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Equity Trading Volume and its Relationship with Market Volatility: Evidence from Indian Equity Market

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Abstract

This study investigates stock market volatility asymmetry and its relationship with equity trading volume in the Indian stock market using daily data over the period from 2nd January 1997 to 30th May 2013. We employ GARCH, EGARCH and GJR-GARCH models to examine the volatility pattern in the stock market. We also decompose the conditional variance into a transitory and permanent component, modeled by asymmetric CGARCH, in order to check the short run and long run movements of volatility. Further, contemporaneous trading volumes are augmented in the volatility model to empirically verify the validity of Mixture of Distribution Hypothesis (MDH) and the level of volatility persistence. The findings show significant volatility asymmetry in the Indian equity market, supporting the leverage effect hypothesis. Secondly, we find a positive contemporaneous relationship between volume and volatility, validating the argument of MDH. Moreover, the results show that the volatility shocks are highly persistent even after incorporating trading volume, contradicting the seminal findings of Lamoureux and Lastrapes (1990).

1. INTRODUCTION

The study of stock market volatility and its relationship with equity trading volume has been receiving considerable attention in finance research. The literature in financial economics acknowledges several stylized facts (e.g. fat tail distributions, volatility clustering, persistence, asymmetric news effects etc.) about the stock return series. Several scholars tried to model volatility by incorporating such stylized facts. However, there is a little consensus regarding an appropriate model to describe the asset return. The autoregressive conditional heteroskedasticity (ARCH) model introduced by Engle (1982) and its generalization, Bollerslev's (1986) GARCH

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model, provide a systematic framework for volatility modelling. But, the GARCH model is not able to capture an important stylized fact, known as volatility asymmetry, first detected by Black (1976). Statistically, the asymmetric effect occurs when an unexpected drop in stock price (bad news), increase the predictable volatility, more than the unexpected increase in stock price (good news) of similar magnitude does. The literature provides two classes of explanations: the leverage effect hypothesis (Black, 1976; Christie, 1982); and the volatility feedback hypothesis (Pindyck *et al.*, 1987; Campbell & Hentschel, 1992).

Numerous studies empirically examine volatility asymmetry in equity markets and verify these two aforementioned explanations. Some studies which report volatility asymmetry in developed markets are, among others, Campbell and Hentsell (1992), Engle and Ng (1993), Bekaert and Wu (2000), Wu (2001), Smith and Yamagata (2011). Jayasuriya *et al.*, 2009) analyze the asymmetric volatility in emerging and mature markets using an asymmetric power-GARCH model. Their findings reveal that emerging markets often react somewhat more to news; each of the markets exhibit asymmetric volatility; and they find strong evidence of asymmetric volatility in a sub period when the overall level of volatility is high. Emenike and Friday (2012) also find volatility asymmetry, but in the absence of leverage effect, for the Nigerian stock market. On the other hand, there are some studies of emerging markets documenting a symmetric pattern of volatility (e.g. for Amman stock exchange of Jordan *et al.*, 2005; for Kuala Lumpur Composite Index, Mum *et al.*, 2008; for Iran *et al.*, 2011). Clearly, the empirical evidence of volatility asymmetry for emerging markets is inconclusive.

Furthermore, one of the important issues within the study of return volatility is the presence of ARCH effect or the level of volatility persistence. It is believed that the excess stock return can be predicted by available information since it is used in investment decisions. However, the flow of information that arrives into the market is very difficult to identify and quantify as a variable. Thus, researchers often use equity trading volumes as a proxy for such information (Brailsford, 1996). It has been argued that return and volume are two major pillars around which the stock market revolves. An investigation of the volatility-volume relationship would enable us to have an idea about the structure of the market, information dissemination, market size, and the observed kurtosis in empirical stock return distribution (Karpoff, 1987; Poon & Granger, 2003). In other words, an investigation of the volume-volatility nexus would provide an understanding of how new information gets impounded on stock prices. The literature provides two prominent and interrelated theoretical explanations on the relationship between trading volume and volatility. The first is the Mixture of Distribution Hypothesis (MDH) introduced by Clark (1973) and subsequently supported by many scholars such as Epps and Epps (1976), Tauchen and Pitts (1983), Harris (1986), Lamoureux and Lastrapes (1990), and Andersen (1996), among others. The MDH suggests a positive contemporaneous relationship between trading volume and stock price movement.

The second is the Sequential Information Arrival Hypothesis (SIAH) developed by Copeland (1976) and Jennings *et al.* (1981), assuming that traders receive new information in sequential random style. According to SIAH, the information is private and sequential. The information signal is observed by each trader at a time and not received by all the traders simultaneously thus forming one of the series of incomplete equilibria. The equilibrium establishes as long as all traders receive the same set of information (Alsubaie & Najand, 2009). Therefore according to SIAH the relationship is lead lag. The implication of this hypothesis is that the price volatility in the market might be potentially predictable through the knowledge of such information. On the other hand, MDH believes that the shift to new information is immediate and the partial equilibrium of the sequential information does not occur (See Clark, 1973; Epps & Epps, 1976). Studies supporting the MDH, argue that once the instantaneous rate of information is captured in the volatility model, the GARCH effect will no longer exist (See e.g. Lamoureux and Lastrapes (1990) which documents it for 20 actively traded stocks in the US market from 1980 to 1984). Subsequently, several studies have attempted to explain the presence of GARCH effect by considering trading volume in the volatility model. Their conclusion, however, is still ambiguous.

Andersen (1996) modifies MDH and tests it for five major stocks on the New York Stock Exchange. His findings support the standard as well as the modified MDH. Similarly, Gallo and Pacini (2000) investigate it for US, and Brailsford (1996) for Australia. Both of the studies documental declines in the level of volatility persistence. For emerging markets, Pyun *et al.* (2000); Wang *et al.* (2005), investigate the volume-volatility relationship for Korea and China respectively, and end up providing a similar conclusion. Bohl and Henke (2003), Alsubaie and Najand (2009) examine this relationship using individual stocks from Warsaw Stock Exchange and Saudi Stock Market respectively; both document that inclusion of trading volume in the volatility equation reduces the volatility persistence in most but not all the cases.

