Trading Volume, Volatility and Leverage:
A Dynamic Analysis of the Indian Stock Market

Naliniprava Tripathy [*] ***Aditya Prakash Gore*** [†] ***and Mayank Arora*** [‡]

ABSTRACT

This study investigates the relationship between leverage effect and daily stock returns, volume and volatility for the 30 stocks included in the Bombay Stock Exchange SENSEX index in India during the period January 2005 to June 2009, by using GARCH, ARCH, EGARCH and TARCH models. The analysis shows that there exist substantial ARCH effects in the residuals and the volatility shocks are quite persistent in the market. The study found that the recent news and the old news both have an impact on the volatility of the stock. This study also finds evidence of leverage and asymmetric effect on stock market. The study concludes that bad news generate more impact on change in trading volumes and volatility of the market. It is also observed that asymmetric GARCH models provide better fit than the symmetric GARCH model. So it is evident from the study that systematic variations in trading volume are assumed to be caused only by the arrival of new information.

Key words: *Trading volume, BSE SENSEX, Stock price, GARCH, ARCH, EGARCH, TARCH*

INTRODUCTION

Trading volume and volatility indicate potential importance as indicators of the current stock market activity on the one hand and a potential source of information for the future behavior of stock market on the other hand. Numerous papers have documented the fact that high stock market volume is associated with volatile returns. An increase in stock market volatility brings a large stock price change of advances or declines. It has also been noted that volume tends to be higher when stock prices are increasing than when prices are falling. Pricing of securities depends on volatility of each asset. Therefore, price changes indicate the average reaction of investors to news. The arrival of new information makes investors to adapt their expectations and this is the main cause for price and return changes. However, since investors are heterogeneous when interpreting new information, stock returns may stay unchanged even though new information is brought to the market. On the other hand, stock returns may only change if there is positive trading volume.

According to the efficient market hypothesis, past price or volume changes in a competitively traded stock market do not help predict future prices. However, recent studies have questioned the efficient market hypothesis and have supported the notion that stock market excess returns can be predicted by publicly available information (Fama & French, 1995; Pesaran & Timmennan, 1995; Ferson & Harvey, 1993).Various studies reported that there are significant relationships between volume and stock price movement and volatility, due to the fact that trading volume is a source of risk because of the flow of information. For example, Saatccioglu and Starks (1998) found that volume led stock prices changes in four out of the six emerging markets. Blume, et al, (1989) stated that a

[*] Associate Professor (Finance), Indian Institute of Management Shillong, Mayurbhanj Complex, Nongthammai, Shillong, Meghalaya, India, PIN 793 014, Phone: +91-364-2308037, Fax: +91-364-2230041, Email: nt@iimshillong.in, nalini_prava@yahoo.co.in

[†] Final year PGP Participant, Indian Institute of Management Shillong, India, Phone: +91 94367 00531, +91 99690 07150, Email: aditya08@iimshillong.in, gore.aditya@gmail.com (Conference presenter)

[‡] Final year PGP Participant, Indian Institute of Management Shillong, India, Phone: +91 94367 00528, Email: mayank08@iimshillong.in, marora.1986@gmail.com (Conference presenter)

portion of the losses on S & P stocks in October, 1987 were related to the magnitude of the trading volume. Chan et al. (2000) found that trading volume for foreign stocks is strongly associated with NYSE opening price volatility. Säfvenblad, 2000 found that Swedish index returns exhibit high autocorrelation when trading volume is low. Swanminathan (2000) finds that past trading volume can be used to predict future stock price momentum. However, Jones, et al, (1994) found that the positive volatility-volume relation documented by numerous researchers reflected positive relationship between volatility and the number of transactions. Mei, et al. (2005) found that trading caused by investors' speculative motives could explain a significant fraction of the price difference between the dual-class shares. Griffin, et al. (2007) investigated the dynamic relation between market-wide trading activity and returns in 46 markets and reported strong positive relationship between turnover and past returns. In addition, other studies reported that stock trading volume represents the highest positive correlation to the emerging stock price changes; thus represent the most predicted variables in increasing price volatility in both emerging and developing stock markets (Sabri, 2004, Sabri, 2008b). The analysis of the relationship between stock prices, returns on stock index and volumes traded has been conducted from various perspectives. More recently, the use of conditional volatility to investigate the relationship between stock returns and trading volume became very popular. Although conditional volatility have always been used, realized volatility, which is also called historical volatility is the sum of squared intraday returns over a certain interval such as a day, has recently attracted the attention of financial economists and econometricians as an accurate measure of the true volatility.
In the last three decades, a large number of countries had initiated reform process to open up their economies. Emerging markets have received huge inflows of capital in the recent past and became viable alternative for investors seeking international diversification. Among the emerging markets, India has received it's more than fair share of foreign investment inflows since its reform process began. One reason could be that India was not affected by the Asian crisis and has maintained its high economic growth during that period (Gupta and Basu 2005). Today India is one of the fastest growing emerging economies in the world. The reform process in India officially started in 1991. As a result, demand for investment funds is growing significantly and capital market growth is expected to play an increasingly important role in the process. The capital market reforms in India present a case where a judicious combination of competition, deregulation and regulation has led to sustained reforms and increased efficiency (Datar and Basu 2004). At this transitional stage, it is necessary to assess the level of efficiency of the Indian stock market in order to establish its longer term role in world economy. The analysis of stock market is an important segment through which countries exposure to the outer world could be readily felt. This research is motivated to focuses the predictability of stock returns and the role of trading volume and volatility in the dynamics of the price discovery process in India. Since both volume and volatility both serve as measures of information flow (e.g. Andersen, 1996), examining the links between stock returns, volume and volatility provides us further understanding of how new information is impounded in stock prices. In this context, deeper understanding of the role of trading volume and volatility in the dynamics of stock prices may help investors to identify future patterns of the stock market which can be exploited in their investment decisions.

This paper adds to the growing literature on the stock market by a further examination of the return-volume relationship and we raise three research questions. First, the presented study reinvestigates the effects on volatility of the Indian stock market issue using GARCH model to see to what extent the change could be attributed to the trading volume. Secondly, we examine whether the stock market's reaction to the arrival of news changed when trading commenced. During the last few years leverage effect has became quite noticeable, particularly in stock markets. Changes in stock prices tend to be negatively related to changes in volatility (Black, 1976; Christie, 1982). This has been attributed to the leverage effect where stock price declines increase the financial leverage and consequently, the degree of risk (volatility). To capture this, many researchers have developed different asymmetric GARCH models [exponential GARCH (EGARCH) by Nelson (1991) and TGARCH by Zakoian (1994)]. Since the vanilla GARCH model specifies a symmetric volatility response to market news, it cannot capture the leverage or asymmetric response. GARCH model fails to respond differently to positive and negative shocks. No prior study made so far to find asymmetric effect of stock return, trading volume in stock market volatility in India. So, thirdly we use EGARCH and TGARCH model to determine asymmetric effect of stock return in stock market volatility in India to obtain new insights. Therefore, the presented work improves the earlier studies and offers a value addition to the existing literature and proves to be useful to the investors as well as regulators. The paper is organized as follows: In section 2 we review the existing literature on the volume-volatility-return dynamics. In section 3 describe the methods used in our empirical investigation. In section 4 we show our findings Section 5 we make our concluding remarks.

