Volatility, Open Interest and Trading Volume: Evidence from Indian Capital Market

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ABSTRACT:

This study investigates the relationship between daily returns, Open Interest and trading volume for Nifty, an Index of National stock exchange of India. Study findings reveal that GARCH model is an appropriate model to forecast the volatility. The study finds that the persistency of volatility is very high and very less than the unity, implying that current information can be used to predict future volatility. When open interest and trading volume is included in the analysis, the study reveals that the persistency of the volatility is present. The decomposition of volume into expected and unexpected components indicates that the expected component of volume significantly changes in volatility.

Introduction:

The relationship between asset returns, open interest and trading volume appear to be leptokurtic and highly persistent. It helps to understand the structure of financial markets not only in the terms of information arrivals but also the dissemination of this information among the participants. This relationship has significant implications for derivatives pricing. Our study will extend the empirical literature on the relation between the conditional volatility of asset return, open interest and trading volume. The study contains the following. First, it examines the relation between trading volume open interest and conditional volatility in a rapidly developing emerging market and provides evidence on the price discovery by examining the CNX nifty, which is 50 stock index of National stock exchange of India. Second, this study uses the data on aggregate basis. Third, it explores whether the effect of trading activity on volatility is homogeneous by dividing activity into its expected and unexpected components and allowing each component to have a separate effect on observed price volatility. The study also shows that the presence of persistency of conditional volatility smaller than unity. This would imply that current information can be used in predicting future volatility. We did not find any leverage effect, and this result is not similar with those results where leverage effect was present.

Review of Literature:

Bessembinder and Seguin (1992) examined that the greater futures trading activity volume and open interest are associated with greater equity volatility. They found that active futures markets are associated with decreased rather than increased volatility and a positive relationship between equity volatility, contemporaneous trading volumes in the spot equity and equity futures market. Donders, Kouwenberg and Vorst (2000) studied the impact of earnings announcements on implied volatility, trading volume, open interest and spreads in the stock options market. They find that implied volatility increases before announcement days and drops afterwards. Also option trading volume is higher around announcement days. During the days before the announcement open interest tends to increase, while it returns to regular levels afterwards. Changes in the quoted spread largely respond to higher trading volume and changes in implied volatility. The effective spread increases on the event day and on the first two days following the earnings announcement.
Board and Sandmann & Sutcliffe, (2001) applied the hypothesis that the higher is the volume in the futures market, the greater is the destabilizing effect on the stock market. Their result shows that, contemporaneous information less futures market trading has no significant effect on spot market volatility.

Bohl and Henke (2003) shows support for the Polish stock market, they reported that volatility persistence tends to disappear when trading volume is included in the conditional variance in their study of Polish stock market.

Girard and Biswas (2007) investigate the relation between volatility and volume in 22 developed markets and 27 emerging markets. Compared to developed markets, emerging markets show a greater response to large information shocks and exhibit greater sensitivity to unexpected volume. They found that negative relation between expected volume and volatility in several emerging markets, which can be attributed to the relative inefficiency in those markets. Also they shows that when volume is decomposed into expected and unexpected components, volatility persistence decreases.

Pati and Kumar (2007) examine the volatility dynamics and investigates the Samuelson Maturity Hypothesis, a source of non-stationary in the volatility of futures price, in the context of the Indian Futures Market. They concluded that that time-to-maturity is not a strong determinant of futures price volatility, but the rate of information arrival proxied by volume and open interest are the important sources of volatility.

Deo, Srinivasan and Devanadhen (2008) examine the empirical relationship between stock return, trading volume and volatility for select Asia-Pacific Stock Market. They suggest that the returns are influenced by volume and volume is influenced by returns for most of the markets. Therefore, trading volume contributes some information to the return and volatility for determining contemporaneous and lagged volume effect after incorporation.

Vipul (2008) examined the Interdependence of the mispricing, volatility, volume and open interest of stock futures and the volatility and volume of their underlying shares. The results are evidence of significant mispricing that persists for one day but is not explained by other variables. An increase in the volatility of futures is generally followed by an increase in the volatility of the underlying. The volatility and volume of futures and the underlying exhibit alternating increase/decrease cycles with up to five–day lags. These properties can be very useful in forecasting the mispricing and the volatility, volume and open interest for futures and their underlying shares.