On the other hand, there is a strand of literature which finds little evidence of the effect of trading volume on volatility persistence. For example, Sharma *et al.* (1996) show that inclusion of trading volume as a proxy for information arrival in the conditional volatility model is not able to diminish the volatility persistence completely. Darrat *et al.* (2003) document a positive correlation between trading volume and volatility for only three out of thirty stocks of US stock market under investigation. For the other twenty-seven stocks, no significant correlation was reported. However, their findings support SIAH. Sabbaghi (2011) investigates this relationship using national equity index of five developed (G5) markets and finds that trading volume fails to reduce the volatility persistence in the aggregate equity index. Girard and Biswas (2007) examine the asymmetric volatility and volatility persistence across 22 developed markets and 27 emerging markets and conclude that volatility persistence as well as the volatility asymmetry is higher in developed markets. Huang and Yang (2001) examine the validity of MDH for Taiwan Stock Exchange. Their findings do not support MDH, and show that there is little difference in the volatility persistence before and after inclusion of trading volume as an exogenous variable. Similar findings are documented by Ahmed *et al.* (2005) for Kuala Lumpur Stock Exchange. However, this study finds a positive and significant effect of trading volume on the conditional volatility.

Given the mixed evidence of the volume–volatility relationship and also the volatility persistence for both the developed and developing stock markets we further examine this issue using recent data from Indian stock market.

In the Indian context, the literature on the asymmetric volatility-volume nexus is scant but growing. While there is a reasonable amount of study describing asymmetric volatility in the equity market, very few works, in our knowledge, are devoted to the volume-volatility nexus. Karmakar (2007) examines the volatility pattern and risk-return relationship using the daily stock price index of CNX Nifty over the period from July 1990 to December 2004. The findings show that the conditional variance is an asymmetric function of past innovations. Secondly, he documents a positive but insignificant relationship between risk and return. Mohanty (2009) examines the asymmetric nature of volatility by considering four market indices namely, BSE Sensex, BSE 100, CNX Nifty and CNX 500. His findings support the presence of leverage effect. Krishnan and Mukherjee (2010) examine the volatility pattern using the daily Nifty index for the period from February 1997 to January 2006. Their results also reveal the presence of volatility asymmetry supporting the leverage effect hypothesis. Similar findings are obtained by Goudarzi and Ramanarayanan (2011) who studied the asymmetric volatility for the period of 2000 to 2009 using daily returns of the BSE 500 stock index. Mahajan and Singh (2009) examine the volume-volatility relationship using daily data of the BSE Sensex over the period from 1996 to 2006.

Their findings indicate that there is a positive and significant relationship between volatility and trading volume but the GARCH effect remains significant. Pati and Rajib (2010) examine the volume-volatility relationship for the NSE Nifty stock index futures, and document that inclusion of trading volume in the volatility model reduces the level of volatility persistence but the GARCH effect does not completely vanish.

Despite tremendous growth, the Indian stock market is still in a developmental stage. During the last few years the trading volume in the equity segments of the stock exchange has witnessed a massive growth. According to the report of National Stock Exchange (NSE), the compound annual growth rate of the trading volumes of all the stock exchange taken together has been 12.5 percent over the period 2001-02 to 2012-13. These days the NSE has gained utmost popularity among the trading members contributing 83 percent of total turnover in India as on 2012-13. However, the report also acknowledges that during this period the equity market was volatile too, for instance, in May-2013 the monthly volatility of CNX Nifty and BSE Sensex were 1.2 percent and 1.1 percent respectively (See. ISMR, 2013). An investigation of the volatility pattern and the volume-volatility relationship is expected to be helpful in financial decision making and effective market operation in an emerging equity market like India. For example, a positive relationship i.e. the stock price moves up on a given day with increasing volume, may be perceived as the signal that buyers are able to absorb the increasing selling pressure. As it is believed that the volume analysis enables the market participants to know the likely volatility of the market, the investigation of volume-volatility relationship also provides the idea of how the investors behave in the stock market.

The purpose of the present study is to re-examine the volatility pattern using the most popular conditional volatility models such as EGARCH, GJR-GARCH that capture the volatility asymmetry. An asymmetric component GARCH model is also modeled that capture the commonly held stylized facts about conditional volatility as well as the short-run and long-run volatility components. Secondly, we further investigate the volume-volatility relationship and verify the validity of MDH.While doing so; we also check whether the level of volatility persistence is reduced by incorporating trading volume in the volatility model. The empirical results indicate the presence of volatility asymmetry, which supports the leverage effect hypothesis; and a positive contemporaneous relationship between volume and volatility. However, the volatility persistence or the GARCH effect remain high even after considering the rate of information arrival into the market as proxied by trading volume.

The rest of the paper is organized as follows. In Section 2, we discuss the econometric models used in this study to establish the results. Data sources and preliminary analysis are presented in Section 3. The empirical findings are reported and discussed in Section 4and finally Section 5states the conclusion from the study.

2. EMPIRICAL METHODS

It is widely acknowledged that the variances of stock returns are time varying. In general, the autoregressive conditional heteroskedasticity (ARCH) model of Engle (1982) and its generalisation, the GARCH model of Bollerslev (1986), capture the changing variances and provide a systematic framework in modelling volatility. The GARCH (1, 1) model can be represented as follows.

$$r_t = \mu_t + \varepsilon_t \qquad (1)$$

$$\varepsilon_t = Z_t\sqrt{h_t} \qquad (2)$$

$$h_t = \omega + \alpha\varepsilon_{t-1}^2 + \beta h_{t-1} \qquad (3)$$

where r_t is the stock return from time *t-1* to *t*, μ_t is the conditional mean given by $\mu_t \equiv E(r_t|F_{t-1})$, h_t represents the conditional variance of r_t given by $h_t \equiv Var(r_t|F_{t-1})$, $Z_t \sim i.i.d.$ with $E(Z_t) = 0$, $E(Z_t^2) = 1$, and by definition ε_t is serially uncorrelated with mean zero, but the conditional variance of ε_t equals h_t which may be changing through time. Equation (3) is conditional on $\omega > 0$, $\alpha > 0$, $\beta \geq 0$ and $\alpha + \beta < 1$. The GARCH model explains variance by two distributed lags, one on past squared residuals(ε_{t-1}^2) to capture high frequency effects, and the second is the lagged values of the variance itself(h_{t-1}), to capture long term influences.

