find out the presence of ARCH effect in the residuals of the return series. From the Table- 1.4 it is inferred that the ARCH test statistics is highly significant. Since, P value are lower than zero and null hypothesis are rejected at 1% level, which confirms presence of ARCH effects in the residuals and hence the results warrant for the estimation of GARCH family models.

Once we assure ARCH effect in a financial time series dataset we may further investigate GARCH effect in order to fulfill our specific objective of this paper. It computes autocorrelation of the error term. However, if it appears from the table of GARCH results (Table–1.5) in three different times and it's indicating volatility clustering and persistent. In computer software and multimedia sector, we have five companies, out of which during the pre global financial meltdown period one highest and lowest average value of ARCH and GARCH are .988 and .919. During post global financial meltdown period highest and lowest average value of ARCH and GARCH ($\sim_j + {}_i$) are .983 and .813. Again in overall time period highest and lowest average value of ARCH & GARCH are .993 and .919. Study shows that during three time zones average value of ARCH & GARCH of companies in computer software and multimedia sector are maximum this clearly proves that the high volatility among these scripts returns. The long term volatility level of stock price return series indicated through larger coefficient in GARCH equation. The coefficient results of ARCH effect shows mixed results during different time zones of our study period. The average value of an ARCH and GARCH effect of all five companies are found to be closer during different time zones clearly indicates greater persistence of external shock towards return.

Again, EGARCH model also applied in five scripts of computer software and multimedia sector. This model is divided between (a) mean equation and (b) variance equation. The residual of mean equation is used in variance equation to estimate the different coefficients. Stock price return series have found to be ARCH effect in three different time period. In the pre global financial meltdown period all select companies have negative '¥' value indicates that leverage effect exist in return series. These leverage coefficients are significant mostly at 1% and 5% level of significance. β value (representing GARCH effect) in EGARCH model in pre global financial meltdown period are near to one and high level of persistence exist. In this period only Zee Entertainment 'p' value found to be insignificant.

Again during post globalization financial meltdown period four companies (except Infosys) '¥' value (leverage effect) found to be negative and significant at 1% level of significance (corresponding 'p' values have also been found to be insignificant in case of Wipro and Infosys). However, we have gathered different experience in case of overall time period. The asymmetric effect captured by parameter (¥) in EGARCH model is negative and statistically significant at 1% level of significance provides the presence of leverage effect. Leverage effect indicates that positive shocks have less effect on conditional variance when compared to the negative shocks. The results of select five companies daily stock returns revel the fact that β is close to one indicating high persistence with slow decay of volatility shocks for post global financial meltdown period.

However, for all these select scripts β is distinctly lower during the pre – global financial meltdown period than β during the post-global financial meltdown period and overall time period. This indicates that shocks are less persistent, decaying faster during pre-global financial meltdown period. Our intention is to examine the leverage effect from the coefficient. If gamma value (¥) is found to be negative and significant and confirming 'p' value is found to be very small, then it affirms leverage effect. Leverage effect is negative correlation between past return and future volatility of expected return. By leverage we generally mean the ratio of debt and equity. However, in exponential GARCH model it indicates greater the risk of volatility or variance of the firm. In stock market, effect of unfavorable news have a greater impact that the favorable ones. In conditional variance equation, this is perfectly captured by E-GARCH model.

Conclusion & Findings

Measurement of volatility is vital for determining cost of capital for financial assets, also for leverage and investment. This study attempts to model the volatility of stock price return in NSE listed computer software & multimedia stocks from 1.4.2001 to 31.03.2016, which includes volatility clustering, leptokurtic distribution and leverage effect. To capture the symmetry effect both ARCH and GARCH are employed. The primary empirical findings of the stock price return data are far from normality, where as it showed existence of conditional Heteroscedasticity, in the other words volatility clustering. In maximum cases GARCH (1,1) model, the sum of the coefficient (~ +) is near to one, which implies that the volatility is highly persistent. The coefficient (¥) measures leverage parameter showed that only four companies are found negative effect. According to EGARCH model in financial time series good news has an impact on ARCH term, while bad news has impact on ARCH as well as GARCH term. As a whole, if increased risk did not increase the returns since the coefficient is insignificant for the selected variables for the study period.