LITERATURE REVIEW

The stock return-volume relation in both developed and emerging financial markets has been subject to extensive research. This section presents a brief review of the literature relating to developed financial markets, emerging stock markets and the Indian stock market, respectively. Smirlock and Starks (1985) find that the return-volume relation is asymmetric and later, Smirlock and Starks (1988) find a strong positive lagged relationship between volume and absolute price changes using individual stock data. Hiemstra and Jones (1994) use non-linear Granger causality tests to examine the non-linear causal relation between volume and return and find there is a positive bi-directional relation between them. Bhagat and Bhatia (1996) also employ daily data to test the causal relationship between volume and return, finding return causes volume rather but not *vice versa*. Basci et al (1996) use weekly data on 29 individual stocks in Turkey and find the price level and volume are co integrated. Saatcioglu and Starks (1998) use monthly data from six Latin American stock markets to test the relation between price changes and volume, finding a positive price-volume relation and a causal relationship from volume to stock price changes but not *vice versa*. Silvapulle and Choi (1999) use daily Korean Composite Stock Index data to study the linear and non-linear Granger causality between stock price and trading volume, finding that there is a significant bi-directional linear and non-linear causality between the two series. Lee and Swaminathan (2000) used monthly returns and daily trading volume of all the firms listed on NYSE and American Exchange (AMEX) and find that momentum and trading volume appear to predict subsequent returns in the US equity market. Bekaert and Wu (2000) not only support this finding, but also suggest that negative shocks generate a greater response in volatility than positive shocks of an equal magnitude, evidence of the speed of information transmission in markets. Thus, the findings of past studies are strong indications of information content of volatility on the markets, which could be used by investors to earn abnormal profit.

Ratner and Leal (2001) examine the Latin American and Asian financial markets and find a positive contemporaneous relation between return and volume in these countries except India. At the same time they observed that there exists a bi-directional causal relation between return and volume. In summary, the return and volume are strongly related contemporaneously but there is little evidence that either can be used to predict the other. Medeiros and Doornik (2006) investigated the empirical relationship between stock returns, return volatility and trading volume using data from the Brazilian stock market. The study found out there is a contemporaneous and dynamic relationship between return volatility and trading volume and return volatility contains information about upcoming trading volumes. Atmeh and Dobbs (2006) investigated the performance of moving average trading rules in the Jordanian stock market and found that technical trading rules can help to predict market movements. Zolontoy and Melenberg (2007) studied the dynamic relationship between trading volume, volatility, and stock returns at the international stock markets and found no evidence of the trading volume affecting the serial correlation of stock market returns, as predicted by Campbell et al. (1993) and Wang (1994). Second, the stock market volatility has a negative and statistically significant impact on the serial correlation of the stock market returns, consistent with the positive feedback trading model of Sentana and Wadhwani (1992). Third, the lagged trading volume is positively related to the stock market volatility, supporting the information flow theory. Fourth, they found the trading volume to have both an economically and statistically significant impact on the price discovery process and the co-movement between the international stock markets. Overall, these findings suggested the importance of the trading volume as an information variable. Rashid Sabri (2008) explained the impact of trading volume on stock market volatility in the Arab Economy. The study found that there is an increasing in both trading volume and stock price volatility and volume-stock price movements are significantly integrated for all selected markets in the study. Diebold and Yilmaz (2008) found out a clear link between macroeconomic fundamentals and stock market volatilities, with volatile fundamentals translating into volatile stock markets. Kiymaz & Girard (2009) found that the persistency of conditional volatility is high and very close to unity implying that current information can be used to predict future volatility. By including trading volume in the analysis the study finds that even though the persistence of the conditional volatility is present, it is lower with the introduction of volume.

TIME SERIES DATA & METHODOLOGY

The required time series data is based on daily closing price of BSE SENSEX, actively traded 30 scripts and Trading volume have been collected from Bombay Stock Exchange for a period of five years from January 2005 to June 2009. Returns are proxied by the log difference change in the price index. The stock return is calculated as the continuously-compounded return using the closing price:

$$R_t = \ln\left(\frac{P_t}{P_{t-1}}\right) * 100\%$$

Where ln (P_t) denotes the natural logarithm of the closing price at time t. We use daily turnover by volume as the raw trading volume series (Vol_t).

The data is first tested for normality (i.e. whether the returns follow a normal curve). In statistics, the Jarque-Bera test is a goodness-of-fit measure of departure from normality, based on the sample kurtosis and skewness. The test is named after Carlos M. Jarque and Anil K. Bera. The test statistic JB (for Jarque-Bera) is defined as

$$JB = \frac{n}{6} * \left(S^2 + \frac{(K-3)^2}{4} \right)$$

where n is the number of observations (or degrees of freedom in general); S is the sample skewness, K is the sample kurtosis, the statistic JB has an asymptotic chi-square distribution with two degrees of freedom and can be used to test the null hypothesis that the data are from a normal distribution. The null hypothesis is a joint hypothesis of the skewness being zero and the excess kurtosis being 0, since samples from a normal distribution have an expected skewness of 0 and an expected excess kurtosis of 0 (which is the same as a kurtosis of 3). As the definition of JB shows, any deviation from this increases the JB statistic. In the recent past financial market volatility modelling, especially temporal variation has been a fascinating topic in financial market research. The impact of stock price, trading volume on the stock market volatility has to be examined by using a suitable and appropriate model. It is well- accepted fact that many financial time series contain a unit root, i.e. the series are non-stationary and it is generally acknowledged that stock index and stock index futures series might not be exception. Stationary time series is one whose mean, variance and covariance are unchanged by time shift. Non-stationary time series have time varying mean or variance or both. Knowledge of non-stationary of the time series is significant in the modelling of economic relationships because standard statistical techniques that assume stationarity may give invalid inferences in the presence of stochastic trends. In case of non-stationarity data, ordinary least squares can produce spurious results. Such a model would be termed as "spurious regression". Therefore, prior to modelling any relationship, non-stationarity must be tested. This eliminates any possibility of being trapped in spurious regression. The data considered for the study is time series, which is non-stationary whereas the examination of first difference often reveals wide swings, which is predominantly the volatility effect suggesting that the variance of the time series varies over time. For application of GARCH and ARCH model on SENSEX, the initial step in the estimation involves the determination of the times series property of each variable individually by conducting unit root tests. The most popular unit root test is the ADF (Augment Dickey - Fuller, 1979) test. The test simply includes AR (1) process:

$$X_t = p * X_{t-1} + e_t$$

Where X_t is a stationary series and p is a parameter and e_t is white noise error term, which follows zero mean with a unit variance.

Dicky and Fuller (1979) consider three different regression equations that can be used to test for the presence of a unit root.

$$X_t = p * X_{t-1} + e_t$$

$$X_t = \alpha_0 + p * X_{t-1} + e_t$$

$$X_t = \alpha_0 + p * X_{t-1} + \alpha_{1t} + e_t$$

The difference between the three regressions concerns the presence of the deterministic elements a_0 and a_{1t}. Equation '1' is a pure random walk model, equation '2' adds an intercept or drift term and equation '3' includes both a drift and linear time trend. If p=1, the series contains a unit root. In this test the null hypothesis is Ho: P=1 in which case it is said X has a unit root. The alternative is H1: p<1. If the alternative hypothesis is correct then X is stationary. But if the null hypothesis is correct, then the variable is non-stationary so the tests do not apply here. If the e_t violates the above assumption then equation is to be modified with p-lagged changes in the dependent variable as an additional regression, which is as follows:

The Augmented Dickey-Fuller test simply includes AR (p) terms of the ΔX_t, term in the three alternative models.

$$\Delta X_t = \gamma * X_{t-1} + \sum_{i=1}^{p} \beta_i * \Delta X_{t-1} + e_t$$

$$\Delta X_t = \alpha_0 + \gamma * X_{t-1} + \sum_{i=1}^{p} \beta_i * \Delta X_{t-1} + e_t$$

$$\Delta X_t = \alpha_0 + \gamma * X_{t-1} + \alpha_{2t} + \sum_{i=1}^{p} \beta_i * \Delta X_{t-1} + e_t$$

Where, Δ is the difference operator, t is time trend, e_t is error term and α_0, γ, β_i are the parameters to be estimated. The difference between the three regressions again concerns the presence of the deterministic elements $a_0$and a_{2t}. If γ=0, the series contains a unit root.

Conditional volatility and trading volume

Volatility of the stock markets is measured by using Standard Deviation or GARCH model. GARCH model has been a preferred measure of volatility by many researchers. The GARCH model provides for Heteroscedasticity in the observed returns. It is a time series modelling technique that uses past variance and the past variance forecasts to forecast future variances. The ordinary regression model proved to be inefficient because of the untenability of one of its key assumptions that the errors have the same variance throughout sample. It is called Homoscedasticity. If the error variance is not constant, the data is said to be Heteroscedasticity. It is observed that the model that takes into account the changing variance can make more efficient use of the data.