However, the GARCH model has at least two major drawbacks (Nelson, 1991). *First*, the non-negative constraints imposed on the parameters to ensure that h_t remains non negative for all *t* with probability 1. The *Second* important limitation is that it does not address the leverage effects or the volatility asymmetry. Several models have therefore been evolved to capture these properties; the most popular are EGARCH model developed by Nelson (1991), and the GJR GARCH model developed by Glosten *et al.* (1993). Accordingly we employ EGARCH (1, 1) and GJR-GARCH (1, 1) respectively as follows:

$$\ln(h_t) = \omega + \beta \ln(h_{t-1}) + \gamma\left(\varepsilon_{t-1}/\sqrt{h_{t-1}}\right) + \alpha\left[|\varepsilon_{t-1}|/\sqrt{h_{t-1}}\right] \quad (4)$$

and

$$h_t = \omega + (\alpha + \gamma N_{t-1})\varepsilon_{t-1}^2 + \beta h_{t-1} \quad (5)$$

with $N_{t-1} = \begin{cases} 1 & if\, \varepsilon_{t-1} < 0, \\ 0 & if\, \varepsilon_{t-1} \geq 0. \end{cases}$

The log of the conditional variance in (4) implies that the asymmetric effect is exponential rather than quadratic and that the forecast of conditional variance is guaranteed to be non-negative. In equation (4), a positive ε_{t-1} contributes $\alpha(1+\gamma)|\varepsilon_{t-1}|/\sqrt{h_{t-1}}$ to the log volatility, whereas a negative ε_{t-1}gives $\alpha(1-\gamma)|\varepsilon_{t-1}|/\sqrt{h_{t-1}}$. Hence, the parameter γ signifies the leverage effect of ε_{t-1}. In real applications, the γ coefficient (in Eq. 4) is expected to be negative implying that negative return shocks generate more volatility than positive return shocks. The coefficient β represents the volatility persistence. Similarly, in equation (5),*α*, *β*, and *γ* are non negative parameters satisfying conditions similar to those in the GARCH model. In this model, a positive ε_{t-1} contributes $\alpha\varepsilon_{t-1}^2$ to h_t, whereas a negative ε_{t-1} has a large impact $(\alpha+\gamma)\varepsilon_{t-1}^2$ with $\gamma > 0$. The model uses *zero* as its threshold to separate the impacts of past shocks. In this model, the contribution of shocks to short run persistence is $\alpha + (\gamma/2)$, and to long run persistence it is $\alpha + \beta + (\gamma/2)$.

It is also argued that some volatility components may have very big short-run effect, but die out quickly; some of them may have relatively smaller short run effects but last for a longer period (See Ding & Granger, 1996). Andersen and Bollerslev (1997) and Muller *et al.* (1997) argue that the volatility should be decomposed into its components as the information arrival into the market is heterogeneous; thereby it imparts both long-run and short-run volatility. In order to determine whether the permanent or transitory components dominate the observed volatility, an extension of GARCH model known as the component GARCH model or CGARCH was developed by Engle and Lee (1999).The variance equation of component GARCH (1, 1) model can be expressed as:

$$h_t - q_t = \alpha(\varepsilon_{t-1}^2 - q_{t-1}) + \beta(h_{t-1} - q_{t-1})$$

$$q_t = \omega + \rho(q_{t-1} - \omega) + \phi(\varepsilon_{t-1}^2 - h_{t-1}) \quad (6.1)$$

The first equation describes the transitory component, $h_t - q_t$, which converges to zero with power of (α+β). The second equation describes the long run componentq_t, which converges to ω with power of ρ. The conditional variance is covariance stationary when both transitory and permanent components are covariance stationary (i.e. α+β < 1, and ρ < 1, respectively). They also represent respectively the short run and long run volatility persistence. When 1 >ρ > (α+β), the transitory component decays more quickly than the permanent component. Combining equations (6) and (6.1) the CGARCH (1, 1) model can be shown as a (non linear) restricted GARCH (2, 2) (Ding & Granger, 1996).

The CGARCH model is extended by allowing for the volatility asymmetry. The asymmetric CGARCH model combines the component model with the TGARCH model, introducing the asymmetric effect in the transitory equation and can be represented in the form:

$$q_t = \omega + \rho(q_{t-1} - \omega) + \phi(\varepsilon_{t-1}^2 - h_{t-1})$$
$$h_t - q_t = \alpha(\varepsilon_{t-1}^2 - q_{t-1}) + \gamma(\varepsilon_{t-1}^2 - q_{t-1})D_{t-1} + \beta(h_{t-1} - q_{t-1}) \quad (7.1)$$

Where, D is the dummy variable indicating negative shocks, and $\gamma > 0$ indicates the presence of transitory leverage effect in the conditional variance.

To test whether the above discussed models fully capture the presence of asymmetry, we considered a diagnostic test provided by Engle and Ng (1993). Engle and Ng have proposed the Sign Bias Test (SBT), the Negative Size Bias Test (NSBT) and the Positive Size Bias Test (PSBT) based on news impact curve of the estimated volatility model. Their SBT takes S_{t-1}^- as an indicator dummy that takes the value of one, if ε_{t-1} is negative, and zero otherwise. The NSBT utilize the variable $S_{t-1}^-\varepsilon_{t-1}$, that captures different effect that large and small negative return shocks have on volatility, which are not predicted by the volatility model. The PSBT utilize $S_{t-1}^+\varepsilon_{t-1}$ where S_{t-1}^+ is defined as $1 - S_{t-1}^-$. These three tests can be represented respectively as follows.

$$\hat{\varepsilon}_t^2 = a + b.S_{t-1}^- + v_t \quad (8a)$$
$$\hat{\varepsilon}_t^2 = a + b.S_{t-1}^-\varepsilon_{t-1} + v_t \quad (8b)$$
$$\hat{\varepsilon}_t^2 = a + b.S_{t-1}^+\varepsilon_{t-1} + v_t \quad (8c)$$

where, v_t is an *iid* error term. The tests for sign and size bias involve a t-test on the coefficient *b*; a statistically significant *b* indicates presence of sign bias, negative size bias or positive size bias. For example, in equation (8a) a significant *b* implies the positive and negative shocks have different impacts on volatility. A more general test involves testing whether volatility depends on both the sign and size of past shocks, conducting these tests jointly. The joint test is based on the following regression:

$$\hat{\varepsilon}_t^2 = a + b_1 S_{t-1}^- + b_2 S_{t-1}^-\varepsilon_{t-1} + b_3 S_{t-1}^+\varepsilon_{t-1} + v_t \quad (9)$$

The null hypothesis of no sign and size bias corresponds to $H_0 : b_1 = b_2 = b_3 = 0$; and it can be tested with a Lagrange Multiplier (LM) test that asymptotically follows χ^2 distribution with 3 df under the null hypothesis of no asymmetric effect.

