Investigating impact of volatility persistence, market asymmetry and information inflow on volatility of stock indices using bivariate GJR-GARCH

Sinha, Pankaj and Agnihotri, Shalini

Faculty of Management Studies, University of Delhi

28 July 2014

Investigating impact of volatility persistence, market asymmetry and information inflow on volatility of stock indices using bivariate GJR-GARCH

Pankaj Sinha and Shalini Agnihotri
Faculty of Management Studies,
University of Delhi

Abstract

Joint dynamics of market index returns, volume traded and volatility of stock market returns can unveil different dimensions of market microstructure. It can be useful for precise volatility estimation and understanding liquidity of the financial market. In this study, the joint dynamics is investigated with the help of bivariate GJR-GARCH methodology given by Bollerslev (1990), as this method helps in jointly estimating volatility equation of return and volume in one step estimation procedure and it also eliminates the regressor problem (Pagan ,1984).Three indices of different market capitalization have been considered where, S&P BSE Sensex represent large capitalization firms, BSE mid-cap represents mid-capitalization firms and BSE small-cap index represents small capitalization firms. The study finds that there exist negative conditional correlation between volume traded and return of large cap index. There is unidirectional relation between index returns and volume traded since change in volume can be explained by lags of index returns. The relation between volume traded and volatility is found to be positive in case of large-cap index but it is negative in the case of mid-cap and small-cap indices. It is observed that there exist bidirectional causality between volatility and volume traded in all the three indices considered. Volatility is affected by pronounced persistence in volatility, mean-reversion of returns and asymmetry in market. The rate of information arrival measured by IDV(Intra-day volatility) is found to be a significant source of the conditional heteroskedasticity in Indian markets since the presence of volume (proxy for information flow) in volatility equation, as an independent variable, marginally reduces the volatility persistence, whereas presence of IDV, as a proxy for information flow, completely vanishes the GARCH effect. Finally, it is observed that

volume traded spills over from large cap to mid-cap index, from large-cap to small-cap index and from mid-cap to small-cap index, in response to new information arrival.
Keyword: Bivariate GJR-GARCH, Trading volume, Volatility, Stock return, Volatility Persistence, Asymmetry in markets
JEL Classification: C12, C32, G12

1. Introduction

In financial markets volatility is an important risk factor. Asset pricing models and portfolio allocation methods rely on its precise estimation. Precision in volatility estimation can be particularly useful for investment firms and risk management purposes. Volatility is affected by pronounced persistence in volatility, mean-reversion of returns and asymmetry in market. In recent times, stock markets across the world have been experiencing high levels of volatility. Understanding dynamic relation among stock return, trading volume and volatility is of interest to academicians and risk managers as this relation may lead to better forecasting of stock return volatility and pricing of derivatives in Indian markets. There is growing body of literature that suggest that use of volatility predicted from more sophisticated time-series models will lead to more accurate option valuations, asset pricing, risk assessment and risk management. Secondly, this understanding can lead to better estimation of the distribution of stock returns. Volatility exhibits the phenomena of persistence i.e. clustering of large moves and small moves (of either sign) in the price process, a well-documented feature of volatility of assets. Persistence in variance of a random variable, evolving through time, refers to the property of momentum in conditional variance. According to Lamoureux and Lastrapes (1990) daily returns are generated by mixture of distributions, in which the rate of daily information arrival is the stochastic mixing variable. Autoregressive conditional heteroskedasticity (ARCH) in daily stock return data reflects time dependence in the process of generating information flow to the market. Daily trading volume, used as a proxy for information arrival time, is shown to have significant explanatory power regarding the variance of daily returns. The degree to which conditional variance is persistent in daily stock return data is an important issue. Poterba and Summers (1986) showed that the extent to which stock return volatility affects stock prices depends critically on the permanence of shock to the variance. The implication of such volatility clustering is that volatility shocks today will influence the expectation of volatility many periods in the future. Volatility is defined as;

Let the expected value of the variance of returns k periods ahead in the future is represented as:

$$h_{t+k|t} = E_t[(r_{t+k} - m_{t+k})^{2}] \quad (1)$$

Where $h_{t+k|t}$ represents volatility k periods ahead conditioned on information set at t, r_{t+k} and m_{t+k} represents return and average return at $t + k$ period, respectively. The forecast of future volatility then will depend upon information in today's information set such as today's returns. Volatility is said to be persistent if today's return shock have large effect on the forecast variance many periods ahead in the future.

Lamoureux & Lastrapes(1990) suggested volume traded of stocks can be taken as a proxy for the information flow in the markets. If volume traded is acting as a proxy for information flow in the markets then persistence in volatility can be reduced by incorporating volume in the volatility equation, since information arrival into markets is one of the appealing theoretical explanations for the presence of heteroskedasticity in the financial returns . According to Rozga & Arneric (2009) when volatility persistence is high, reaction of volatility on past market movements are low, and shocks in volatility disappears slowly. When volatility persistence is low, reaction of volatility on past market movements are much intensive, and shocks in volatility disappears quickly. The purpose of this study is to empirically examine the dynamic (causal) relation among stock market returns, trading volume, and volatility of stock index returns. It also studies volatility persistence and mean spillover of volume traded from large-cap to mid-cap index, from mid-cap to small-cap index and vice versa. The asset pricing models do not have place for volume data (Ross, 1987), and researchers are still uncertain about the precise role of volume in the analysis of financial markets as a whole, volume data may contain information useful for modeling volatility or the returns themselves. By examining the dynamic relation between volume and returns, one can study how the nature of investor heterogeneity determines the behavior of asset pricing. It is shown that heterogeneity among investors give rise to different volume behavior and return volume dynamics. This implies that trading volume conveys important information about how assets are priced in the market.

Since volatility is affected by pronounced persistence in volatility, mean-reversion of returns and asymmetry in market. It would be interesting to investigate the effect of predetermined variables such as volume; Intra-day volatility and Overnight indicator that may influence the volatility as these variables affect persistence in volatility. It is also important to analyze relation between return and trading volume as it can provide insight into the structure of financial markets, as stock prices are noisy which can't convey all available information of market dynamics. Therefore, studying the joint dynamics of stock price returns, trading volume, volatility and volatility persistence is essential to improve the understanding of the volatility forecasting and stock markets microstructure. The paper investigates this problem in subsequent six sections. Section 2 acquaints the reader with the literature survey. Section 3 acquaints the reader with the data and summary statistics. Section 4 describes the methodology used. Section 5 presents the results and sections 6 concludes the study.

2. Literature Review

2.1 Trading volume and volatility

There are numerous studies which document the relationship between stock market trading volume and return volatility. For example, Granger and Morgenstern (1963) investigated the relation between price change and aggregate exchange trading volume. Crouch (1970) studied relation between contemporaneous absolute price change and trading volume. Westerfield (1977) Tauchen and Pitts (1983) and Rogalski (1978) documented relation between price change and trading volume. Epps and Epps (1976) used transactions data from 20 stocks and they found a positive relation between the variances of price changes and the trading volume levels.

Clark(1973) and Lamoureux and Lastrapes (1990, 1994) link price volatility with the underlying information flow in the markets and use volume as a measure of the information flow. Clark(1973) showed that the time series of market returns is not drawn from a single probability distribution but rather from a mixture of conditional distributions with varying degrees of efficiency in generating the expected return. The autoregressive mixing variable considered is the rate at which information arrives at the market; it explains the presence of GARCH effects in daily stock price movements. Further, trading volume is considered the standard proxy for this mixing variable, trading volume and volatility must be positively correlated as they jointly depend upon common underlying variable. This variable could be the rate at which information flows to the market. Lamoureux and Lastrapes(1990) gave Mixture of Distributions Hypothesis (MDH), they studied the empirical relation between volume and volatility of stocks, they used econometric framework to test whether there are GARCH effects remaining after the conditional volatility specification includes the contemporaneous trading volume, which is a proxy for information arrival. They find that for individual stocks, volatility persistence falls significantly once contemporaneous trading volume is included in the volatility equation. Support for MDH is large Gallo and Pacini (2000) used Volume, Intra-day volatility (IDV) and overnight indicator (ONI) as proxy for information arrival. Kim and Kon (1994) provide support for this notion in U.S. stock markets while evidence is found in U.K. stock markets by Omran and McKenzie (2000). With respect to less developed markets, Pyun, Lee, and Nam (2000) provide positive evidence from the Korean stock market; Bohl and Henke (2003) showed support from the Polish stock market, while Lucey (2005) finds mixed evidence for the MDH in the Irish stock market. The results contradicting the findings of Lamoureux and Lastrapes (1990) are Chen (2001), Chen, Firth, and Rui (2001).