Financial time series usually exhibits a characteristic called volatility clustering which means that large changes tend to follow large changes and small changes tend to follow small changes. GARCH model accounts for certain characteristics like thick tails and volatility clustering that are commonly associated with financial time series. Graphical analysis and computation of some basic statistics like Kurtosis and Skewness can help to provide relevant empirical evidence of the presence of volatility clustering tendencies. The thick tail phenomena in the data are known as excess kurtosis. Time series data that exhibit a thick tail distribution is often referred to as Leptokurtic. Generally, the presence of Leptokurtic tendencies on the time series returns suggests the presence of volatility clustering; hence the modelling of such phenomena is recommended through the adjustment of Auto Regressive Conditional Heteroscedasticity. The Generalized Autoregressive Conditional Heteroscedasticity (GARCH) model is a variation of the Auto Regressive Conditional Heteroscedasticity (ARCH) model developed by Engle in 1982. Bollerslev originally proposed the GARCH model in 1986. A distinguishing feature of this model was that the error variance might be correlated over time because of the phenomenon of volatility clustering. Following Antonion & Holmes (1995) and others, the return series is modelled as a univariate GARCH process. Today, the most widely used model to estimate the conditional (hence time-varying) variance of stock and stock-index returns is the Generalized Autoregressive Conditional Heteroscedasticity (GARCH) model. In analyzing the behaviour of volatility due to derivative products, it is necessary to eliminate the influences of other factors. The GARCH (1, 1) is estimated for measuring volatility. The GARCH (1, 1) framework has been found to have the best specification in both the works.

Since the information flow into the market is widely unobservable, we use trading volume as a proxy. Systematic variations in trading volume are assumed to be caused only by the arrival of new information. Trading volume typically exhibit the assumed time dependence. We specify the stochastic process of stock returns as a simple GARCH (1,1) process with an autoregressive term in the mean equation and trading volume as an additional predetermined regressor in the conditional variance equation.

The GARCH (1, 1) Model

Any GARCH model consists of two distinct specifications. The first is the conditional mean equation. The simple

GARCH models used in practice take the simple possible conditional equation:

$$R_t = R_{t-1} * \beta + \varepsilon_t$$

Where R $_t$ is the daily return on equity and R_{t-1} is the lagged return, β is a fixed parameter vector and ε_t is the residual error term for the day t, ε_t is treated as a collective measure of news at times t. A positive ε_t suggests the arrival of good news, while a negative ε_t suggests the arrival of bad news. The second equation in a GARCH model is the conditional variance equation. The conditional variance equation is a function of three terms:

$$h_t = \alpha_0 + \sum_{i=1}^{q} \beta_i * \varepsilon_{t-1}^2 + \sum_{j=1}^{p} \beta_j * h_{t-1}$$

Where α_0 is mean. 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). Last periods forecast variance is h_{t-1} (the GARCH term). GARCH (1, 1) refers to the presence of a first-order GARCH term (the first term in parentheses) and first-order ARCH term (the second term in parentheses). 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.

Asymmetry and Leverage Effects

Though ARCH and GARCH models are responds to good and bad news and quite useful in forecasting and modelling volatility, they lack in capturing "leverage effect" and information asymmetry. The rational and underlying logic of asymmetric or leverage effect is that the distribution of stock return is highly asymmetric. Bad news is followed by larger increase in price volatility than good news (positive returns) of the same size. It is known that the magnitude of the response of asset prices to shocks dependents on whether the shock is negative or positive. To demonstrate this point Engle and Ng (1990) mapped the relationship between the conditional variance of asset returns to exogenous shocks which resulted in what they termed a news impact curve. They found evidence of asymmetry is stock returns. In an attempt to explain the asymmetry of volatility in speculative prices, Black (1976) posited that when stock price falls the value of the associated company's equity declines. As a result, the debt-equity ratios of firms tend to rises, thereby signalling that the company has become riskier. Increased risk is considered an indicator for higher volatility. Used in this context, it is widely accepted that the statistically interpretation of Black's leverage effect implies that negative surprises increases predictable volatility in asset markets more than positive surprises. Another explanation of asymmetry is called the volatility feedback hypothesis (Campbell and Hentschel, 1992). This was developed to explain stock price volatility. A negative shock to volatility increases the future risk premia. This would cause the stock price to fall if the future dividends are expected to remain the same. Schwert (1989) also agreed with this explanation. 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.Some scholars argue that the asymmetry effect may stem from the feedback from volatility to stock price as changes in volatility trigger change in risk premiums.

Nelson (1991) proposed an exponential GARCH model or EGARCH model which is the earliest extension of the GARCH model that incorporates asymmetric effects in returns from speculative prices based on a logarithmic expression of the conditional variability of variable under analysis. Later on the Threshold ARCH (TARCH) model was introduced by Zakoian (1994).The TARCH model developed by Glosten et al. (1993) is considered to be most suitable in estimating the impact of positive and negative shocks on volatility. To answer the third research question regarding leverage effect and changes in the asymmetric pattern of the impact of positive and negative return shocks on conditional volatility we estimated the volatility equation by using EGARCH,TARCH and CARCH model.

The EGARCH Model

Glosten et al. (1994) illustrated how to allow the effects of good and bad news to have different effects on volatility in their TARCH model. In the volatility equation positive and negative shocks can have different effects on subsequent volatility. The first asymmetric GARCH model that precipitated considerable academic interest was the

EGARCH or exponential GARCH model proposed by Nelson (1991). The conditional variance equation in the EGARCH (1, 1) model is

$$\log h_t = \omega + \beta * \log h_{t-1} + \alpha * \frac{|\varepsilon_{t-1}|}{\sqrt{h_{t-1}}} + \gamma * \frac{|\varepsilon_{t-1}|}{\sqrt{h_{t-1}}}$$

Where, h_t is an asymmetric function of past ε_t, ω, β, α, γ are constant parameters.

Note that the left hand side is the lag 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. In this model specification, β is the GARCH term that measures the impact of last period's forecast variance. A positive β indicates volatility clustering implying that positive stock price changes are associated with further positive changes and vice versa. α is the ARCH term that measures the effect of news about volatility from the previous period on current period volatility. γ measures the leverage/asymmetric effect. Ideally γ is expected to be negative implying that bad news has a bigger impact on volatility than good news of the same magnitude. The sum of the ARCH-GARCH coefficients indicates the extent to which a volatility shock is persistent over time. A persistent volatility shock raises the asset price volatility.

The TARCH Model

The TARCH model is another volatility model that allows asymmetric effects. TARCH or Threshold ARCH was introduced independently by Zakeian (1990) and Glosten et al. (1993).The conditional variance is

$$h_t = \omega + \alpha * \varepsilon_{t-1}^2 + \gamma * \varepsilon_{t-1}^2 * d_{t-1} + \beta * h_{t-1}$$

Where $d_t = 1$ if $\varepsilon_t < 0$ and $d_t = 0$ otherwise. In this model, γ is used to capture the asymmetrical effect of good news such as favourable business cycle conditions and demand supply conditions and bad news such as political instability, oil prices shocks and increase inflation volatility. Accordingly, good news (ε_t<0), and bad news (ε_t>0), have differential effects on the conditional variance. Good news has an impact onα, while bad news has an impact α +γ. The presence of leverage effects can be tested by the hypothesis that $\gamma = 0$. The impact is asymmetric if $\gamma \neq 0$. Negative γ implied positive return shocks generate less volatility than negative return shocks. Higher specification of the TARCH model is

$$h = \omega + \sum_{i=1}^{q} \alpha * \varepsilon_{t-1}^2 + \gamma * \varepsilon_{t-1}^2 * d_{t-1} + \sum_{j=1}^{p} \beta_j * h_{t-j}$$

EMPIRICAL RESULTS AND ANALYSIS

Descriptive Statistics:

Table 1: Descriptive Statistics - Daily Stock Returns & Volume Change

Variable	Mean*	Std. Dev.*	Skewness	Kurtosis	Jarque-Bera	Probability
BSE Returns	0.140036	1.386586	-0.477375	6.279991	240.2052	0
Dailty Volume Change	-0.00687	40.35393	-0.051349	16.8898	3971.291	0
ACC	0.222341	2.092286	-0.306985	7.633896	449.7448	0
Bharti Airtel	0.197219	2.114249	-0.037606	4.198245	29.66979	0
BHEL	0.213135	2.189856	0.314363	7.065504	348.3444	0
DLF Universal Limited	-0.11337	5.041625	0.030545	6.19728	210.4919	0
Grasim Industries	0.141221	2.186307	0.577279	8.957733	758.0346	0
HDFC	0.145215	2.154561	0.077905	5.138486	94.62983	0
HDFC Bank	0.133997	1.957684	0.466752	4.217546	48.45005	0
Hindalco Industries	-0.43291	10.53173	-20.51036	443.7776	4033667	0
Hindusan Unilever Limited	0.083871	2.128013	0.327326	4.410327	49.7621	0
ICICI Bank	0.169717	2.089907	-0.024067	3.81232	13.62988	0.001097
Infosys	0.145505	1.802711	0.200657	5.390181	120.9068	0
ITC Limited	-0.33098	10.16958	-20.9303	456.1936	4263565	0
Jaiprakash Associates	0.258562	3.287046	0.531892	5.61417	163.9569	0
Larsen & Toubro	0.214713	2.250469	0.238052	4.629737	59.33598	0
Mahindra & Mahindra Limited	0.217374	2.086687	-0.267136	4.84188	75.70483	0
Maruti Udyog	0.136877	2.274401	0.224248	5.804364	166.017	0
NTPC	0.083484	1.846307	0.156839	4.646585	57.83171	0
ONGC	0.088874	1.888748	-0.393302	4.371404	51.44792	0
Ranbaxy Laboratories	-0.23672	3.963935	-12.12601	222.8456	1006942	0
Reliance Communications	0.140435	3.040705	-0.316393	6.83802	311.4427	0
Reliance Industries	0.16852	2.296238	-4.023494	56.67324	60629.66	0
Reliance Infrastructure	-0.018	2.143116	0.464716	9.220223	814.1741	0
State Bank of India	0.125042	1.937333	-0.347027	4.809708	77.32654	0
Strelite Industries	0.072647	3.733405	-0.436466	6.149333	219.8363	0
Sun Pharmaceutical Industries	0.105885	1.845981	-0.045901	4.492032	45.99522	0
Tata Consultancy Services	0.104636	1.884246	-0.26697	5.834284	171.2174	0
Tata Motors	0.096062	2.279595	-0.412842	4.339101	50.94263	0
Tata Power	0.067326	2.106171	-0.006161	4.56568	50.46013	0
Tata Steel	0.037081	2.522575	-0.149648	5.753993	157.9576	0
Wipro	0.078625	2.160094	-0.059223	5.243926	103.9301	0

*Values in percentages

The summery statistics for the BSE, trading volume and stock return are given in Table 1. All returns are calculated as the first difference of the log of the daily closing price. Figures 1 and 2 present the returns of the BSE index and volume of change over time in stock market. Table 1 shows the descriptive statistics of stock returns over the period mentioned above. The mean of the BSE Returns is 0.14%. Some of the stocks exhibit returns greater than the SENSEX, namely ACC, Bharti Airtel, Reliance Industries, etc. On the other hand, some stocks like Hindustan Unilever Limited, NTPC, ONGC, etc. have below-average returns. The daily volatility of the index is 1.39%. All the stocks individually are more volatile than the index, as seen from the above table.

The kurtosis for all the stocks is more than 3 (excess kurtosis), thus they are leptokurtic, i.e., the frequency distribution assigns a higher probability to returns around zero as well as very high positive and negative returns. The Jarque-Bera statistic for all the 32 variables is significantly greater than zero (due to the leptokurtic data). Thus, Jarque-Bera statistics shows that all the series are leptokurtic, exhibit non-normality and indicate the presence of Heteroscedasticity. Hence, GARCH (1, 1) model is the suitable for testing of hypothesis.

Daily Stock Returns and Daily Volume

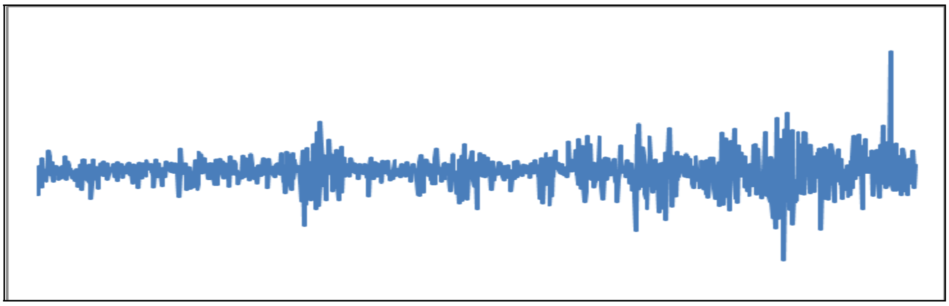

Figure 1: Daily Stock Price 2005-2009

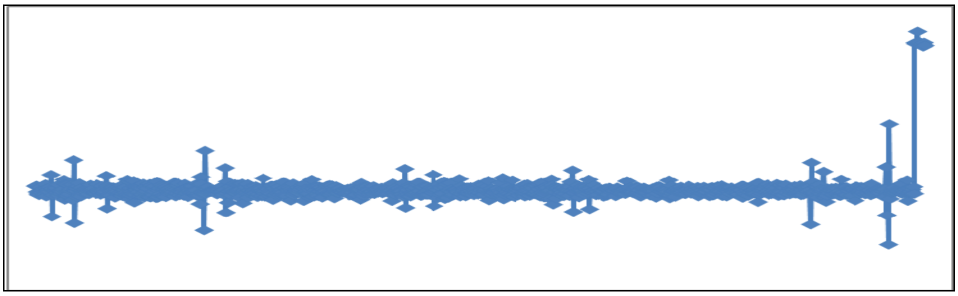

Figure 2: Daily Volume Change 2005-2009

Augmented Dickey-Fuller Test Equation

The study here employs the unit root test to examine the time series properties of concerned variables. Unit root test describes whether a series is stationary or non-stationary. For the test of unit root the present study employees the Augmented Dickey Fuller test. ADF test is used to measure the stationarity of time series data which in turn tells whether regression can be done on the data or not. The output is presented in the Table 2.On observing the outputs of ADF tests, it is seen that the ADF test statistic for all 32 variables is less than the critical values at 1%, 5% and 10% confidence level. So, the null hypothesis is rejected and the data is found to be stationary. Therefore, the ordinary least squares won't produce spurious results and therefore, we can apply regression to the data.

Table 2: Augmented Dickey-Fuller Unit Root Test

	ADF Test Statistic
BSE Returns	-15.88363
Dailty Volume Change	-17.13358
ACC	-14.91552
Bharti Airtel	-16.73419
BHEL	-16.61525
DLF Universal Limited	-9.861798
Grasim Industries	-13.35737
HDFC	-17.91719
HDFC Bank	-16.86864
Hindalco Industries	-15.09298
Hindustan Unilver Limited	-16.03236
ICICI Bank	-16.07147
Infosys	-16.64817
ITC Limited	-15.07099
Jaiprakash Associates	-15.4292
Larsen & Toubro	-15.45663
Maruti Udyog	-16.05228
Mahindra & Mahindra	-16.51123
NTPC	-16.30566
ONGC	-15.62916
Ranbaxy Laboratories	-14.18805
RELIANCE COMM	-14.0376
Reliance Infrastructure	-15.38321
RIL	-16.08394
SBI	-16.21989
STERLITE	-12.43129
SUN PHARMA	-15.82336
TATA MOTORS	-15.85374
TATA POWER	-16.16146
TATA STEEL	-15.24466
TCS	-17.02623
WIPRO	-16.58773

MacKinnon Critical Values

1% Critical Value*	5% Critical Value	10% Critical Value
-3.439	-2.8646	-2.5684

*MacKinnon critical values for rejection of hypothesis of a unit root

Evidence of ARCH/GARCH Effects

Estimation of ARCH/GARCH models typically done using the Maximum Likelihood Estimation technique. When using this technique, model selection is based on two metrics: Akaike Information Criterion (AIC) and Schwartz Bayesian Criterion (SBC).The model with lower value of AIC and SBC fits the data best.