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Table 1: Descriptive Statistics results of Daily Adjusted Return

Company Name	Pre Global Recession Period				Post Global Recession Period			
	Mean	S. D.	Kurtosis	Skewness	Mean	S. D.	Kurtosis	Skewness
Wipro	0.0011	0.031	11.46	0.28	0.0004	0.021	6.9	-0.03
Infosis	0.0012	0.026	14.01	-0.64	0.0006	0.02	14.46	-0.24
MphasiS	0.0021	0.034	9.76	0.73	0.0006	0.026	13.84	0.02
HCL Technology	0.0009	0.034	8.43	-0.42	0.0011	0.025	8.49	0.346
Zee Entertainmen	0.0011	0.036	9.25	-0.02	0.0008	0.025	6.02	0.097
Mphasis	0.0021	0.034	9.76	0.73	0.0004	0.021	6.9	-0.03

(Source: Compilation of Stock price returns data using EViews 8.0)

Table 2: Descriptive Statistics and Normality Test results of Daily Adjusted Return

Company Name	Overall Period				Normality Test Result			
	Mean	S. D.	Kurtosis	Skewness	J-B	Prob.	**Decision Rule – Ho Rejected when P value <5%** (Ho: Return series are normal)	Data series normality
Wipro	0.0007	0.025	11.77	0.19	12016.9	.000	Rejected	Not normal
Infosys	0.0008	0.023	15.12	-0.48	23040.8	.000	Rejected	Not normal
Mphasis	0.0012	0.03	11.99	0.48	12731.8	.000	Rejected	Not normal
HCL Technology	0.001	0.029	9.11	-0.13	5833.6	.000	Rejected	Not normal
Zee Entertainment	0.0009	0.03	9.59	0.021	6764	.000	Rejected	Not normal

(Source: Compilation of Stock price returns data using EViews 8.0)

Table 3: Stationarity Test Results of Overall Return series

List of Companies	ADF Test statistic			PP Adjusted Test statistic			**Decision Rule** (Test statistics value is more negative than critical value, then we reject Null Hypothesis)	**Decision on Ho** (Ho : Unit root in Data series)	**Data series Stationarity**
	Intercept Only	Both Trend & Intercept	At Level	Intercept Only	Both Trend & Intercept	At Level			
Wipro	-10.33	-10.32	-10.23	-62.2	-62.2	-62.12	More negative test statistics (P=0.000)	Ho rejected & Return series do not have any unit root	Stationary series
Infosys	-38.22	-38.22	-38.22	-59.5	-59.5	-59.38	More negative test statistics (P=0.000)	Ho rejected & Return series do not have any unit root	Stationary series
Mphasis	-14.37	-14.46	-14.19	-61.73	-61.73	-61.67	More negative test statistics (P=0.000)	Ho rejected & Return series do not have any unit root	Stationary series
HCL Technology	-26	-25.99	-25.82	-60.27	-60.27	-60.08	More negative test statistics (P=0.000)	Ho rejected & Return series do not have any unit root	Stationary series
Zee Entertainment	-33.27	-33.27	-33.2	-60.44	-60.43	-60.24	More negative test statistics (P=0.000)	Ho rejected & Return series do not have any unit root	Stationary series

(Source: Compilation of Stock price returns data using EViews 8.0)

Table 4: Heteroskedasticity Test Results – ARCH Test

Company Name	Pre		Post		Overall		Decision on Ho (Null hypothesis of homoskedasticity of residuals is rejected if P–Value<0.05)	ARCH effects are present or not
	F-statistic with Prob. value	Obs* R-squared with Prob. Of Chi square	F-statistic with Prob. value	Obs* R-squared with Prob. Of Chi square	F-statistic with Prob. value	Obs* R-squared with Prob. Of Chi square		
Wipro	157.61 (0.000)	142.81 (0.000)	135.30 (0.000)	127.66 (0.000)	384.21 (0.000)	348.53 (0.000)	Rejected	ARCH effects are present
Infosys	86.91 (0.000)	82.26 (0.000)	23.79 (0.000)	23.56 (0.000)	153.67 (0.000)	147.67 (0.000)	Rejected	ARCH effects are present
Mphasis	133.37 (0.000)	122.64 (0.000)	100.91 (0.000)	96.62 (0.000)	262.98 (0.000)	245.80 (0.000)	Rejected	ARCH effects are present
HCL Technology	281.2 (0.000)	237.12 (0.000)	33.93 (0.000)	33.45 (0.000)	405.52 (0.000)	365.96 (0.000)	Rejected	ARCH effects are present
Zee Entertainment	62.61 (0.000)	60.18 (0.000)	142.14 (0.000)	133.75 (0.000)	190.32 (0.000)	181.18 (0.000)	Rejected	ARCH effects are present

(Source: Compilation of Stock price returns data using EViews 8.0)

Table 5: (GARCH Model)