In order to investigate the impact of trading volume on stock market volatility, volume could be included in the volatility model as an exogenous variable. This has been done to capture the impact of instantaneous rate of information arriving in the market (See Lamoureux and Lastrapes, 1990; Brailsford, 1996; Gallo and Pacini, 2000). We follow a similar approach and the volume augmented volatility models such as GARCH (1, 1), EGARCH (1, 1) GJR-GARCH (1, 1) and asymmetric CGARCH (1, 1) are defined respectively as follows.

$$h_t = \omega + \alpha\varepsilon_{t-1}^2 + \beta h_{t-1} + \theta Vol_t \quad (10)$$
$$\ln(h_t) = \omega + \beta\ln(h_{t-1}) + \gamma(\varepsilon_{t-1}/\sqrt{h_{t-1}}) + \alpha[|\varepsilon_{t-1}|/\sqrt{h_{t-1}}] + \theta Vol_t$$
(11)
$$h_t = \omega + (\alpha + \gamma N_{t-1})\varepsilon_{t-1}^2 + \beta h_{t-1} + \theta Vol_t \quad (12)$$
With $N_{t-1} = \begin{cases} 1 & if\, \varepsilon_{t-1} < 0, \\ 0 & if\, \varepsilon_{t-1} \geq 0 \end{cases}$

and
$$q_t = \omega + \rho(q_{t-1} - \omega) + \phi(\varepsilon_{t-1}^2 - h_{t-1})$$
$$h_t - q_t = \alpha(\varepsilon_{t-1}^2 - q_{t-1}) + \gamma(\varepsilon_{t-1}^2 - q_{t-1})D_{t-1} + \beta(h_{t-1} - q_{t-1}) + \theta Vol_t \quad (13.1)$$

The trading volume variable Vol_t is considered as an exogenous variable in all of the above volatility models, representing the information arrival into the market. The coefficient θ measures the impact of contemporaneous trading volume on stock return volatility. When θ is statistically significant and positive, the estimation supports the argument of MDH.

3. DATA SAMPLE AND DESCRIPTIVE STATISTICS

Daily data of S&P CNX Nifty from 2nd January 1997 to 30th May 2013 are extracted from the website of National Stock Exchange India. Nifty represents one of the benchmark indices of the Indian equity markets, consisting of 50 major stocks of Indian companies and covering 22 sectors of the Indian economy. It represents about 67 percent of the free float market capitalization of the stocks listed in National Stock Exchange India. The closing prices are converted into log returns, computed as, $r_t = \ln\left(\frac{P_t}{P_{t-1}}\right)$, where, r_t represents the compounded returns at time *t*, P_t and P_{t-1} are the daily stock index at days *t* and *t-1* respectively. Similarly, daily data for number of shares traded are considered for trading volume and calculated as $Vol_t = \ln\left(\frac{V_t}{V_{t-1}}\right)$;where, Vol_t represents the logarithmic changes of daily trading volume. V_t and V_{t-1} are the number of shares traded at days *t* and *t-1* respectively. Number of shares traded has been used as a proxy for trading volume in many previous studies to incorporate the information arrival into the market. (See Lamoureux & Lastrapes, 1990; Brailsford, 1996; Gallo & Pacini, 2000; Darrat *et al.*, 2003; Alsubaie & Najand, 2009; Sabbaghi, 2011 among others).

The descriptive statistics of the index returns and trading volume are presented in Table 1. The mean values of both return r_t and volume change Vol_t are positive for both the market indices implying that the price series and trading volume have increased over the sample period. The t-ratio for mean values is also presented which clearly indicates that the average return is statistically indistinguishable from zero. The skewness statistics indicate that the returns are negatively skewed and the trading volumes are positively skewed. The value of kurtosis is larger than 3 which imply that both the returns series and volume returns are fatter tail than the standard normal distribution. In addition, the significant Jarque-Bera test statistics indicate the series are not normally distributed. Finally, the significant LM statistic indicates the presence of ARCH effects which justifies the use of GARCH type models.The stationarity of the data series has been established by the standard procedure of unit root testing, by employing the Augmented Dickey Fuller (ADF), Phillips-Perron (PP) and the Kwiatkowski-Phillips-Schmidt-Shin (KPSS) tests. All the three tests confirm the stationarity of the data series.

Table 1: Descriptive statistics

	Returns	**Trading volume**
Mean	0.00045 (1.76)*	0.00039 (0.074)
Std. dev.	0.0165	0.3386
Maximum	0.1633	5.490
Minimum	-0.1305	-4.6884
Skewness	-0.195	0.263
Kurtosis	9.770	44.437
Jarque-bera	7849.997	293152.200
Probability	0.000	0.000
Observations	4097.000	4097.000
Q(36)	89.72***	786.65***
Q^2(36)	1008.3***	927.57***
LM test	19.62***	916.63***
Unit root test		
ADF test		
Constant, No trend	-60.380***	-31.990***
Constant, trend	-60.370***	-31.990***
PP test		
Constant, no trend	-60.310***	-611.790***
Constant, trend	-60.290***	-609.400***
KPSS test		
Constant, no trend	0.066	0.050
Constant, trend	0.062	0.050

Note: t-statistics are in parenthesis. *and *** indicates statistical significant at 0.10 and 0.01 level respectively. This table presents descriptive statistics for S&P CNX Nifty. This table also presents results of three types of unit root tests viz. Augmented Dickey-Fuller, Phillips-Perron and Kwiatkowski-Phillips-Schmidt-Shin tests. Daily prices data are obtained from NSE India and range 02/01/1997 to 30/05/2013

Figure 1 exhibits (a) closing price; (b) return series and (c) squared return series of CNX Nifty for the sample period stated above. A clear observation from this figure is that there are stretches of time where the volatility is relatively high and there are stretches of time where the volatility is relatively low indicating a volatility clustering. In addition, the autocorrelation function of squared daily return is presented in Table 2 which also supports the volatility clustering. The volatility clustering statistically implies a strong correlation in the squared returns. The results of volatility clustering and the presence of ARCH effect in the return series provides justifications for the next stage analysis of the GARCH type models which involves estimating the conditional variance.