Chen (2001) investigated volume effects in the context of an EGARCH model and found that, volatility persistence remains across the nine national markets in their sample. Chen, Firth, and Rui (2001) said persistence in volatility is not eliminated when lagged or contemporaneous trading volume is incorporated into the GARCH model.

The second set of information based models, given by Copeland (1976) and Jennings, Starks, and Fellingham (1981), assume asymmetric dissemination of information. They said new information is disseminated sequentially to traders, and uninformed traders cannot infer the presence of informed traders perfectly. Informed traders take positions and adjust their portfolios accordingly, resulting in a series of sequential equilibrium before a final equilibrium is attained. This sequential dissemination of information from trader to trader is correlated with the number of transactions. Consequently, new arrival of information to the market results not only in price movements but also a rise in trading volume. Further, rise in information shocks generates increases in both trading volume and price movements.

The third set of information based model is given by Harris and Raviv (1993) known as, Difference of Opinions theory they assumed that investors are homogenous with respect to their prior beliefs and the new information they receive. However, where investors differ from one another is in their beliefs about the effect of new public information on asset prices. The asymmetry in their interpretation of the common information drives investors to speculative trading and this result in trading volume and absolute price changes being positively correlated. Admati and Pfleiderer (1988) documented that, volume and price movements are clustered in time because traders who have the choice of timing their trades at their discretion choose to trade when recent volume is large. Their multi-period model assumes that traders are motivated by either information or liquidity. All traders do not share the same information and informed trader's trade when they have some private information. On the other hand, liquidity or noise traders are motivated by factors other than expected payoffs through future price movements. For instance, some institutional traders may be trading due to liquidity needs of their clients. Irrespective of the trader's motivation, both information and liquidity have some discretion regarding the timing of their trades leading to endogenously determined trading patterns. This strategic timing of trading partially explains the positive relation between trading volume and the variability of stock returns.

2.2 Trading volume and stock return

Osborne (1959) studied the return and volume relation from a variety of perspectives. Silvapulle and Choi (1999) used daily Korean composite stock index data to study the linear and nonlinear Granger causality between stock price and trading volume, and find a significant causality between the two series. Ranter and Leal (2001) examine the Latin American and Asian financial markets they find a positive contemporaneous relation between return and volume in all of the countries in their sample except India. Chen, Firth, and Rui (2001) find mixed results of the causality between price and volume. Similarly, Lee and Rui (2002) do not find evidence of trading volume to predict stock returns in four Chinese stock exchanges. Chordia and Swaminathan (2000) studied the interaction between trading volume and the predictability of short-term stock returns. They find that, daily returns of stocks with high trading volume lead daily returns of stocks with low trading volume. They attribute this empirical result to the tendency of high volume stocks to respond promptly to market-wide information. Chordia and Swaminathan said that trading volume plays an important role in market wide information dissemination. According to Chordia, Huh, and Subrahmanyam (2006) past returns are the most significant predictor of turnover and find that higher positive and negative returns lead to substantially higher turnover. Hiemstra and Jones (1994) studied dynamic relation between stock return and percentage change in trading volume using Granger causality. Jain and Joh (1988), used intraday data from a market index they find a similar correlation over one hour intervals.

Gallant, Rossi, and Tauchen (1992) examined the relation between S&P 500 index returns and trading volume in the NYSE and find evidence of returns leading trading volume. Using data from stocks traded on the NYSE. Gervais and Mingelgrin (2001) report that period of high trading volume tend to be followed by periods of positive excess returns whereas periods of low volume tend to be followed by negative excess returns. These findings also suggest that a positive relation exists between returns and trading volume and that returns precedes volume.

He and Wang (1995) develop a rational expectations model of stock trading in which investors have different information concerning the underlying value of the stock. They examined the way in which trading volume relates to the information flow in the market, and how investors' trading reveals their private information. Their model shows how over time, trading volume is closely related to the flow and nature of information in the market. They developed a multi-period model with heterogeneous investors and differential information. Investors have asymmetric private and public information and trade competitively based on this asymmetry. Chuang (2012) studied the contemporaneous and causal relation between stock return, trading volume and volatility in ten Asian stock markets using bivariate GJR-GARCH model. They documented positive relation between trading volume and stock returns but mixed results for trading volume and volatility of stock indexes.

3. Data and summary statistics

S&P BSE Sensex 30, BSE mid-cap index and BSE small-cap index have been considered for analysis. Daily closing, open, high, low price and volume traded of indices are taken from Bloomberg database. The data covers sample period from January 6th, 2005 to December 31st, 2013. Daily log returns are calculated on adjusted closing price of indices. According to Lo and Wang (2000), log of volume (number of shares traded in a day) is taken as a measure of raw trading volume. The studies by Gallant, Rossi, and Tauchen (1992), Lo and Wang (2000), Chen (2001) and Chuang (2012) reported strong evidence of both linear and nonlinear time trends in trading volume series. We tested trend stationary in trading volume by regressing the series on a deterministic function of time. For all the three indices, log volume is regressed on linear and quadratic deterministic time trend in equation (2) to make the volume series stationary by detrending. In case of Sensex, the log volume series is found to have significant linear deterministic time trend. Therefore, the residuals of linear time trend regression is used as detrended volume. Whereas, in the case of mid-cap and small-cap index both linear and quadratic time trend are found to be highly significant therefore, regression residuals of linear and quadratic time trend are used as detrended volume. Following regression is used to obtain detrended volume series.

$$v_t = \alpha + \beta_1 \, t + \, \beta_2 t^2 + \varepsilon_t \qquad (2)$$

Where, v_t is natural log volume traded in a day in each stock market index.

Apart from considering detrended trading volume, we have also considered IDV (Intra- day volatility) and ONI (Over-night indicator) measure used as a proxy for information flow for the indices considered.

Table 1 Summary Statistic

Summary statistic							
Index	**Large cap**	**Mid Cap**	**Small Cap**	**Index**	**Large cap**	**Mid Cap**	**Small Cap**
Panel A: Return series				**Panel B: Detrended trading volume**			
Observations	2233	2233	2233	Observations	2233	2233	2233
Mean	0.000532	0.000363	0.000296	Mean	1.92E-18	7.16E-19	7.60E-19
Median	0.00101	0.001871	0.002163	Median	0.000183	0.000189	9.24E-05
Maximum	0.1599	0.111113	0.086601	Maximum	1.77E-02	8.31E-03	3.61E-03
Minimum	-0.116044	-0.120764	-0.108357	Minimum	0.005739	0.001734	0.00114
Std. Dev.	0.016301	0.015311	0.015748	Std. Dev.	0.002084	9.10E-04	0.000595
Skewness	0.097264	-0.838204	-0.893373	Skewness	1.776526	3.30059	1.250894
Kurtosis	10.48405	10.04302	7.917771	Kurtosis	11.06623	19.80929	5.941447
Jarque-Bera	5214.882***	4876.734***	2547.195***	Jarque-Bera	7228.241***	30343.46***	1387.349***
LB-Q(8)	479.59***	814.09***	848.54***	LB-Q(8)	933.26***	6092.2***	3006.2***
LB-Q(11)	693.96***	894.34***	946.72***	LB-Q(11)	1074***	7128.7***	3276.7***
LM TEST(10)	2.904641***	12.62611***	22.78948***	LM TEST(10)	329.8837***	1309.989***	657.3763***
ARCH(10)	31.82867***	53.89687***	50.36925***	ARCH(10)	49.65657***	813.864***	185.4702***
ADF Test	(43.9121)***	(38.28912)***	(35.30004)***	ADF Test	(7.454505)***	(4.605358)***	(7.758133)***
KPSS	0.151109	0.131038	0.161893	KPSS	0.353791	0.230517	0.139288