Table 3: Maximum Likelihood Estimates for the GARCH (1, 1) Model without Trading Volume

Stocks	Coefficient	Std. Error	t-Statistic	Prob.
ACC	0.018551	0.004949	3.748773	0.0002*
Bharti Airtel	0.035882	0.005316	6.749968	0*
BHEL	0.030345	0.005094	5.956572	0*
DLF Universal Limited	0.001209	0.001749	0.691531	0.4892
Grasim Industries	0.03461	0.005516	6.274065	0*
HDFC	0.038944	0.00471	8.268196	0*
HDFC Bank	0.03013	0.005295	5.690025	0*
Hindalco Industries	0.00075	0.000676	1.109363	0.2673
Hindusan Unilever Limited	0.065811	0.004651	14.15098	0*
ICICI Bank	0.08526	0.005194	16.41511	0*
Infosys	0.127049	0.006918	18.36621	0*
ITC Limited	-0.001885	0.000552	-3.417795	0.0006*
Jaiprakash Associates	0.004587	0.003296	1.391649	0.164
Larsen & Toubro	0.040447	0.004928	8.207094	0*
Mahindra & Mahindra Limited	0.005991	0.006082	0.984935	0.3247
Maruti Udyog	0.021734	0.006257	3.473413	0.0005*
NTPC	0.029559	0.005454	5.420133	0*
ONGC	0.053576	0.005148	10.40629	0*
Ranbaxy Laboratories	0.008227	0.001261	6.523717	0*
Reliance Communications	-0.00118	0.002805	-0.42078	0.6739
Reliance Industries	0.072035	0.003366	21.40133	0*
Reliance Infrastructure	0.036069	0.004895	7.367998	0*
State Bank of India	0.041903	0.005908	7.092134	0*
Strelite Industries	0.00125	0.002291	0.545688	0.5853
Sun Pharmaceutical Industries	0.009431	0.00563	1.675069	0.0939
Tata Consultancy Services	0.026271	0.005681	4.623994	0*
Tata Motors	0.034721	0.005856	5.929455	0*
Tata Power	0.005765	0.004786	1.204577	0.2284
Tata Steel	0.061982	0.004554	13.60909	0*
Wipro	0.058661	0.005505	10.65676	0*
C	0.012815	0.008397	1.526262	0.1269

		Variance Equation		
Intercept ARCH (0) y0	0.024	0.002976	8.06497	0
ARCH (1) y1	0.519161	0.130017	3.99302	0.0001*
GARCH (1) y2	-0.029515	0.014051	-2.100606	0.0357**

* Statistically Significant at 1% level
** Statistically Significant at 5% level
*** Statistically Significant at 10% level

Diagnostic Statistics	
Adjusted R-squared	0.97909
Log likelihood	138.614
Akaike info criterion	-0.4235
Schwarz criterion	-0.1343
Durbin-Watson stat	2.09067
F-statistic	700.571

The Table 3 presents the maximum likelihood estimation of GARCH (1, 1) model without taking trading volume for the stock returns from 2005 to 2009. It is estimated for the presence of any ARCH/ GARCH effects. The analysis shows that lagged squared disturbance is statistically significant and error variance are correlated, that is , there exist substantial ARCH effects in the residuals and therefore a model that accounts for these effects would describe the data better. A residual ARCH LM test on the fitted GARCH (1, 1) model reveals that this model captures the Heteroscedasticity effectively.

Returns for all stocks are significant at 1% significance level except a few having probability values greater than 10% (or 0.1) like DLF Universal Limited, Hindalco Industries, Jaiprakash Associates, Sterlite Industries, Tata Power etc.

In the conditional variance equation, y_1 and y_2 are news coefficients. y_1 is coefficient for latest news which is statistically significant at 1% level indicating that the recent news has an impact on the volatility of the spot market. Similarly y_2 coefficient is also significant at 5% level and suggests that old news too is influencing the market volatility. The null hypothesis rejected and alternative hypothesis is accepted.

A high value of R-square depicts a very high degree of explained variation. Apart from this AIC and SIC criteria used in the study indicating lower for the regression which is quite reasonable and fit for our model. Further Durbin-Watson value is sufficiently close to 2 suggests autocorrelation or specification errors. Since the Durbin-Watson statistic is greater than 2, the error terms are not auto correlated. A high value of F-Statistic states that the statistical model is fit and appropriate.

Table 4: Maximum Likelihood Estimates of GARCH (1, 1) Model with trading volume

Stocks	**Coefficient**	**Std. Error**	**t-Statistic**	**Prob.**
Daily Volume	4.71E-05	0.000206	0.228174	0.8195
ACC	0.01878	0.005041	3.725267	0.0002*
Bharti Airtel	0.035474	0.00524	6.769313	0*
BHEL	0.030985	0.005169	5.994082	0*
DLF Universal Limited	0.001096	0.001848	0.593359	0.5529
Grasim Industries	0.035185	0.005577	6.309225	0*
HDFC	0.038975	0.004892	7.96679	0*
HDFC Bank	0.030867	0.005331	5.789826	0*
Hindalco Industries	0.000767	0.000688	1.115255	0.2647
Hindusan Unilever Limited	0.065081	0.004903	13.27357	0*
ICICI Bank	0.08562	0.005317	16.10444	0*
Infosys	0.126502	0.007033	17.98755	0*
ITC Limited	-0.001862	0.000523	-3.55928	0.0004*
Jaiprakash Associates	0.004718	0.003415	1.381527	0.1671
Larsen & Toubro	0.041124	0.005087	8.084125	0*
Mahindra & Mahindra Limited	0.00538	0.006203	0.867293	0.3858
Maruti Udyog	0.021178	0.00635	3.334878	0.0009*
NTPC	0.029547	0.005526	5.346963	0*
ONGC	0.053975	0.005186	10.40744	0*
Ranbaxy Laboratories	0.008396	0.001253	6.701654	0*
Reliance Communications	-0.001338	0.002978	-0.44932	0.6532
Reliance Industries	0.07096	0.003672	19.32475	0*
Reliance Infrastructure	0.035916	0.00498	7.212851	0*
State Bank of India	0.041943	0.006057	6.924787	0*
Strelite Industries	0.001158	0.002374	0.487863	0.6256
Sun Pharmaceutical Industries	0.010321	0.005688	1.814607	0.0696***
Tata Consultancy Services	0.027819	0.00588	4.73103	0*
Tata Motors	0.035202	0.006085	5.784741	0*
Tata Power	0.005609	0.004925	1.138799	0.2548
Tata Steel	0.06179	0.004543	13.60065	0*
Wipro	0.057196	0.005614	10.18763	0*
C	0.012366	0.008769	1.410121	0.1585
		Variance Equation		
Intercept ARCH (0) y0	0.025452	0.003192	7.97255	0*
ARCH (1) y1	0.394923	0.112277	3.517397	0.0004*
GARCH (1) y2	-0.033737	0.033951	-0.9937	0.3204

* Statistically Significant at 1% level

** Statistically Significant at 5% level

*** Statistically Significant at 10% level

Diagnostic Statistics	
Adjusted R-squared	0.97912
Log likelihood	138.415
Akaike info criterion	-0.4187
Schwarz criterion	-0.1209
Durbin-Watson stat	2.08497
F-statistic	680.771

The Table 4 presents the maximum likelihood estimation of GARCH (1, 1) model with trading volume for the stock returns from 2005 to 2009 is estimated for the presence of any ARCH/ GARCH effects.

Returns for all stocks are significant at 1% significance level except a few having probability values greater than 10% (or 0.1) like DLF Universal Limited, Hindalco Industries, Jaiprakash Associates, Sterlite Industries, Tata Power etc.