Table 2: Autocorrelation functions of daily squared log returns

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
*	*	1	0.205	0.205	172.34	0.000
*	*	2	0.154	0.117	269.57	0.000
*		3	0.101	0.052	311.32	0.000
*	*	4	0.128	0.088	378.79	0.000
*	*	5	0.125	0.074	442.97	0.000
*		6	0.090	0.030	476.51	0.000
*		7	0.114	0.064	529.81	0.000
		8	0.070	0.010	550.10	0.000
*		9	0.098	0.048	589.81	0.000
*		10	0.122	0.071	650.90	0.000
*		11	0.097	0.030	689.67	0.000
		12	0.062	-0.003	705.69	0.000
*		13	0.082	0.034	733.44	0.000
*		14	0.077	0.019	757.76	0.000
*		15	0.076	0.019	781.33	0.000

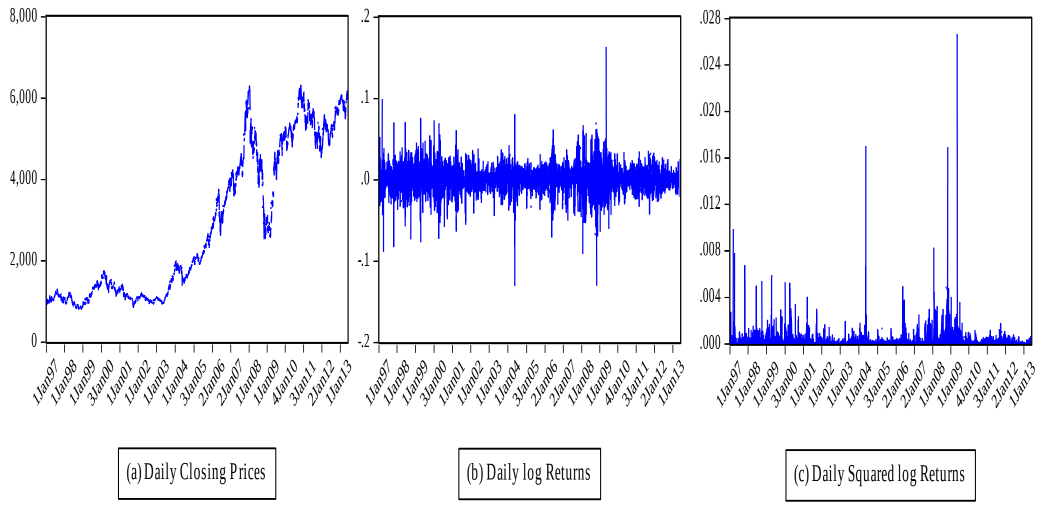

Figure 1: Time series plot of CNX Nifty daily closing prices, returns and squared returns (2nd Jan 1997 to 30th May 2013)

Estimated results and discussion

First, we analyze a restricted version of the models discussed in section 2, setting the coefficient of trading volume to be zero. Then we analyze the volume augmented volatility models by including the trading volume as an explanatory variable to check whether a positive relationship of volume and volatility exist and whether the volatility persistence or the GARCH effect is diminished. We estimate the standard

GARCH (1, 1) model as well as two other parametric models which are capable of capturing the leverage and size effects: the EGARCH (1, 1) model of Nelson (1991) and the Threshold GARCH (1, 1) model of Glosten *et al.* (1993). According to Engle and Ng (1993) these two asymmetric volatility models have the best parameterisation among the five different asymmetric volatility models they compared in the study. We also estimate an asymmetric component GARCH model in order to check the effect of long-run and short-run volatility components. All the models are estimated using the Log Likelihood estimators assuming Gaussian normal distribution for GARCH (1, 1), GJR-GARCH (1, 1), asymmetric CGARCH (1, 1) and Generalised Error Distribution (GED) for EGARCH (1, 1) models. The choice of GED is due to Nelson's (1991) original paper and also due to the presence of excess kurtosis in the return series. The results are based on the robust standard errors as corrected by the procedure of Bollerslev and Wooldridge heteroskedasticity consistent covariance.

Table 3 presents the estimated results without considering trading volume, whereas, Table 4 presents the estimated results with the inclusion of trading volume. Since our aim is to measure the conditional variance series, the results reported are from the variance equations only. The results of GARCH (1, 1) model are reported in the second column in Table 3. The coefficients of all three parameters (ω, α and β) in the conditional variance equations are positive and highly significant, satisfying the non-negativity constraint of the GARCH model. The significant value of the parameter α indicates that the news about volatility from the previous day has explanatory power on current volatility. Similarly, the significant β parameter indicates the explanatory power of current volatility. It is observed that the estimated β coefficient is larger than the coefficient, implying that volatility is more sensitive to its lagged values than it is to new surprise in the market place. To put it simply, the lagged effect of volatility is stronger than new innovations. The persistence of conditional volatility process (α+β) is close to 1, indicating that the volatility is highly persistent. This implies that average variance remains high, since the increase in conditional variance due to shocks will decay slowly. The log likelihood ratio statistics are large suggesting that the model is well fitted and successfully capture the temporal dependence in volatility.