Note:

- Critical values of KPSS test at 1%, 5% and 10% are 0.739,0.463,0.347 respectively
- ***,**.* denote significance at 1%,5% and 10% respectively. Negative values are represented in brackets ( )
- LB-Q is Ljung–Box test for autocorrelation with number of lags in brackets.
- ADF stands for Augmented Dicky Fuller test, which has null hypothesis that series has unit root.
- KPSS stands for Kwiatkowski Phillips Schmidt Shin test, which has null hypothesis that series does not have unit root,
- Time Period considered for the analysis is from January 6th, 2005 till December 31st, 2013.
- LM test is Lagrange multiplier test for serial correlation, which has null hypothesis of no serial correlation among lags.
- ARCH test is used for checking heteroskedasticity in data, which has null hypothesis of homoscedasticity.

From Table 1, it is observed that mean returns are decreasing with decreasing market capitalization. Daily standard deviation of returns is highest in Sensex. Sensex returns are positively skewed and all the three indices show kurtosis more than three. The kurtosis value is decreasing with decrease in market capitalization. Jarque-Bera test statistics is significant for all the three indices, indicating that the stock indices returns are not normally distributed. Ljung-Box statistics is highly significant for all the three indices considered in the study, indicating the presence of autocorrelation in all the sample indices. The autocorrelation was found much stronger in mid-cap and small-cap indices returns than in Sensex. Engle ARCH LM(Lagrange multiplier) test with 10 lags was applied to test the presence of ARCH effect and time varying volatility. The LM test statistics is highly significant at 5% level, indicating the presence of heteroskedasticity in all the three indices considered. Therefore, GARCH family models were used to model the heteroskedasticity. Further, Engle and Ng (1993) tests were used to check asymmetry in volatility. Sign bias test examines the impact of asymmetric response of positive and negative return shocks on volatility. Negative sign bias test examines different effects that large and small negative return shocks have on volatility which is not predicted by the GARCH specification. Positive sign bias test examines different effects that large and small positive return shocks have on volatility which is not predicted by the GARCH specification. Engle and Ng test involves estimating a GARCH (1, 1) model in the first stage; then the estimated standardized squared residuals $\hat{\mu}_t^2$ is used in following regression:

Sign bias test: $\hat{\mu}_t^2 = \lambda_0 + \lambda_1 s_{t-1}^{-} + \nu_t$ (3)

Negative size bias test: $\hat{\mu}_t^2 = \lambda_0 + \lambda_1 s_{t-1}^{-}\hat{\mu}_{t-1} + \nu_t$ (4)

Positive size bias test: $\hat{\mu}_t^2 = \lambda_0 + \lambda_1 s_{t-1}^{+}\hat{\mu}_{t-1} + \nu_t$ (5)

Where s_{t-1}^{-} is an indicator dummy variable that takes value of 1 if, $\hat{\mu}_{t-1}$<0 (bad news) and 0 otherwise and s_{t-1}^{+}=1-s_{t-1}^{-} that takes value of 1 if, $\hat{\mu}_{t-1}$>0 (good news) and 0 otherwise.

Table 2

Engle and Ng test on residuals of GARCH model(test for asymmetry)					
Large cap	**Estimate**	**Mid cap**	**Estimate**	**Small cap**	**Estimate**
SBT	(0.217543)***	SBT	(0.378391)***	SBT	(0.374575)***
NSBT	0.193765***	NSBT	0.264308***	NSBT	0.246405***
PSBT	(0.195806)***	PSBT	0.32674***	PSBT	0.259524***

Note:

***, ** and * denote significance at 1%, 5% and 10% respectively.
Negative values are represented in brackets
SBT is Sign bias test, NSBT is negative size bias test and PSBT is positive size bias test

Table 2 represents Engle and Ng asymmetric tests. The Sign bias test, Negative sign bias test and positive sign bias test confirms the asymmetry in volatility in all the three indices considered as regression coefficient are significant therefore conforming use of asymmetric GARCH model. From Table 1, it is observed that mean returns of detrended volume series is almost zero, being the residual series obtained from linear and quadratic time trend regression. Standard deviation is found to be smaller for volume series as compared to return series. Jarque-Bera test statistics is significant for all the three indices volume traded series, indicating that the stock indices volume traded series is not normally distributed. Ljung- Box statistics is found highly significant for all the three indices detrended volume series considered in the study, indicating autocorrelation in all the sample series. It is also observed from Table 1 that the detrended trading volume series is more auto-correlated than the return series. This shows that the detrended trading volume is much more persistent. LM test statistics is highly significant at 5% level, indicating the presence of heteroskedasticity in all the three indices detrended volume series considered, this suggest the use of GARCH family models to model the heteroskedasticity. Stationarity of return series and detrended volume series is checked with the Augmented Dicky Fuller (ADF) test and Kwiatkowski Phillips Schmidt Shin (KPSS) test statistic. The null hypothesis for ADF is that, the series has unit root whereas, null hypothesis of KPSS says that, series does not have unit root. The return series and detrended volume series are found to be stationary using both KPSS and ADF diagnostic tests whereas, the log volume series was stationary according to ADF test but, it is not stationary according to KPSS test statistics, therefore, detrended volume series is used in the study.

4. Methodology

Lamourex and Lastrapes (1990) assumes that the volume is weakly exogenous with respect to the returns, which is possibly a strong hypothesis. If the price movements within the day go mainly in one direction creating a local trend, they may attract further trades and therefore affect the volume. Therefore, to better understand the dynamics associated with the volume and volatility we have used Bivariate GJR-GARCH methodology using conditional constant correlation model of Bollerslev (1990).In this study, the joint dynamics is investigated with the help of bivariate GJR- GARCH methodology given by Bollerslev (1990), as this method helps in jointly estimating volatility equation of return and volume in one step estimation procedure and it also eliminates the regressor problem (Pagan ,1984)Bollerslev and Wooldridge (1992) showed that, GARCH parameters are consistently estimated by Gaussian maximum likelihood even when normality assumption is violated. Bollerslev et al. (1988) proposed VECH model of multivariate GARCH methodology major drawbacks of the VECH model are the difficulty to guaranty a positive definite variance covariance matrix. This model was followed by the Constant Conditional Correlation (CCC) model, proposed by Bollerslev (1990) with only drawback is the assumption of constant correlations which is often unrealistic in empirical applications. In this study Constant Conditional Correlation (CCC) model is used.

Bollerslev (1990) specifies the elements of the conditional covariance matrix as follows:

$$h_{iit} = c_i + a_i \varepsilon_{it-1}^2 + d_i I_{it-1}^- \varepsilon_{it-1}^2 + b_i h_{iit-1} \tag{6}$$

$$h_{ijt} = \rho_{ij} \sqrt{h_{iit} h_{jjt}} \tag{7}$$

Where, h_{iit} represents variance of asset i at time t conditioned on the information set of asset i and ρ_{ij} represents correlation between asset i and j, a_i, d_i and b_i represents coefficient of ARCH term, asymmetric term and GARCH term respectively.