In the conditional variance equation, y_1 and y_2 are news coefficients. y_1 is coefficient for latest news which is statistically significant at 1% level indicating that the recent news has an impact on the volatility of the spot market. On the contrary, y_2 coefficient is statistically insignificant and suggests that old news is not influencing the market volatility. Systematic variations in trading volume are assumed to be caused only by the arrival of new information.

A high value of R-square depicts a very high degree of explained variation. Apart from this AIC and SIC criteria used in the study indicating lower for the regression which is quite reasonable and fit for our model. Further Durbin-Watson value is sufficiently close to 2 suggests autocorrelation or specification errors. Since the Durbin-Watson statistic is greater than 2, the error terms are not auto correlated. A high value of F-Statistic states that the statistical model is fit and appropriate.

Leverage/Asymmetric Effect

It is very often observed that downward movement of the markets is followed by higher volatilities than upward movement of the same magnitude. So it is important to use TARCH and EGARCH models to test asymmetric shocks to volatility. Sometimes the simple GARCH models cannot capture some important features of the data. To investigate the leverage effect we have used TARCH (1, 1) model introduced independently by Zakoian (1994).If the bad news has a greater impact on volatilities than good news, a leverage effect exists. ARCH model helps to explain the volatility of spot market when some degree asymmetric is present in the data.

Table 5: TARCH (1, 1) Parameters without trading volume

Stocks	Coefficient	Std. Error	t-Statistic	Prob.
ACC	0.016762	0.004787	3.501806	0.0005*
Bharti Airtel	0.035173	0.005001	7.033214	0*
BHEL	0.033606	0.005192	6.473036	0*
DLF Universal Limited	0.001235	0.001888	0.654228	0.513
Grasim Industries	0.037924	0.0055	6.895618	0*
HDFC	0.039054	0.0051	7.6577	0*
HDFC Bank	0.027655	0.005395	5.126559	0*
Hindalco Industries	0.000805	0.000713	1.129272	0.2588
Hindusan Unilever Limited	0.063833	0.004826	13.22672	0*
ICICI Bank	0.085602	0.00526	16.27336	0*
Infosys	0.127205	0.007089	17.9448	0*
ITC Limited	-0.001519	0.00047	-3.235844	0.0012*
Jaiprakash Associates	0.004522	0.003367	1.343053	0.1793
Larsen & Toubro	0.041093	0.005132	8.007626	0*
Mahindra & Mahindra Limited	0.005755	0.006116	0.941037	0.3467
Maruti Udyog	0.019589	0.006346	3.086959	0.002*
NTPC	0.032953	0.005429	6.069569	0*
ONGC	0.054685	0.005389	10.1468	0*
Ranbaxy Laboratories	0.008388	0.001208	6.946241	0*
Reliance Communications	-0.001643	0.003156	-0.520454	0.6027
Reliance Industries	0.077332	0.003922	19.71543	0*
Reliance Infrastructure	0.033729	0.005188	6.501329	0*
State Bank of India	0.042658	0.005993	7.117457	0*
Strelite Industries	0.001157	0.002392	0.483509	0.6287
Sun Pharmaceutical Industries	0.009159	0.005578	1.641966	0.1006
Tata Consultancy Services	0.028443	0.006071	4.6847	0*
Tata Motors	0.036509	0.005731	6.370174	0*
Tata Power	0.004775	0.005026	0.949955	0.3421
Tata Steel	0.061925	0.004491	13.7876	0*
Wipro	0.053433	0.005663	9.435791	0*
C	0.017988	0.008885	2.024578	0.0429**

		Variance Equation		
Intercept ARCH (0) y0	0.024699	0.002517	9.811712	0*
ARCH (1) y1	0.683321	0.213492	3.20069	0.0014*
(RESID<0)*ARCH (1) γ(Asymmetry)	-0.575443	0.214651	-2.680826	0.0073*
GARCH (1) y2	-0.010844	0.005447	-1.990802	0.0465**

* Statistically Significant at 1% level
** Statistically Significant at 5% level
*** Statistically Significant at 10% level

Diagnostic Statistics	
Adjusted R-squared	0.97886
Log likelihood	146.087
Akaike info criterion	-0.4497
Schwarz criterion	-0.152
Durbin-Watson stat	2.09133
F-statistic	672.335

Table 6: TARCH (1, 1) Parameters with trading volume

Daily Returns	Coefficient	Std. Error	t-Statistic	Prob.
ln(Daily Volume)	9.00E-05	0.000207	0.434645	0.6638
ACC	0.0181	0.004784	3.783196	0.0002*
Bharti Airtel	0.035215	0.005023	7.011052	0*
BHEL	0.033704	0.005209	6.470047	0*
DLF Universal Limited	0.001106	0.0019	0.582079	0.5605
Grasim Industries	0.036945	0.00548	6.741322	0*
HDFC	0.039997	0.005162	7.747731	0*
HDFC Bank	0.026999	0.005422	4.979755	0*
Hindalco Industries	0.000807	0.000735	1.097447	0.2724
Hindusan Unilever Limited	0.062942	0.004903	12.83872	0*
ICICI Bank	0.086301	0.00531	16.25335	0*
Infosys	0.127167	0.007099	17.91435	0*
ITC Limited	-0.001606	0.000492	-3.267869	0.0011*
Jaiprakash Associates	0.004805	0.003387	1.418859	0.1559
Larsen & Toubro	0.040768	0.005147	7.920911	0*
Mahindra & Mahindra Limited	0.005609	0.00616	0.910536	0.3625
Maruti Udyog	0.020677	0.006426	3.217679	0.0013*
NTPC	0.032679	0.005454	5.991848	0*
ONGC	0.055177	0.005434	10.15345	0*
Ranbaxy Laboratories	0.008501	0.001203	7.065017	0*
Reliance Communications	-0.00181	0.003197	-0.566318	0.5712
Reliance Industries	0.078857	0.004261	18.50597	0*
Reliance Infrastructure	0.032862	0.00522	6.295201	0*
State Bank of India	0.041904	0.006085	6.886572	0*
Strelite Industries	0.001355	0.002407	0.56314	0.5733
Sun Pharmaceutical Industries	0.009154	0.005594	1.636463	0.1017
Tata Consultancy Services	0.027284	0.00616	4.428913	0*
Tata Motors	0.036127	0.005853	6.172482	0*
Tata Power	0.004531	0.005109	0.886959	0.3751
Tata Steel	0.061583	0.004504	13.67423	0*
Wipro	0.053727	0.005691	9.440164	0*
C	0.017733	0.008874	1.998304	0.0457**
Variance Equation				
Intercept ARCH (0) y0	0.025157	0.002504	10.04477	0*
ARCH (1) y1	0.649223	0.205221	3.163538	0.0016*
(RESID<0)*ARCH (1) γ(Asymmetry)	-0.570385	0.205326	-2.77795	0.0055*
GARCH (1) y2	-0.010622	0.005229	-2.031312	0.0422**

* Statistically Significant at 1% level
** Statistically Significant at 5% level
*** Statistically Significant at 10% level

Diagnostic Statistics	
Adjusted R-squared	0.97869
Log likelihood	147.438
Akaike info criterion	-0.4512
Schwarz criterion	-0.1449
Durbin-Watson stat	2.09198
F-statistic	647.779

The Table 5 presents the TARCH (1, 1) parameters model without taking trading volume for the stock returns from 2005 to 2009. In the conditional variance equation; y_1, the coefficient for latest news which is statistically significant at 1% level indicating that the recent news has an impact on the volatility of the spot market. Similarly y_2 coefficient is also significant at 5% level and suggests that old news too is influencing the market volatility. Also TARCH model takes the leverage effect into account. The effect can be seen in the (RESID<0)*ARCH (1) term. As the coefficient of this term γ is not equal to zero, the impact is asymmetric. Also, the value of γ is negative, which implies that the volatility increases leads to fall in stock price that will have a negative effect on the financial leverage of the company.