Table 3: Parameter estimation of volatility model without trading volume

Parameters	**GARCH(1, 1)**	**EGARCH (1, 1)**	**GJR GARCH (1, 1)**	**Asymmetric CGARCH (1, 1)**
Ω	5.27E-06	-0.498	6.83E-06	0.0002
	[3.52]***	[-9.47]***	[4.17]***	[2.57]**
A	0.119	0.227	0.064	-0.052
	[6.56]***	[12.88]***	[3.04]***	[-2.11]**
B	0.867	0.961	0.857	0.801
	[45.38]***	[170.95]***	[47.28]***	[13.82]**
Volatility persistence	98%	96%	97%	83%, 99%
Γ		-0.087	0.111	0.169
		[-7.84]***	[3.82]***	[5.09]***
P				0.990
				[182.79]***
ϕ				0.068
				[5.54]***
Log likelihood	11507.22	11621.79	11531.95	11533.19
Q(15)	62.237 (0.00)	62.88 (0.00)	63.305(0.00)	64.005(0.00)
$Q^2(15)$	9.90 (0.82)	9.58 (0.84)	6.702 (0.96)	7.383(0.94)
AIC	-5.615	-5.760	-5.627	-5.626
SBC	-5.609	-5.661	-5.619	-5.615

LM(15) for ARCH effect	9.52 (0.84)	9.70 (0.83)	6.76 (0.96)	6.96(0.95)
Sign bias test	-0.0290	0.0093	0.051	0.230
	[-0.27]	[0.084]	[0.470]	[11.27]
	(0.78)	(0.93)	(0.63)	(0.04)
-ve Size bias test	-0.169	-0.0315	-0.021	-0.033
	[-2.41]	[-0.42]	[-0.291]	[-0.44]
	(0.015)	(0.67)	(0.77)	(0.65)
+ve Size bias test	-0.179	-0.105	-0.106	-0.026
	[-2.26]	[-1.297]	[-1.318]	[-0.32]
	(0.023)	(0.19)	(0.18)	(0.74)
Joint LM test	22.41	4.216	5.572	14.45
Probability Value χ^2	(0.00005)	(0.239)	(0.112)	(0.002)

Note: *, ** and *** indicate statistical significant at 0.10, 0.05 and 0.01 level respectively. T-statistics are in brackets and p-values are in parenthesis. SBC: Schwarz Bayesian Criterion, AIC: Akaike Information Criterion and LM: Lagrange Multiplier Daily price data is obtained from NSE India ranging from 02/01/1997 to 30/05/2013

The diagnostic test statistics are also presented in order to check the potential residual ARCH effect in the estimated models. The standardized residuals and the squared standardized residuals are obtained and the Ljung–Box (Q) statistics are computed up to lag 15 to test the null hypothesis of no autocorrelation up to order 15. Though the Q (15) statistics indicates the standardized residuals are serially dependent, the Q^2 (15) statistics suggests the standardized residuals are non-linearly independent. The insignificant LM statistics also indicate that there is no residual ARCH effect, suggesting that the GARCH (1, 1) model is well-specified. However, from Table 3 it is evident that the probability value for joint test (LM test that follows a chi square distribution with 3 df) is statistically significant rejecting the null hypothesis of no sign and size biases. This indicates that the estimated GARCH model show asymmetric response of volatility to past shocks. Our next step is therefore to estimate the EGARCH and GJR-GARCH models which allow for an asymmetric response of volatility to past shocks.

The estimated result of EGARCH (1, 1) from Table 3 shows that the γ parameter corresponding to $\varepsilon_{t-1}/\sqrt{h_{t-1}}$ is significantly different from zero and is negative. The result indicates that a positive ε_{t-1} contributes $0.207\ (|\varepsilon_{t-1}|/\sqrt{h_{t-1}})$ to the log volatility, whereas a negative ε_{t-1} gives$0.246(|\varepsilon_{t-1}|/\sqrt{h_{t-1}})$. Clearly, this result is consistent with the hypothesis that negative return shocks because higher volatility than positive return shocks of the same magnitude, confirming the results of past Indian studies (e.g., Karmakar, 2007; Mohanty, 2009; Krishnan and Mukherjee, 2010). The significant γ and α parameters imply that once the asymmetric impact of innovations is accounted for, the absolute size of the innovation is also important. Further, the volatility shocks are highly persistent, meaning the shocks die out rather slowly.

From the diagnostic test statistics it is evident that the insignificant Q^2(15) statistic implies that the standardized residuals are non-linearly independent. The insignificant LM(15)statistics also indicates that there is no residual ARCH effect, suggesting that the model is well-specified. The results of sign and size bias tests indicate that the null hypothesis of no sign and size bias is accepted. The probability values of joint tests statistics are insignificantly different from zero, suggesting that there is no sign and size bias. It is therefore evident that the asymmetric volatility model (EGARCH) is better suited to the data series. The asymmetric nature of the estimated EGARCH (1, 1) model is complemented with the news impact curve as presented in Figure 2. This figure clearly indicates that CNX Nifty return series exhibits volatility asymmetry i.e. the asymmetric impact of negative and positive shocks of the same magnitude. Bad news or negative shocks cause more volatility than good news or positive shocks.

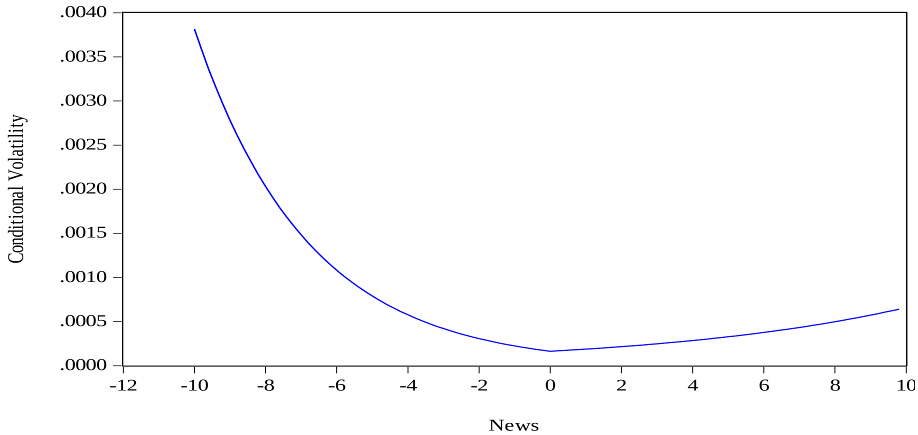

Figure 2: News Impact Curve of estimated EGARCH (1, 1) model without trading volume

The results of GJR-GARCH (1, 1) from Table 3 also show that the estimated γ parameter is significantly different from zero and is positive. The results indicate that a positive ε_{t-1} contributes $0.064\varepsilon_{t-1}^2$ to h_t, whereas a negative ε_{t-1} has a comparatively large impact $(0.064 + 0.111) = 0.175\varepsilon_{t-1}^2$ with $\gamma_1 > 0$. Similar to the results of the EGARCH model, this result also supports the presence of the leverage effect. In this model, the contribution of shocks to short-run persistence is computed to be 0.064 + (0.111/2) = 0.1195, and long-run persistence is 0.064 + 0.857 + (0.111/2) = 0.976. It may be noted that in this model also, the Q^2 (15) statistics suggests the standardized residuals are non-linearly independent. The insignificant LM statistic suggests that the model is well specified. The probability values of joint tests statistics for sign and size bias tests are insignificant, suggesting there is no sign and size bias.