Let y_t denote $N \times 1$ time-series vector of interest with time varying conditional covariance matrixH_t , i.e.

$$y_t = E(y_t | \psi_{t-1}) + \epsilon_t \tag{8}$$

$$Var(\epsilon_t | \psi_{t-1}) = H_t$$

Where,$\psi_{t-1}$is the σ field generated by all the available information up through time t - 1, and $H_t$is almost surely positive definite for all t. Also, let h_{ijt} denote the ij_{th} element in H_t and $y_{it}$and

ϵ_{it} the ith element in y_t and ϵ_t respectively. Then a natural scale invariant measure of the coherence between y_{it} and y_{jt} evaluated at time t - 1 is given by the conditional correlation.$h_{ijt} = \rho_{ijt}\sqrt{h_{iit}h_{jjt}}$. An appealing feature of the model with constant conditional correlations relates directly to the simplified estimation and inference procedures. To that end, rewrite each of the conditional variances as,

$h_{iit} = \omega_i \sigma_{it}^2 i = 1, \dots \dots, N$

With ω_i is a positive time invariant scalar and $\sigma_{it}^2 > 0$

the full conditional covariance matrix, H_t, may be partitioned as $H_t = D_t \Gamma D_t$ where, D_t denotes $N \times N$stochastic diagonal matrix with elements $\sigma_{1t}, \dots \dots .. \sigma_{Nt}$ and Γ is $N \times N$time invariant matrix with typical element $\rho_{ij}\sqrt{\omega_i}\omega_j$.

ARCH estimation uses maximum likelihood to jointly estimate the parameters of the mean and the variance equations. Assuming multivariate normality, the log likelihood contributions for GARCH models is given by:

$$L(\theta) = -\frac{TN}{2} log(2\pi) - \frac{1}{2}\sum_{t=1}^{T}(ln|H_t| + \varepsilon_t' H_t^{-1} \varepsilon_t) \quad (9)$$

Where, θ denotes all the unknown parameters to be estimated inε_t *and* H_t, *N* is the number of assets (i.e. the number of series in the system) and *T* is the number of observations. The maximum likelihood estimate for θ is asymptotically normal, and thus traditional procedures for statistical inference are applicable. Numerical optimization algorithm of Marquardt is used to maximize this non-linear log likelihood function.

Volume is also affected by within the day price movements and it is not weakly exogenous relative to returns, alternative proxies for information flow suggested by Gallo and Paccini (2000) is also used in the study. The indicators are as follows:

4.1 Overnight Indicator (ONI)

Returns are difference between adjusted closing price, the difference between the opening price of a day and the closing price of the day before represents an interesting indicator of the number of trades during the day therefore, it may act as a variable on the basis of which the decision to trade during the day can be made. The difference between opening price of day t and closing of day t-1 is likely to affect the trading during the day which results in an impact on the daily volatility. As a result, it can capture the persistence in the conditional heteroskedasticity.

Therefore, it helps us in taking out the stock returns volatility the component which is due to the surprise between open and previous close price. By doing so, persistence in the estimated volatility can be reduced. It is calculated as follows:

$$ONI = \log({}^{open_t}/_{close_{t-1}}) \tag{10}$$

4.2 Intra-day volatility (IDV)

IDV is calculated as the difference between the highest and the lowest price divided by the closing price. IDV is taken as an indicator of the vivaciousness of trade within the day. The IDV is calculated as follows:

$$IDV = \frac{p_t^h - p_t^l}{p_t^c} \tag{11}$$

Where, p_t denotes the highest (h), the lowest (l), and the closing (c) price on day t, respectively.

5. Result and analysis

Mean equations of index returns and trading volume is in the form of restrictive bi-variate Vector autoregressive model (VAR) specification. It is used to test causality running between return and volume. The contemporaneous relation is estimated with the help of correlation coefficient estimated from conditional multivariate GARCH specification. Short run causality between volume and return of indices is tested with the help of Wald's test. Examination of causality in VAR will suggest source of return spillovers. The Chi-square test followed by Wald will not by construction, be able to explain how long these effects will last, therefore VAR impulse responses are also used in the study. Lag lengths of the mean equations are determined using Akaike information criterion (AIC). Joint lag coefficients of volume and return are tested using Wald's coefficient test which follows Chi-square distribution with degree of freedom equals to the lag length chosen. From Table 3 panel 2, the conditional mean equation of stock index return it is evident that, lags of volume chi-square coefficient is not significant, therefore null hypothesis of lagged index volume does not cause stock return is accepted. Therefore, it is proved that lagged index volume does not cause stock index return, whereas lags of stock return causes mean return as the Chi-square test statistic is found to be significant. Equations estimated are as follows:

Mean equations:

$$v_t = c_v + \sum_{i=1}^{p} \theta_{v,i} v_{v,t-1} + \sum_{i=1}^{p} \mu_{v,i} r_{v,t-1} + \varepsilon_{v,t} \tag{12}$$

$$r_t = c_r + \sum_{i=1}^{p} \theta_{r,i} v_{r,t-1} + \sum_{i=1}^{p} \mu_{r,i} r_{r,t-1} + \varepsilon_{r,t} \tag{13}$$

Variance Equation:

$$\sigma_{v,t}^2 = \omega_v + \alpha_v \varepsilon_{v,t-1}^2 + \beta_v \sigma_{v,t-1}^2 + \vartheta_v s_{v,t-1}^- (\varepsilon_{v,t-1})^2 \tag{14}$$

$$\sigma_{r,t}^2 = \omega_r + \alpha_r \varepsilon_{r,t-1}^2 + \beta_r \sigma_{r,t-1}^2 + \vartheta_r s_{r,t-1}^- (\varepsilon_{r,t-1})^2 + \varphi v_t \tag{15}$$

Variance Equation with ONI as indicator of information flow:

$$\sigma_{r,t}^2 = \omega_r + \alpha_r \varepsilon_{r,t-1}^2 + \beta_r \sigma_{r,t-1}^2 + \vartheta_r s_{r,t-1}^- (\varepsilon_{r,t-1})^2 + \varphi_r ONI \tag{16}$$

Variance Equation with IDV as indicator of information flow:

$$\sigma_{r,t}^2 = \omega_r + \alpha_r \varepsilon_{r,t-1}^2 + \beta_r \sigma_{r,t-1}^2 + \vartheta_r s_{r,t-1}^- (\varepsilon_{r,t-1})^2 + \varphi_r \text{ IDV} \tag{17}$$

Here subscript v represent volume and subscript r is for return of indices,v_t represents mean volume traded, $\theta_{v,i}$ is coefficient of lags of volume traded, $\mu_{v,i}$ coefficients of lags of return on indices in mean equation of volume traded.$\theta_{r,i}$ is coefficient of lags of volume traded in return equation and $\mu_{r,i}$ coefficients of lags of return on indices in mean equation of return. $r_t$represents mean return of index. $\sigma_{v,t}^2$ represents variance of volume traded and $\sigma_{r,t}^2$ represents varianceof mean returns of indices. $\alpha_v$is ARCH term in volume equation, β_v is GARCH coefficient in volume equation and ϑ_v represents asymmetric term in volume equation. φv_trepresents, contemporaneous volume traded in volatility equation of returns.α_r , β_r and ϑ_r represents ARCH term, GARCH term and asymmetric term in volatility equation of returns.

From Table 3 panel 1, it is evident that both lags of index return and lags of trading volume causes volume. The results are same for all the three indices. Therefore we can say that, volume follows return. Variance decomposition is also used in the study it gives the proportion of variation of returns explained by returns itself and the proportion of variance in return explained by volume and vice versa. The impulse response explains the response of returns to shocks in returns and volume and vice versa. From fig 1 it is evident that, in case of Sensex response of return to return die after two periods. Response of volume to volume lags is highly correlated and it does not die after 10 periods. Response of volume to shock in return is not significant according to impulse responses. Response of return to shock in volume is negative in case of Sensex, until 2nd lag and it becomes positive after 3rd lag this explains the lead lag relationship between return and volume. From fig 2, it is evident that, in case of mid-cap response of return to return die after 5 periods. Response of volume to return dies after 20 periods. Response of return to volume is almost zero. From fig 3, small-cap response of volume to return does not die after 20 lags. Therefore we can say that, with the decrease in market capitalization volume return lead lag relationship is becoming stronger.

Table 3: Chi-square values for Wald test and coefficients of mean and variance equation of volume traded and return of indices. The following GJR-GARCH model is estimated.