The Table 6 presents TARCH (1, 1) model with trading volume for the stock returns from 2005 to 2009. The observations are similar with the findings of without taking trading volume. The coefficient of this term γ is not equal to zero, the impact is suggesting asymmetric consistent with previous findings (Ratner and Leal, 2001) that the response of trading volume to an upward return is stronger than that to a downward return.. So the results suggest that the value of γ is negative, which implies that the volatility increases and negative influence to trading volume as well.

Table 7: EGARCH (1, 1) Parameters without trading volume

Stocks	Coefficient	Std. Error	t-Statistic	Prob.
ACC	0.01537	0.004624	3.324065	0.0009*
Bharti Airtel	0.037327	0.004558	8.189158	0*
BHEL	0.030261	0.004603	6.573737	0*
DLF Universal Limited	0.001005	0.001596	0.630006	0.5287
Grasim Industries	0.040244	0.004699	8.564149	0*
HDFC	0.039693	0.004307	9.215827	0*
HDFC Bank	0.029265	0.004696	6.231384	0*
Hindalco Industries	0.000742	0.000647	1.147558	0.2512
Hindusan Unilever Limited	0.062245	0.004075	15.27493	0*
ICICI Bank	0.088584	0.004755	18.6291	0*
Infosys	0.130367	0.006051	21.54524	0*
ITC Limited	-0.002234	0.000525	-4.251697	0*
Jaiprakash Associates	0.004811	0.003183	1.511595	0.1306
Larsen & Toubro	0.037675	0.004469	8.430921	0*
Mahindra & Mahindra Limited	0.004082	0.005176	0.788634	0.4303
Maruti Udyog	0.016764	0.004771	3.513397	0.0004*
NTPC	0.032962	0.004961	6.644688	0*
ONGC	0.052394	0.004779	10.96286	0*
Ranbaxy Laboratories	0.008927	0.001192	7.488546	0*
Reliance Communications	-0.002452	0.002666	-0.919938	0.3576
Reliance Industries	0.090073	0.003304	27.25975	0*
Reliance Infrastructure	0.030326	0.004463	6.79566	0*
State Bank of India	0.041662	0.005362	7.770215	0*
Strelite Industries	0.001641	0.002011	0.816091	0.4144
Sun Pharmaceutical Industries	0.004271	0.005188	0.823301	0.4103
Tata Consultancy Services	0.028349	0.005188	5.464098	0*
Tata Motors	0.036606	0.005179	7.068025	0*
Tata Power	0.00486	0.004157	1.169	0.2424
Tata Steel	0.060317	0.004135	14.5853	0*
Wipro	0.051239	0.004986	10.27639	0*
C	0.011005	0.007973	1.380286	0.1675

		Variance Equation		
Intercept ARCH (0) y0	-4.848081	0.447971	-10.82231	0*
GARCH (1) y1	0.627755	0.09708	6.466341	0*
ARCH (1) y2	0.109433	0.062513	1.750559	0.08***
EGARCH (1) γ(Asymmetry)	-0.233478	0.129223	-1.806789	0.0708***

* Statistically Significant at 1% level

** Statistically Significant at 5% level

*** Statistically Significant at 10% level

Diagnostic Statistics	
Adjusted R-squared	0.977867
Log likelihood	144.3566
Akaike info criterion	-0.442739
Schwarz criterion	-0.144989
Durbin-Watson stat	2.088715
F-statistic	641.6267

Table 8: EGARCH (1, 1) Parameters with trading volume

Daily Returns	Coefficient	Std. Error	t-Statistic	Prob.
ln(Daily Volume)	-7.92E-06	0.000179	-0.044291	0.9647
ACC	0.015354	0.004823	3.18349	0.0015*
Bharti Airtel	0.037294	0.004733	7.879816	0*
BHEL	0.029886	0.004765	6.27178	0*
DLF Universal Limited	0.001095	0.001647	0.664687	0.5063
Grasim Industries	0.039859	0.004933	8.080581	0*
HDFC	0.039341	0.004446	8.848076	0*
HDFC Bank	0.029042	0.004919	5.904016	0*
Hindalco Industries	0.000768	0.000617	1.24427	0.2134
Hindusan Unilever Limited	0.062811	0.004196	14.96862	0*
ICICI Bank	0.08862	0.004869	18.19987	0*
Infosys	0.130641	0.006378	20.48192	0*
ITC Limited	-0.002154	0.000535	-4.02747	0.0001*
Jaiprakash Associates	0.004486	0.003199	1.402133	0.1609
Larsen & Toubro	0.038645	0.004722	8.183965	0*
Mahindra & Mahindra Limited	0.004608	0.005296	0.87012	0.3842
Maruti Udyog	0.015826	0.005085	3.112491	0.0019*
NTPC	0.033401	0.005107	6.539993	0*
ONGC	0.052131	0.004949	10.53274	0*
Ranbaxy Laboratories	0.009056	0.001186	7.638532	0*
Reliance Communications	-0.002206	0.002744	-0.803779	0.4215
Reliance Industries	0.089735	0.003667	24.46845	0*
Reliance Infrastructure	0.02977	0.004573	6.510069	0*
State Bank of India	0.042574	0.005501	7.738806	0*
Strelite Industries	0.001342	0.002118	0.633344	0.5265
Sun Pharmaceutical Industries	0.005342	0.00531	1.006163	0.3143
Tata Consultancy Services	0.027774	0.005385	5.158022	0*
Tata Motors	0.037158	0.005372	6.917215	0*
Tata Power	0.004044	0.004323	0.935542	0.3495
Tata Steel	0.060443	0.004214	14.345	0*
Wipro	0.052318	0.005104	10.24989	0*
C	0.009786	0.008217	1.190879	0.2337

Variance Equation				
Intercept ARCH (0) y0	-4.485103	0.54836	-8.179122	0*
GARCH (1) y1	0.632388	0.1017	6.218202	0*
ARCH (1) y2	0.126363	0.067719	1.865985	0.062***
EGARCH (1) γ(Asymmetry)	-0.139343	0.155058	-0.898652	0.3688

* Statistically Significant at 1% level

** Statistically Significant at 5% level

*** Statistically Significant at 10% level

Diagnostic Statistics	
Adjusted R-squared	0.97788
Log likelihood	145.878
Akaike info criterion	-0.4448
Schwarz criterion	-0.1386
Durbin-Watson stat	2.09007
F-statistic	623.603

To test the leverage effect we have also used EGARCH model, which is exhibited in Table 7 (without trading volume) and Table 8 (with trading volume). As y1 is positive, this indicates presence of volatility clustering implying that positive stock price changes are associated with further positive changes and vice versa. The empirical evidence suggests the existence of leverage effect and news impact is asymmetric (γ). As γ is negative, it concludes that bad news generate more impact on volatility of the market.

CONCLUSION

This paper examines the relationship of stock market returns, trading volume and volatility for 30 BSE SENSEX stocks select over the period from January 2005 to June 2009. This paper has used the GARCH (1, 1) model, asymmetric TARCH and EGARCH model to empirically examine the persistence of shocks to volatility and to determine the whether or not there is asymmetry in the pattern of volatility. The paper specifically tested the hypothesis of variability in volatility, which implies that volatility is greater when stocks price are moving downwards than upwards .Statistical inferences were drawn from the data by means of significance tests and over all goodness of fit of all the models as reported by the Akaike info criterion &Schwarz criterion. The results reflect that there is a significant contemporaneous relationship between trading volume and absolute value of price changes. The study found that the recent news has an impact on the volatility of the stock market. Also, the past news coefficient is statistically significant (except in the case of GARCH (1, 1) Model with Trading volume) and suggests that old news is influencing the market volatility. So it is evident from the study that systematic variations in trading volume are assumed to be caused only by the arrival of new information. EGARCH (1, 1) &TARCH model is an appropriate method for evaluating stock returns and including trading volume in conditional variance specification. So by employing these two models, the findings suggest that there is an existence of leverage effect and news impact is asymmetric. So the study concludes that bad news generate more impact on volatility of the market and trading volume. One explanation may be that normally investors have a higher aversion to down side risk, so they react faster to bad news.

REFERENCES

Andersen, T.G., 1996, Return volatility and trading volume: An information flow interpretation of stochastic volatility, Journal of Finance, 51, 169-204.