Finally, the last column of Table 3 presents the result of asymmetric component GARCH (1, 1) model. In this model also, all the parameters are statistically significant. The asymmetric parameter γ is positive and significant, indicating transitory leverage effect in the conditional variance equation. From this model, it can be seen that the short-run volatility persistence is 83% and the long-run persistence level is 99% which is close to but less than 1, clearly implying that the transitory component decays more quickly than the permanent component and that the long run component converges very slowly to the steady state. The model is well-specified based on all the residual based diagnostic tests. However, based on the value of log likelihood and also the AIC and SBC, the EGARCH (1, 1) model seems to be the best fitted model among all the models tested. The estimated volatility series of the EGARCH model is then compared with the realized volatility* series by taking the weekly and monthly averages. Figure 3 presents the results of the comparison of weekly and monthly realized volatilities with the conditional volatility. The figures clearly indicate that both weekly and monthly realized volatilities are analogous to the weekly and monthly conditional volatility respectively. This also implies that the estimated EGARCH model is well fitted to the data.

* We calculated the weekly and monthly realized volatility of daily CNX Nifty return using the formula RV= $\sqrt{\sum_{n=1}^{N} Rt_{n,t}^2}$ multiplied by the square root of number of trading days. Where, Rt is log return and N is number of trading days in a week or month. We considered 5 trading days for a week and 21 trading days for a month.

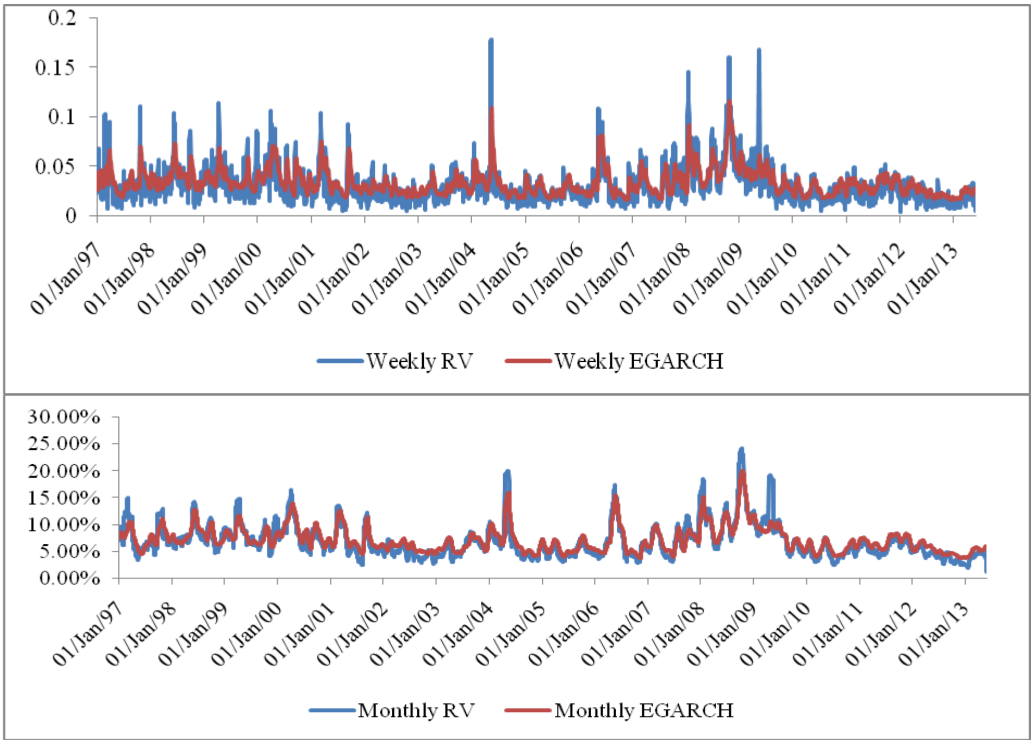

Figure 3: Comparison of realized volatility and conditional volatility (EGARCH)

Our findings suggest that the conditional variance is an asymmetric function of past innovations, supporting the leverage effect hypothesis. The results are consistent with the findings of Karmakar (2007), Mohanty (2009), and Krishnan and Mukherjee (2010) for Indian stock markets. However, this finding is contradictory to studies which documented no asymmetric volatility, based on other emerging markets (See, Rousan & Al-Khouri (2005), Mum *et al.* (2008), Oskooe and Shamsavari (2011). It seems that the investors in the Indian stock market are more risk averse and more sensitive towards the negative news rather than positive news.

Now, moving on to the next part of our analysis i.e., the effect of contemporaneous trading volumes on return volatility, we include trading volume in the volatility equation as an exogenous variable. The results are reported in Table 4. It is clear from the table that all the estimated parameters from all the four volatility models are statistically significant. Once again, it is evident that the asymmetric parameter is statistically significant and, as expected, has negative and positive signs for EGARCH and GJR GARCH respectively, indicating the existence of the leverage effect. The short run leverage effect is also found to be significant. The parameter θ, representing the contemporaneous trading volume, is found to be positive and statistically significant at 1% level in all the four models. These findings suggest that contemporaneous volume has a positive and significant impact on volatility. These findings consistent with the argument of Mixture of Distribution Hypothesis (MDH). The insignificant values of LB-Q^2 (15) and LM (15) statistics and the insignificant coefficients of sign and size bias tests due to Engle and Ng (1993) show the models are correctly specified. Here too, we can see that the EGARCH model performs best among the four models considered (See the LL stat and the AIC, SBC criteria). The findings of positive contemporaneous relationship between volume and volatility is consistent with many previous studies conducted for developed markets (e.g. Lamoureux & Lastrapes, 1990; Andersen, 1996; Brailsford, 1996 among others) as well as some studies conducted for emerging markets (e.g. Wang *et al.*, 2005; Bohl & Henke, 2003; Alsubaie & Najand, 2009 among others).