Lag length is chosen using Akaike information criterion (AIC). $W\theta_{v,i}$, $W\mu_{v,i}$ represents Wald test chi-square coefficients for volume equation with degree of freedom equal to lag length chosen, it has null hypothesis that joint lag Wald coefficients is equal to zero. $W\theta_{r,i}, W\mu_{r,i}$ represents, Wald test chi-square coefficients for mean equation. v_t is trading volume at time t and r_t is stock return at time t. subscript v is for volume traded equation and subscript r is for return of stock index equation.

$$v_t = c_v + \sum_{i=1}^{p} \theta_{v,i} v_{v,t-1} + \sum_{i=1}^{p} \mu_{v,i} r_{v,t-1} + \varepsilon_{v,t} \quad (12)$$

$$r_t = c_r + \sum_{i=1}^{p} \theta_{r,i} v_{r,t-1} + \sum_{i=1}^{p} \mu_{r,i} r_{r,t-1} + \varepsilon_{r,t} \quad (13)$$

$$\sigma_{v,t}^2 = \omega_v + \alpha_v \varepsilon_{v,t-1}^2 + \beta_v \sigma_{v,t-1}^2 + \vartheta_v s_{v,t-1}^- (\varepsilon_{v,t-1})^2 \quad (14)$$

$$\sigma_{r,t}^2 = \omega_r + \alpha_r \varepsilon_{r,t-1}^2 + \beta_r \sigma_{r,t-1}^2 + \vartheta_r s_{r,t-1}^- (\varepsilon_{r,t-1})^2 + \varphi v_t \quad (15)$$

$$\sigma_{r,t}^2 = \omega_r + \alpha_r \varepsilon_{r,t-1}^2 + \beta_r \sigma_{r,t-1}^2 + \vartheta_r s_{r,t-1}^- (\varepsilon_{r,t-1})^2 + \varphi_r ONI \quad (16)$$

$$\sigma_{r,t}^2 = \omega_r + \alpha_r \varepsilon_{r,t-1}^2 + \beta_r \sigma_{r,t-1}^2 + \vartheta_r s_{r,t-1}^- (\varepsilon_{r,t-1})^2 + \varphi_r \text{ IDV} \quad (17)$$

Bivariate GJR-GARCH results			
Index	**Large cap**	**Mid cap**	**Small cap**
Panel 1: Conditional Mean equation Wald test results(trading volume)			
Lag Length	**10**	**10**	**7**
Chi-square value			
$W\theta_{v,i}$	7577.091***	10396.58***	17673.45***
$W\mu_{v,i}$	32.05398***	211.3163***	205.362***
Panel:2 Conditional Mean equation Wald test results (Stock index return)			
Chi-square value			
$W\theta_{r,i}$	8.038562	6.884177	5.090475
$W\mu_{r,i}$	29.21583***	154.6224***	193.2422***
Panel 3: Coefficients of conditional variance equation(Trading volume)			
α_v	0.030233*** [0.004232]	0.181516*** [0.014171]	0.213613*** [0.02171]
ϑ_v	0.042004*** [0.042004]	(0.112901)*** [0.015]	0.02403*** [0.036286]
β_v	0.961711*** [0.0013]	0.868757*** [0.007811]	0.649845*** [0.0135]
Panel 4: Coefficients of variance equation with lagged volume (Stock index return)			
α_r	0.022943*** [0.009789]	0.049736*** [0.011]	0.098258*** [0.012]
ϑ_r	0.140235*** [0.019967]	0.143988*** [0.019]	0.1122*** [0.021]
β_r	0.888914*** [0.01067]	0.855942*** [0.009]	0.82357*** [0.010]
φV_{t-1}	0.000854*** [0.00025]	0.00235*** [0.0007]	0.002435** [0.0010]
Log Likelihood	18923.94	21921.97	22178.51

Panel 5:Coefficients of variance equation without volume (Stock index return)			
Index	**Large cap**	**Mid cap**	**Small cap**
α_r	0.026701*** [0.010148]	0.054288*** [0.011]	0.103099*** [0.015]
ϑ_r	0.135474*** [0.019359]	0.140293*** [0.019]	0.111388*** [0.021]
β_r	0.891188*** [0.010241]	0.855621*** [0.009]	0.817175*** [0.011]
Conditional Correlation	(0.083521)*** [0.023]	0.089*** [0.0211]	0.116467*** [0.018]
Log Likelihood	18919.56	21913.18	22176.44
Panel 6: Coefficients of variance equation with contemporaneous volume (Stock index return)			
α_r	0.021575*** [0.009964]	0.048795*** [0.011314]	0.097267*** [0.014049]
ϑ_r	0.151828*** [0.21288]	0.14485*** [0.019597]	0.113409*** [2.16E-02]
β_r	0.882469*** [0.011469]	0.856545*** [0.009253]	0.824417*** [0.01118]
φV_t	0.001245*** [0.000291]	0.002408*** [0.000711]	0.002278** [0.001103]
LB-Q(8)	24.2069	11.07831	55.33105**
LB-Q(11)	31.03955	24.55236	78.92593**
Log Likelihood	18929.55	21918.96	22194.98
Panel 7:Coefficients of variance equation with IDV(Intra-day volatility)			
α_r	0.00391*** [0.016]	0.088397*** [0.028]	0.203221*** [0.33]
ϑ_r	0.016437 [0.026]	0.012995 [0.04]	(0.02913) [0.047]
β_r	0.01108 [0.025]	0.033773 [0.005]	0.017232 [0.034]
$\varphi\, IDV$	0.002265*** [8.60E-05]	0.009258*** [0.0155]	0.001199*** [7.15E-05]
Panel 8: Coefficients of variance equation with lagged IDV			
α_r	(0.004214) [0.0095]	0.050636*** [0.013607]	0.119988*** [0.020]
ϑ_r	0.116793*** [0.022507]	0.126889*** [0.02066]	0.054264*** [0.027]
β_r	0.869794*** [0.015367]	0.850517*** [0.0104]	0.782389*** [0.017]
$\varphi\, IDV_{t-1}$	0.000251*** [4.45E-05]	0.00023** [0.00013]	0.000133*** [3.26E-05]
Panel 9:Coefficients of variance equation with ONI(Overnight indicator)			
α_r	0.029595*** [0.0094]	0.179328*** [0.013]	0.118115*** [0.018]
ϑ_r	0.093767*** [0.01447]	0.083163*** [0.018]	0.095877*** [0.023]
β_r	0.906792*** [0.0078]	0.85057*** [0.0049]	0.811522*** [0.013]
$\varphi\, ONI$	7.86E-05 [0.05179]	0.00000341 [2.60E-07]	0.000258 [0.00023]

Note:

Here LB-Q (8) represents Multivariate Portmanteau test for autocorrelation with 8 lags. Values in [] represents standard error, Values in () represent negative values.

***, **,* denote significance at 1%, 5% and 10% respectively.

%

Negative values are represented in brackets

Table 4

This table represents volatility persistence in variance equation of stock return without volume as explanatory variable, taking lagged volume and contemporaneous volume. in bivariate GJR-GARCH method. Volatility persistence is measured as $\alpha_r + \beta_r + \vartheta_r/2$

Volatility equation of return with lagged volume			
Index	**Large cap**	**Mid Cap**	**Small Cap**
α_r	0.022943	0.049736	0.098258
β_r	0.888914	0.855742	0.82357
$\vartheta_r/2$	0.140235	0.143988	0.1122
Persistence	0.9819745	0.977472	0.977928
Volatility equation of return without volume			
Index	**Large cap**	**Mid Cap**	**Small Cap**
α_r	0.026701	0.054288	0.103099
β_r	0.891188	0.855621	0.817175
$\vartheta_r/2$	0.135474	0.140293	0.111388
Persistence	0.985626	0.9800555	0.975968
Volatility equation of return with contemporaneous volume			
Index	**Large cap**	**Mid Cap**	**Small Cap**
α_r	0.021575	0.048795	0.097267
β_r	0.882469	0.856545	0.824417
$\vartheta_r/2$	0.151828	0.14485	0.113409
Persistence	0.979958	0.977765	0.9783885

Table 5

Variance decomposition of volume:				
	Period	**S.E.**	**Volume**	**RETURN**
Large cap	10	0.001678	99.7639	0.236096
Mid cap	10	0.000584	95.33251	4.667487
Small cap	10	0.000494	87.34689	12.65311
Variance decomposition of return:				
Large cap	10	0.016385	2.373237	97.62676
Mid cap	10	0.01535	0.418645	99.58136
Small cap	10	0.015739	1.779514	98.22049

Note:

Variance decompositions give the proportion of the movements in the dependent variables that are due to their own shocks, versus shocks to other variables.