Basu, P. and Gupta, R., 2005. Is India vulnerable to financial crisis?: Lessons from the Asian experience. Paper presented at The 18th Australian Finance and Banking Conference 2005, Sydney, December, 14-16.

Bekaert, G. and G. Wu, 2000. Asymmetric volatility and risk in equity markets, The Review of Financial Studies, 13, 1-42.

Berry, T., and K.M. Howe, 1994, Public informational arrival, The Journal Finance, 49, 1331-1346.

Berument, H., and H. Kiymaz, 2001. The day of the week effect on stock market volatility. Journal of Economics and Finance 25, 181-193.

Black, F., 1976. Studies of stock price volatility changes. Proceedings of the 1976 meetings of the American Statistical Association, Business and Economics Statistics Section. Washington, DC: American Statistical Association, p. 177-181.

Bohl M.T., and H. Henke, 2003. Trading volume and stock market volatility: The Polish case, International Review of Financial Analysis 12, 513-525.

Bollerslev, T. 1986. Generalized autoregressive conditional heteroscedasticity. Journal of Econometrics, 307-327.

Campbell, J.Y. and L. Hentschel, 1992. No news is good news: an asymmetric model of changing volatility in stock returns. Journal of Financial Economics 31, 281-318.

Campbell, J.Y., S.J. Grossman and J. Wang, 1993. Trading volume and serial correlation in stock returns, Quarterly Journal of Economics 58, 906-939.

Chen et al., 2002. Momentum and Autocorrelation in Stock Returns, The Review of Financial Studies Special 2002 vol. 15. No. 2. pp. 565-573.

Christie, A., 1982. The stochastic behavior of common stock variances: value, leverage, and interest rate effects, Journal of Financial Economics, v. 10, p. 407-432.

Copeland, T. E., 1976, A model for asset trading under the assumption of sequential information arrival, Journal of Finance 31, 1149-1168.

Datar, M. K. and Basu, P. K., 2004. Financial sector reforms in India: Some institutional imbalances, Conference Volume, Academy of World Business, Marketing and Management Development Conference, Gold Coast, Australia, July.

Epps, T., and M. Epps, 1976. The Stochastic Dependence of Security Price Changes and Transaction Volumes: Implications for the Mixture-of-Distributions Hypothesis, Econometrica 44, 305-321.

Fama, E,F. and K. R. French, 1989. Business conditions and expected returns on stocks and bonds, Journal of Financial Economics 25, 23-40.

Fama, E., and K. French, 1992. The crosssection of expected Stock Returns. The Journal of Fmance 47 (June): 427-465.

Fama, E.F., 1990. Stock returns, expected returns and real activity, Journal of Finance 45, 1089-1109.

Ferson, W., and C. Harvey, 1993. The risk and predictability of international equity returns, Review of Financial Studies 6: 521-566.

Foster, F.D., and S. Viswanathan, 1995. Can speculative trading explain the volume-volatility relation? Journal of Business and Economics Statistics 13, 379-396.

Francis X. Diebold & Kamil Yilmaz, 2008. Measuring Financial Asset Return and Volatility Spillovers, With Application to Global Equity Markets, NBER Working Papers 13811, National Bureau of Economic Research, Inc.

Francq, Christian & Zakoian, Jean-Michel, 2009. Testing the Nullity of GARCH Coefficients: Correction of the Standard Tests and Relative Efficiency Comparisons," Journal of the American Statistical Association, American Statistical Association, vol. 104(485), pages 313-324.

French, K., G. Schwert, and R.Stambaugh, 1987. Expected stock returns and volatility, Journal of Financial Economics 19, 3-30.

Gallant, A.R., and P.E. Rossi and G. Tauchen, 1992. Stock prices and volume, The Review of Financial Studies 5, 199-242.

Glosten, L.R., R. Jagannathan, and D.E. Runkle, 1993. On the relation between the expected value and the volatility of the nominal excess returns on stocks, Journal of Finance 48, 1779-1801.

Hamilton, J.D. and G. Lin, Stock market volatility and the business cycle, Journal of Applied Econometrics 11, 573-594.

He, H., and J. Wang, 1995. Differential information and dynamic behavior of stock trading volume, Review of Financial Studies 8, 919-972.

Hiemstra, C. and Jones, J. D., 1994. Testing for linear and nonlinear Granger causality in the stock price-volume relation, Journal of Finance, 49, number 5, 1639–1664.

Jennings, R. H., L.T. Starks, and J.C. Fellingham, 1981, An equilibrium model of asset trading with sequential information arrival, Journal of Finance, 36, 143-161.

Kim, D. And S.J. Kon, 1994. Alternative models for the conditional heteroscedasticity of stock returns, Journal of Business 67, 563-599.

Lamoureux, C., and W. Lastrapes, 1991. Heteroskedasticity in stock return data: volume versus GARCH effects, Journal of Finance 45, 221-229.

Lee, C., and B. Swaminathan, 2000. Price Momentum and Trading volume, Journal of Finance, 55, 2017—2069.

Leon N. K., 2007. An empirical study of the relation between stock return volatility and trading volume in the BRVM, African Journal of Business Management Vol. 1 (7), pp. 176-184.

Li, Y., Donkers, A.C.D., & Melenberg, B., 2006. The Econometric Analysis of Microscopic Simulation Models, CentER Discussion Paper, 2006-99, pp. 1-47.

Lucey, B. M., 2005. Are local or international influences responsible for pre-holiday behaviour of Irish equities, Applied Financial Economics 15, 381-393.

Nelson, D.B., 1991. Conditional heteroscedasticity in asset returns: A new approach. Econometrica 59, 347-370.

Omran, M. And E. McKenzie, 2000. Heteroscedasticity in stock returns data revisited: Volume versus GARCH effects, Applied Financial Economics 10, 553-560.

Pagano, M. and A. Roell, 1992. Auction and dealership markets: What is the difference?, European Economic Review 36, 613-624.

Pagano, M. and A. Roell, 1996. Transparency and liquidity: A comparison of auction and dealer markets with informed trading, Journal of Finance 51, 579-612.

Pesaran, H., and A. Timmermann, 1995. PrediClability of slock returns: robustness and economic significance. Journal of Finance L (4): 1201-1228.

Pyun, C.S., S.Y. Lee, and K. Nam, 2000. Volatility and information flow in emerging equity market: A case of the Korean Stock Exchange, International Review of Financial Analysis 9, 405-423.

Säfvenblad, P. 2000. Trading volume and autocorrelation: empirical evidence from the Stockholm stock exchange, Journal of Banking and Finance, Vol. 24 pp.1275-87.

Schwert, G.W., 1990. Stock Market Volatility, Financial Analyst Journal 46, 23-45.

Sentana, E., Wadhwani, S., 1992. Feedback traders and stock return autocorrelations: evidence from a century of daily data, Economic Journal, Vol. 102 pp.415-25.

Silvapulle, Param & Choi, Jong-Seo, 1999. Testing for linear and nonlinear granger causality in the stock price-volume relation: Korean evidence, The Quarterly Review of Economics and Finance, Elsevier, vol. 39(1), pages 59-76.

Tauchen, G.E. and M. Pitts, 1983. The price variability-volume relationship on speculative markets, Econometrica 51, 485-506.

Theophano Patra & Sunil Poshakwale, 2006. Economic variables and stock market returns: evidence from the Athens stock exchange, Applied Financial Economics, 1466-4305, Volume 16, Issue 13, Pages 993 – 1005.

Torben G. Andersen, 1996. Return Volatility and Trading Volume: An Information Flow Interpretation of Stochastic Volatility, Journal of Finance 51:1, 169-204.

Watanabe, T., 2002. Margin requirements, positive feedback trading and stock return autocorrelations: the case of Japan, Applied Financial Economics, Vol. 12 pp.395-403.

Whitelaw, R.F., 1994. Time variations and covariations in the expectation and volatility of stock market returns, Journal of Finance 49, 525-542.

Zarraga, A., 2003. GMM-based testing procedures of the mixture of distribution model, Applied Financial Economics 13, 841-51.Financial Economics 13, 841-51.