Company Name	Estimated Model with values				AIC	SIC	Log Likelihood	**Decision** (Decision Rule: Volatility of shocks is highly persistence when $\sim_j + {}_i = 1$)
First Period - Coefficients - GARCH (1, 1)								
	$\sim_0$	$\sim_1$	$_1$	$\sim_j + {}_i$				
Wipro	5.16	.157	.794	.951	-4.35	-4.33	3279.1	Very high persistence value
Infosys	1.29	.089	.895	.984	-4.64	-4.63	3498.1	Very high persistence value
Mphasis	9.26	.220	.704	.924	-4.19	-4.17	3157.3	Comparatively low persistence value
HCL Technology	1.37	.085	.903	.988	-4.22	-4.20	3178.9	Very high persistence value
Zee Entertainment	.0001	.138	.781	.919	-3.90	-3.88	2938.8	Comparatively low persistence value
Second Period - Coefficients - GARCH (1, 1)								
Wipro	1.47	.110	.855	.965	-5.09	-5.08	5684.5	Very high persistence value
Infosys	8.72	.202	.611	.813	-5.03	-5.01	5613.2	Comparatively low persistence value
Mphasis	4.90	.164	.774	.938	-4.61	-4.60	5151.6	Comparatively low persistence value
HCL Technology	1.03	.079	.904	.983	-4.73	-4.72	5287.4	Very high persistence value
Zee Entertainment	9.40	.048	.934	.982	-4.69	-4.68	5242.2	Very high persistence value
Overall Period - Coefficients - GARCH (1, 1)								
	$\sim_0$	$\sim_1$	$_1$	$\sim_j + {}_i$				
Wipro	1.51	.116	.863	.979	-4.78	-4.77	8942.2	Very high persistence value
Infosys	4.75	.157	.762	.919	-4.86	-4.85	9092.2	Comparatively low persistence value
Mphasis	5.93	.180	.757	.937	-4.44	-4.43	8306.1	Comparatively low persistence value
HCL Technology	1.04	.082	.905	.987	-4.53	-4.52	8466.6	Very high persistence value
Zee Entertainment	5.37	.037	.956	.993	-4.37	-4.36	8170.1	Very high persistence value

(Source: Compilation of Stock price returns data using E Views 8.0)

Table 6: (E- GARCH Model)

Company Name	Estimated Model with values				AIC	SIC	Log Likelihood	**Decision** (Decision Rule: If ¥ is significant & negative, then leverage effect exists in return series.)
First Period - Coefficients - GARCH (1, 1)								
	$\sim_0$	$\sim_1$	¥	$_1$				
Wipro	-.457	.220	-.098	.959	-4.38	-4.36	3301.65	Leverage effect exists
Infosys	-.162	.092	-.083	.987	-4.67	-4.65	3520.52	Leverage effect exists
Mphasis	-.754	.351	-.049	.922	-4.18	-4.16	3151.44	Leverage effect exists
HCL Technology	-.249	.164	-.040	.982	-4.24	-4.21	3192.48	Leverage effect exists
Zee Entertainment	-.266	.129	-.002	.974	-3.91	-3.89	2947.48	Leverage effect exists
Second Period - Coefficients - GARCH (1, 1)								
	$\sim_0$	$\sim_1$	¥	$_1$				
Wipro	-.468	.230	-.048	.989	-4.44	-4.43	4966.83	Leverage effect exists
Infosys	-1.55	.300	-.011	.983	-4.41	-4.39	4926.46	Leverage effect exists
Mphasis	-.823	.298	.032	.989	-4.47	-4.45	4999.6	Leverage effect not exist
HCL Technology	-.194	.140	-.064	.986	-8.27	-4.26	4773.41	Leverage effect exists
Zee Entertainment	-.114	.076	-.02	.996	-4.14	-4.13	4628.78	Leverage effect exists
Overall Period - Coefficients - GARCH (1, 1)								
	$\sim_0$	$\sim_1$	¥	$_1$				
Wipro	-.402	.232	-.042	.970	-4.79	-4.78	8959.37	Leverage effect exists
Infosys	.693	.223	-.056	.930	-4.87	-4.86	9115.22	Leverage effect exists
Mphasis	-.717	.314	-.041	.932	-4.44	-4.34	8303.95	Leverage effect exists
HCL Technology	-.212	.152	-.040	.986	-4.54	-4.53	8497.65	Leverage effect exists
Zee Entertainment	-.120	.093	.007	.993	-4.37	-4.36	8181.98	Leverage effect not exist

(Source: Compilation of Stock price returns data using E Views 8.0).