Large cap

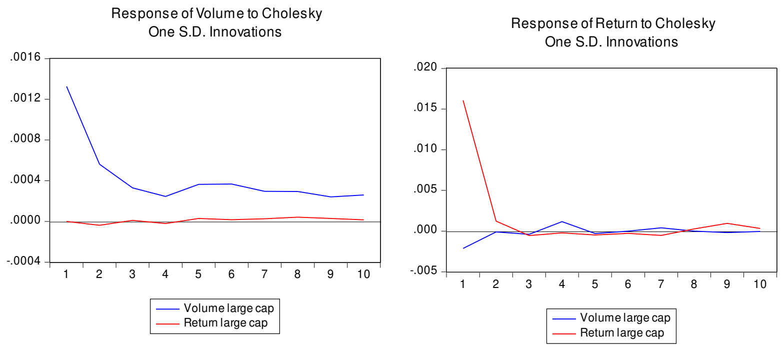

Figure 1

Mid cap

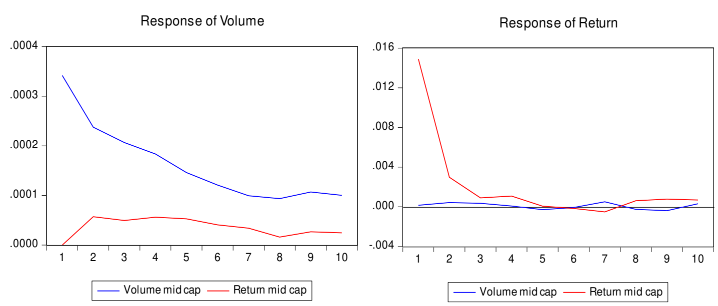

Figure 2

Small cap

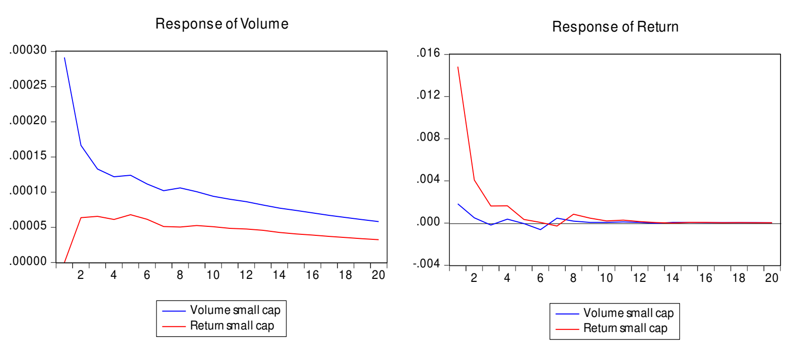

Figure 3

Note:

Impulse responses trace out the responsiveness of the dependent variables in the VAR to shocks to each of the variables in the system. It measures the response of one standard deviation innovation in independent variable on dependent variable.

Table 5 explains the variance decomposition of large cap, mid cap and small cap indices. In case of large cap index, it is found that, 99% variation in volume is explained by its lags and less than 1% is explained by return. More than 97% of variation in return is explained by return of large cap whereas, less than 3 % is explained by volume, incorporating 10 lags. In case of midcap, 95% variation in volume is explained by volume itself, whereas more than 4% is explained by return of the index. In case of return series 99% variation in return is explained by return of index. In case of small cap index 87% variation in volume is explained by volume of index whereas, more than 12% is explained by return of index.

Table 3 gives the model estimates of bivariate GJR–GARCH. It is found that, in the conditional variance equation of volume, the asymmetric term is significant in all the three indices considered. Effect of both contemporaneous volume and lagged volume is considered. In volatility equation of volume, both ARCH and GARCH terms are found to be significant for all the three indices. It is observed that the persistence in volatility decreases with the decrease market capitalization. In the conditional variance equation of return of the indices, the asymmetric term is significant for all the three indices. The persistence in volatility of index return is measured by $\alpha_r + \beta_r + \vartheta_r/2$ from equation 15. The persistence in volatility is decreasing with decrease in market capitalization. From Table 3 panel 5, it is observed that in case of all three indices considered, the coefficient of asymmetric term and innovation terms are significant that means, direction and magnitude of news both are important in estimating conditional volatility but, we can say that, direction of news is more important than the magnitude of news as coefficient of asymmetric term is much larger than lagged innovation term in all the three indices considered. Table 4 gives the volatility persistence of return. It is evident that there is marginal decrease in volatility persistence by including volume term in variance equation of the Sensex and mid-cap indices. For small-cap index, volume does not reduce the volatility persistence. Gallio and Paccini(2000) discuss ONI and IDV as other measures of information flow. From Table 3 panel 9, it is evident that ONI is not significant in explaining information flow in variance equation for large-cap, mid-cap and small-cap indices, whereas IDV is found to be significant in explaining information flow. Inclusion of IDV in the variance equation makes the GARCH effect insignificant in all the three indices considered. From Table 3 panel 6, it is evident that both past innovations in return series and lags of volatility of all the three indices are significant in explaining the current volatility. Inclusion of volume in variance equation is found to be significant in all the three indices indicating that volume traded explains volatility of return. Both contemporaneous and lagged volume coefficients are found to be significant in volatility equation of return of all the three indices. From Table 3 panel 5, it is found that correlation coefficient between volume and return is significant, and there exist negative correlation between volume and stock return in Sensex whereas positive correlation between volume and stock return is found in case of mid-cap and small-cap indices.

5.1 Conditional correlations between volatility and volume traded

To further study the correlation between volatility and volume traded, the volatility of returns of all the indices is estimated without considering volume as exogenous factor in equation 14. The restrictive bivariate GJR-GARCH model is used to estimate volatility and volume traded.

From Table 6, it is evident that there exists positive conditional correlation between volatility of stock return and volume traded in case of Sensex index which is consistent with the past studies. Conditional correlation between volatility of stock return and volume traded is negative in case of mid cap index and small cap index. Therefore, it can be inferred that, in case of Sensex as the volatility increases volume traded also increases. This confirms Tauchen and Pitts(1983) findings, "in markets where number of trades is large the relation between trading volume and return volatility should be positive". In case of small cap and mid cap indices, as the volatility of index returns increases volume traded decreases. This explains that informed traders tend to lead the speculative trading activity and drive bid-ask spreads higher, further diminishing the liquidity of these markets. The negative relation between volume and volatility suggests that both volatility and trading volume are determined by new information flow to the market, traders respond to new information arrival and the number of active trades. As a result in thinly traded and highly volatile markets, infrequent trading can cause prices to deviate substantially from fundamentals. (see Girard &Biswas (2007) and Tauchin and Pitts (1983)). The negative relation between volume and volatility is supported by Sequential information hypothesis of Copeland(1976). In emerging markets dissemination of information is asymmetric and initially only well informed traders take position. As information is sequentially transmitted from trader to trader less informed traders also take position. After a series of intermediate transient equilibrium, a final equilibrium is reached resulting in lower volatility. Therefore we find that, effect of volatility on volume traded is different across different market indices according to market capitalization.