Table 4: Parameter estimation of volatility model with trading volume augmented

Parameters	GARCH (1, 1)	EGARCH (1, 1)	GJR GARCH (1, 1)	Asymmetric CGARCH (1, 1)
ω	3.59E-06 [98.14]**	-0.468 [-8.88]***	3.83E-06 [1.97]**	0.0008 [0.29]
α	0.112 [6.598]***	0.220 [12.92]***	0.079 [2.42]**	-0.068 [-2.71]***
β	0.881 [72.29]***	0.964 [168.06]***	0.874 [51.89]***	0.802 [11.51]***
Volatility Persistence	99%	96%	99%	81%, 99%
γ		-0.087 [-7.70]***	0.077 [1.92]*	0.168 [4.81]***
ρ				0.997 [132.73]***
ϕ				0.083 [6.10]***
θ	3.25E-05 [1472.03]***	0.157 [7.61]***	2.96E-05 [14.85]***	0.000026 [376.01]***
Log Likelihood	11527.01	11626.56	11543.11	11548.02
Q(15)	62.25 (0.00)	62.718 (0.00)	63.168 (0.00)	64.033 (0.00)
Q^2(15)	8.55 (0.89)	4.168 (0.99)	6.029 (0.97)	7.162 (0.95)
AIC	-5.624	-5.672	-5.631	-5.633
SBC	-5.616	-5.661	-5.622	-5.621
LM(15) for ARCH effect	8.232 (0.91)	4.203 (0.99)	6.160 (0.97)	6.913 (0.96)
Sign bias test	-0.028 [-0.25] (0.79)	0.105 [1.35] (0.17)	0.050 [0.42] (0.66)	0.230 [2.040] (0.04)
-ve Size bias test	-0.182 [-2.43] (0.01)	-0.033 [-0.40] (0.68)	-0.047 [-0.59] (0.55)	-0.033 [-0.44] (0.65)
+ve Size bias test	-0.170 [-2.01] (0.04)	-0.083 [-0.94] (0.34)	-0.120 [-1.39] (0.16)	-0.026 [-0.32] (0.74)
Joint LM test	20.44	3.619	7.51	14.45
Probability value χ^2	(0.000)	(0.30)	(0.057)	(0.002)

Note: *, ** and *** indicate statistical significant at 0.10, 0.05 and 0.01 level respectively. T-statistics are in brackets and p-values are in parenthesis. SBC: Schwarz Bayesian Criterion, AIC: Akaike Information Criterion and LM: Lagrange Multiplier Daily price data is obtained from NSE India ranging from 02/01/1997 to 30/05/2013

However, it should be noted that the level of volatility persistence remains significant even after including trading volume in the volatility equations. In fact, the magnitude of volatility slightly increased (See Table 3 and 3 for the comparison) for GARCH, EGARCH and GJR-GARCH models. The value of α + β = 0.993 in the GARCH model, the value of β = 0.964 in EGARCH model, and the value of (α+β+γ/2) = 0.991for GJR GARCH model, that represents the level of volatility persistence indicating the evidence of high volatility persistence. In the asymmetric CGARCH model however, the short-run volatility persistence slightly reduced (from 83% to 81%) after including volume but did not vanish. This indicates that though there is a positive relationship between volume and volatility, the trading volume might not fully capture the rate of information. One reason may be the fact that in India, the trading volume is dominated by the large institutional investors, who might react more to the market fluctuations, and trade accordingly. This finding is inconsistent with Lamoureux and Lastrapes (1990) who strongly argue that the volatility or the GARCH effect vanishes after incorporating trading volume in the variance equation. Our finding is, however, consistent with Sharma *et al.* (1996); Huang and Yang (2001); Ahmed *et al.* (2005); Sabbaghi (2011) and also with Mahajan and Shing (2009) who document that the level of volatility persistence remains significant even after inclusion of trading volume in the variance equation.

4. SUMMARY AND CONCLUSIONS

This study revisits the relationship between trading volume and equity market volatility in an emerging stock market namely India, employing GARCH, EGARCH and GJR-GARCH models, and verifies the implication of Mixture of Distribution Hypothesis. By doing so, it also verifies whether the level of volatility persistence is reduced after considering the trading volume. In addition, it also uses an asymmetric Component GARCH model to decompose the short-run and long-run volatility components using the recent daily data of NSE CNX Nifty Index. The analysis begins by examining the asymmetric nature of equity market volatility and then contemporaneous trading volume is augmented in the variance equations to compare the level of volatility persistence and the volume-volatility relationship. The analysis shows that the National Stock Exchange of India is sensitive to information arrival into the market. Our empirical results confirm that there is substantial volatility asymmetry in this market. More specifically, our finding are summarised as follows.

The asymmetric Component GARCH model indicates the existence of transitory leverage effects. It is found that the transitory components start bigger but die out relatively faster than the long-run components which decay very slowly and are dominant. While estimating EGARCH (1, 1) and GJR-GARCH models, the former is found to be best suited to the data than the latter. The estimated log likelihood statistics of EGARCH model indicate that this model outperforms all the other models tested in this study. The results show that the conditional variance is an asymmetric function of past innovation, where negative shocks cause more volatility than positive shocks of the same magnitude. This may be due to the fact that investors in the Indian equity market have more aversion to downside risk thereby reacting faster to bad news.

Regarding the trading volume and volatility relationship, it is found that contemporaneous trading volumes are significantly and positively related to stock return volatility, confirming the validity of MDH. The study also reveals that the level of volatility persistence remains high even after including the trading volume as an explanatory variable in the volatility model. However, when the volatility is decomposed into short-run and long run components using CGARCH model, the inclusion of trading volume as an exogenous variable slightly reduce the level of volatility persistence.

It can be concluded that while the current trading volume significantly explain the stock return volatility, the trading volume may not be the only source of GARCH effect in the Indian stock market. The present study is limited to the low frequency daily data that are publicly available. Considering the intra-day data with higher frequency and other variable such as bid-ask spread and overnight indicators to proxy for rate of information, may improve the results. Further, the study can be extended by considering individual stocks and comparing with the market indices.

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