Table 6

Conditional correlation and Granger causality test between volume and volatility			
Index	**Large- cap**	**Mid- cap**	**Small-cap**
Conditional Correlation	0.073675** [0.029]	(0.027516)* [0.030]	(0.091138)*** [0.028]
Volume does not Granger causes variance	128.3247***	17.95312*	35.50156***
Variance does not Granger causes volume	22.28712**	22.27961**	29.17906**

Note:

Values in [] represents standard error, Values in () represent negative values.
***,**,* denote significance at 1%,5% and 10% respectively.
In Granger causality test chi-square test statistic value is given.

5.2 Volume traded information transmission among large-cap, mid-cap and small-cap indices.

To test the dynamic relation between volumes traded of the three indices, tri-variate restrictive Vector autoregressive methodology (VAR) is used to study the mean spillover of surprises of volume traded among the three indices considered on the basis of market capitalization. From Table 7,it is evident that lags of volume traded of mid cap and small cap does not Granger cause volume traded in large-cap(Sensex). Whereas, volume traded of large cap Granger causes volume in mid cap. Lags of volume traded in large cap and small cap Granger causes volume in small cap index. The mean volume traded in large cap index affects mean volume traded of mid cap and small cap. Therefore, it can be inferred that, information asymmetry does exist in the market. New information is first reflected in large cap and then it transmits lo lower indices. To study the response period and sign of causality Impulse response methodology is used. From fig 4, it can be observed that response of volume of large cap to volume of large cap is high and it is persistent after 10 lags also. Response of large-cap to mid-cap and small-cap is zero. Mean response of mid-cap to large-cap is positive that means, if volume traded is high in large-cap that causes increase in volume traded of mid-cap and vice-versa. Response of small-cap to large-cap is small but, response of small-cap to mid-cap is quite high and positive. From Table 7, it is observed that correlation between volume traded of large cap and mid-cap, large-cap and small-cap and mid-cap and small-cap are positive and significant. Correlation between large cap and mid-cap and correlation between mid-cap and small-cap are higher as compared to correlation between large-cap and small-cap.

Table 7

Granger causality test among volume traded in large cap, mid cap and small cap index			
Causality H_0	**Chi square test statistic**	**P value**	**Decision**
Mid cap does not cause large cap	15.92904	0.1017	H_0 Accepted
Small cap does not causes large cap	10.45324	0.4017	H_0 Accepted
Large cap does not cause mid cap	42.40741	0	H_0 Rejected
Small cap does not causes mid cap	7.351427	0.6919	H_0 Accepted
Large cap does not cause small cap	43.17664	0	H_0 Rejected
Mid cap does not cause small cap	39.82059	0	H_0 Rejected
Correlation between large cap and mid cap	0.310488	0	H_0 Rejected
Correlation between large cap and Small cap	0.105917	0.0001	H_0 Rejected
Correlation between mid cap and small cap	0.400488	0	H_0 Rejected

Impulse response

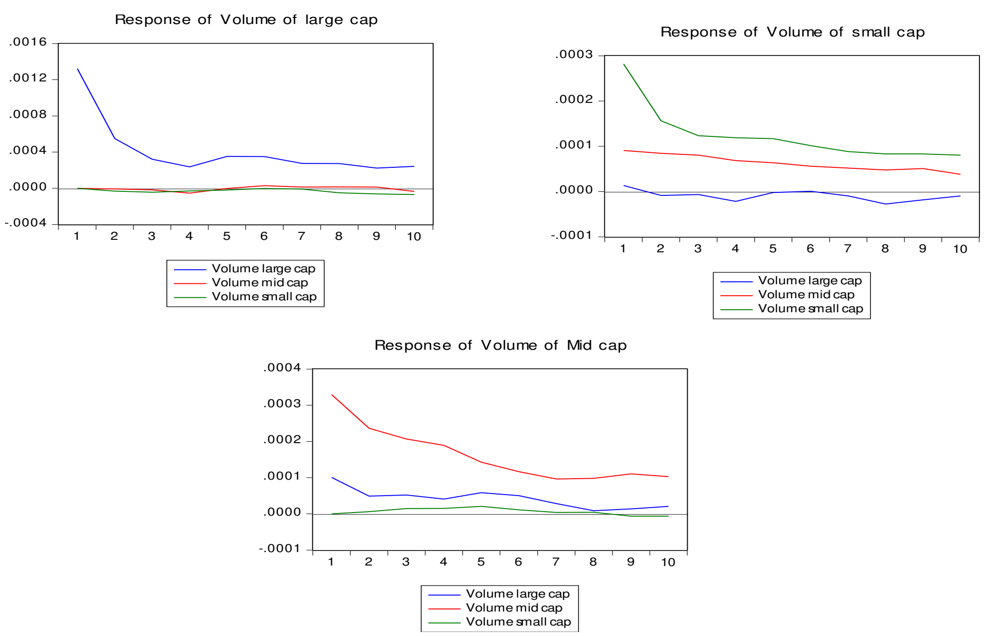

Figure 4

Impulse responses trace out the responsiveness of the dependent variables in the VAR to shocks to each of the variables in the system. It measures the response of one standard deviation innovation in independent variable on dependent variable.

6. Conclusion

The study investigates relationships among return, trading volume and return volatility of three different market capitalized indices and effect of information flow on volatility persistence. Bivariate VAR for mean equations and bivariate GJR-GARCH methodology for the variance equation are used to study joint dynamics of volume, return and volatility in financial markets. Three indices of different market capitalization have been considered where, S&P BSE Sensex represents large capitalization firms, BSE mid-cap represents mid-capitalization firms and BSE small-cap index represents small capitalization firms. The study investigates the relationship between return, volume, volatility and the spillover of mean trading activity among indices. The study considers volume, IDV and ONI as proxy variables for information dissemination in financial markets. The findings suggest that their exist dynamic and contemporaneous relation between return of index and volume, in all the three indices considered since lags of index return causes volume which confirms the findings of Chordia, Huh, and Subrahmanyam (2006), Gallant, Rossi, and Tauchen (1992) despite using a different methodology, bivariate GARCH. It is observed that, there exist negative correlation between volume and return of Sensex when volume and return is used in bivariate specification. In case of mid cap and small cap indices the correlation between volume and return is found to be positive. It is observed that the persistence in volatility decreases with the decrease in market capitalization. Bidirectional causality is observed in case of volume and volatility for all the indices considered. In case of large cap there is positive conditional correlation between volume and volatility, whereas in case of mid cap and small cap the correlation coefficient is negative. Correlation between volume and volatility is strongest in case of small cap. Therefore, it can be inferred that in case of Sensex, as the volatility increases volume traded also increases. This behavior of Sensex confirms the positive relation between trading volume and return volatility when the number of traders is large. In the cases of mid- cap and small-cap indices, volume traded decreases with the increase in volatility of the indices returns. In case of mid cap and small cap this behavior is in tandem with the argument, "informed traders tend to lead the speculative trading activity and drive bid-ask spreads higher, further diminishing the liquidity of the markets". This shows that the effect of volatility on volume traded is not similar for three market indices with different market capitalization. It is evident that the direction of news is more important than the magnitude of news since the coefficient of asymmetric term in the model is much larger than lagged innovation term coefficient. There is marginal decrease in volatility persistence by including volume in the variance equation of the Sensex returns. The volume does not have any impact on the small cap index in decreasing volatility persistence. Both contemporaneous and lagged volume coefficients are found to be significant in volatility equation of return series of all the three indices considered. When IDV (Intraday volatility) is taken as a measure of information arrival, the GARCH effect vanished completely in all the three indices considered. These results suggest that lagged squared residuals contribute little if any additional information about the variance of the stock return process is accounted in the model, when the rate of information flow is measured in terms of contemporaneous IDV. The rate of information arrival measured by IDV is found to be a significant source of the conditional heteroskedasticity in Indian markets since the presence of IDV, as a proxy for information flow, makes GARCH term insignificant. The mean volume traded in large cap index affects the mean volume traded of mid-cap and small-cap indices. This confirms that the information asymmetry does exist in the market. New information is first reflected in large cap and then it transmits to lower indices. Hence, volume traded and volatility of large cap index can be used to model or predict volatility and volume in case of mid cap and small cap indices. Mean impulse response of mid-cap to large-cap is positive, therefore, increase in volume traded in large-cap causes increase in volume traded of mid-cap and vice-versa. Bivariate conditional correlations among volume traded of large-cap, mid-cap and small-cap are positive and significant. Conditional correlation of volume traded between large-cap and mid-cap is higher as compared to large-cap and small-cap. This confirms there is information asymmetry in markets.

References

Admati, A. R. (1988). A theory of intraday patterns: Volume and price variability. *Review of Financial studies* , 1(1), 3-40.

Bohl, M. T. (2003). Trading volume and stock market volatility. *The Polish case. International Review of Financial Analysis* , 12(5), 513-525.

Bollerslev, T. E. (1988). A capital asset pricing model with time-varying covariances. *The Journal of Political Economy* , 116-131.

Bollerslev, T. (1990). Modelling the coherence in short-run nominal exchange rates: a multivariate generalized ARCH model. *The Review of Economics and Statistics* , 498-505.

Bollerslev, T. (1990). Modelling the coherence in short-run nominal exchange rates: a multivariate generalized ARCH model. *The Review of Economics and Statistics* , 498-505.

Bollerslev, T., & Wooldridge, J. (1992). Quasi-maximum likelihood estimation and inference in dynamic models with time-varying covariances. *Econometric reviews* , 11(2), 143-172.

Campbell, J., Grossman, S., & Wang, J. (1993). Trading volume and serial correlation in stock returns. *Quarterly Journal of Economics* , 905–939.

Chen, G. M., Firth, M., & Rui, O. M. (2001). The dynamic relation between stock returns, trading volume, and volatility. *Financial Review* , 36(3), 153-174.

Chen, J., Hong, H., & Stein, J. C. (2001). Forecasting crashes: Trading volume, past returns, and conditional skewness in stock prices. *Journal of Financial Economics* , 61(3), 345-381.

Chordia, T., & Swaminathan, B. (2000). Trading volume and cross-autocorrelations in stock returns. *The Journal of Finance* , 55(2), 913-935.

Chordia, T., Huh, S., & Subrahmanyam, A. (2007). The cross-section of expected trading activity. *Review of Financial Studies* , 709–740.

Chuang, W. I., Liu, H. H., & Susmel, R. (2012). The bivariate GARCH approach to investigating the relation between stock returns, trading volume, and return volatility. *Global Finance Journal* , 23(1), 1-15.

Clark, P. (1973). A Subordinate Stochastic Process Model with Finite Variance for Speculative Prices. *Econometrica* , 41 (1) (1973), 135-155.

Clark, P. K. (1973). A subordinated stochastic process model with finite variance for speculative prices. *Econometrica: Journal of the Econometric Society* , 135-155.

Copeland, T. (1976). A model of asset trading under the assumption of sequential information arrival. *Journal of Finance* , 1149–1168.

Crouch, R. L. (1970). The volume of transactions and price changes on the New York Stock Exchange. *Financial Analysts Journal* , 104-109.

Engle, R. F., & Ng, V. K. (1993). Measuring and testing the impact of news on volatility. *The Journal of finance* , 48(5), 1749-1778.

Epps, T. W., & Epps, M. L. (1976). The stochastic dependence of security price changes and transaction volumes: Implications for the mixture-of-distributions hypothesis. *Econometrica: Journal of the Econometric Society* , 305-321.

Fama, E. F. (1965). The behavior of stock-market prices. *Journal of business* , 34-105.

Gallant, A. R., Rossi, P. E., & Tauchen, G. (1992). Stock prices and volume. *Review of Financial studies* , 5(2), 199-242.

Gallo, G., & Pacini, B. (2000). The effects of trading activity on market volatility. *The European Journal of Finance* , 6(2), 163-175.

Gervais, S., Kaniel, R., & Mingelgrin, D. H. (2001). The high-volume return premium. *The Journal of Finance* , 56(3), 877-919.

Girard, E., & Biswas, R. (2007). Trading volume and market volatility: developed versus emerging stock markets. *Financial Review* , 42(3), 429-459.

Granger, C. W., & Morgenstern, O. (1963). Spectral analysis of New york stock market pricess. *Kyklos* , 16(1), 1-27.

Harris, M., & Raviv, A. (1993). Differences of opinion make a horse race. *Review of Financial studies* , 6(3), 473-506.

He, H., & Wang, J. (1995). Differential informational and dynamic behavior of stock trading volume. *Review of Financial Studies* , 8(4), 919-972.

Hiemsta, D., & Jones, J. (1994). Testing for Linear and Nonlinear Granger Causality in the Stock Price-Volume Relation. *The Journal of Finance* , 49(5), 1639-1664.

Jain, P. C., & Joh, G. H. (1988). The dependence between hourly prices and trading volume. *Journal of Financial and Quantitative Analysis* , 23(03), 269-283.

Jennings, R. H., Starks, L. T., & Fellingham, J. C. (1981). An equilibrium model of asset trading with sequential information arrival. *The Journal of Finance* , 36(1), 143-161.

Karpoff, J. M. (1986). A theory of trading volume. *The Journal of Finance* , 41(5), 1069-1087.

Kim, D., & Kon, S. J. (1994). Alternative models for the conditional heteroscedasticity of stock returns. *Journal of Business* , 563-598.

Lamoureux, C. G., & Lastrapes, W. D. (1994). Endogenous trading volume and momentum in stock-return volatility. *Journal of Business & Economic Statistics* , 12(2), 253-260.

Lamoureux, C. G., & Lastrapes, W. D. (1990). Persistence in variance, structural change, and the GARCH model. *Journal of Business & Economic Statistics* , 8(2), 225-234.

Lee, B. S., & Rui, O. M. (2002). The dynamic relationship between stock returns and trading volume: Domestic and cross-country evidence. *Journal of Banking & Finance* , 26(1), 51-78.

Lo, A. W., & Wang, J. (2000). Trading volume: definitions, data analysis, and implications of portfolio theory. *Review of Financial Studies* , 13(2), 257-300.

Lucey, B. M. (2005). Does volume provide information? Evidence from the Irish stock market. *Applied Financial Economics Letters* , 1(2), 105-109.

Omran, M. F., & McKenzie, E. (2000). Heteroscedasticity in stock returns data revisited: volume versus GARCH effects. *Applied Financial Economics* , 10.5 (2000): 553-560.

Osborne, M. F. (1959). Brownian motion in the stock market. *Operations research* , 7(2), 145-173.

Pagan, A. (1984). Econometric issues in the analysis of regressions with generated regressors. *International Economic Review* , 221-247.

Poon, S. H., & Granger, C. W. (2003). Forecasting volatility in financial markets: A review. *Journal of economic literature* , 41(2), 478-539.

Pyun, C. S., Lee, S. Y., & Nam, K. (2001). Volatility and information flows in emerging equity market: A case of the Korean stock exchange. *International Review of Financial Analysis* , 9(4), 405-420.

Ranter, M., & Leal, R. (2001). Stock returns and trading volume: Evidence from the emerging markets of Latin America and Asia. *Journal of Emerging Markets* , 6, 5–22.

Rogalski, R. J. (1978). The dependence of prices and volume. *The Review of Economics and Statistics* , 268-274.

Rozga, A., & Arneric, J. (2009). dependence between volatility persistence, kurtosis and degree of freedom. *Investigación Operacional* , 30(1), 32-39.

Silvapulle, P., & Choi, J. S. (1999). Testing for linear and nonlinear Granger causality in the stock price-volume relation: Korean evidence. *The Quarterly Review of Economics and Finance* , 39(1), 59-76.

Tauchen, G. E., & Pitts, M. (1983). The price variability-volume relationship on speculative markets. *Econometrica: Journal of the Econometric Society* , 485-505.

Westerfield, R. (1977). The distribution of common stock price changes: An application of transactions time and subordinated stochastic models. *Journal of Financial and Quantitative Analysis* , 12(05), 743-765.