Kiymaz and Girard (2009) investigates the relationship between daily returns and trading volume for 30 stocks included in the Istanbul Stock Exchange National-30 index. Study findings reveal that GARCH model is an appropriate model to mimic the conditionality of the second moments. They found that the persistency of conditional volatility is high and very close to unity, implying that current information can be used to predict future volatility. When trading volume is included in the analysis, the study finds that even though the persistence of the conditional volatility is present, it is lower with the introduction of volume. Also they concluded that the decomposition of volume into expected and unexpected components shows that the expected component of volume significantly explains the variation in volatility.

Pati and Rajib (2010) estimate time-varying conditional volatility, and examine the extent to which trading volume, as a proxy for information arrival, explain the persistence of futures market volatility using National Stock Exchange S&P CRISIL NSE Index Nifty index futures. They found that the evidence of leverage effect, which indicates that negative shocks increase the futures market volatility more than positive shocks of the same magnitude. In addition, the results indicate that inclusion of both contemporaneous and lagged trading volume in the GARCH model reduces the persistence in volatility, but contemporaneous volume provides a greater reduction than lagged volume. Nevertheless, the GARCH effect does not completely vanish.

Gulati, (2012) examines the relationship between closing price and open interest in Indian stock index futures market. The results show that the information of open interest can be used to predict future prices in the long run. Moreover, the long-run information role of open interest is a good indicator for the usefulness of a technical analysis in markets.
Gębka B. (2012), investigates the dynamic relationship between index returns, return volatility, and trading volume for eight Asian markets and the US. We find cross-border spillovers in returns to be non-existent, spillovers in absolute returns between Asia and the US to be strong in both directions, and spillovers in volatility to run from Asia to the US. Trading volume, especially on the Asian markets, depends on shocks in domestic and foreign returns as well as on volatility, especially those shocks originating in the US. Author found that the intensity of cross-border spillovers seems to have increased following the 1997 crisis, which we interpret as evidence of increased noisiness in prices and diversity in opinions about news originating abroad. Our findings might also help to understand the nature of financial crises, to predict their further developments and consequences.

DATA and METHODOLOGY:

The data consists of the daily prices return, open interest and trading volumes of future contract in CNX Nifty index of National stock exchange. The data spanning from 1st April 2001 to 31st March 2011. The return R_t of nifty were calculated from following formula.

\[ R_t = 100 \left( \log (P_t - P_{t-1}) \right) \]

where, \( P_t \) is the closing price of nifty at time \( t \).

To assess the statistical properties of the daily returns of nifty are reported in Table 1. The total number of observations was 3254. The mean of daily return is 0.050817 and the standard deviation was found 1.729893. The time series was negatively skewed in Nifty. Returns shows the evidence of fat tails in whole period, since the kurtosis exceeds three, which was the normal value, while the problem of leptokurtosis was arise and Jarque bera test also following the non normality distribution. After arising the problem of leptokurtosis, time series are subject to check the stationarity. For this purpose we applied the augmented dickey fuller test. The Dickey fuller test applied on the return series of the spot CNX S&P Nifty Index. The hypothesis developed by Kapetanios et al. (2003) of non-stationary series was used against stationary non-linear alternatives. The established hypotheses are as follows:

- **H_0**: \( \delta = 0 \), (that time series do not show any stationary effect at given level of significance)
- **H_1**: \( \delta < 0 \): (that time series shows the stationary effect at given level of significance)

After complete analysis of table 2, it was clear that time series does not show any stationarity at levelled analysis of augmented dickey fuller test, and accept the null hypothesis that time series were non stationary at levelled analysis and accepts the alternate hypothesis that time series are stationary at levelled analysis. At first difference (lag) time series were found to be stationary.

We used the GARCH (1,1) model which is symmetric in nature. We used this model because we were not interested in the asymmetric characteristics of the GARCH type model. The GARCH (1,1) model gives us space to understand the leptokurtosis and skewness which indicate the departure from normality of the data. We formulate our model GARCH (1, 1) is as follows:

**Mean Equation**

\[ Y_t = \alpha_0 + \alpha_1 X_t + \varepsilon_t \]

where, \( \varepsilon/Y_{t-1} \sim N (0, \sigma^2_t) \)………………..1

**Variance equation**

\[ \sigma^2_t = \beta_0 + \Sigma_{j=1}^p \beta_1 \varepsilon_{t-1}^2 + \Sigma_{j=1}^q \beta_2 \sigma_{t-j}^2 + \gamma_0 D \]………………..2

Where, \( R_t \) is the return of the stock, \( \sigma^2_t \) is the conditional variance at time \( t \). \( \varepsilon^2_{t-1} \) is the squared residual of previous day from mean equation, it is an ARCH term and explain the volatility clustering and the \( \sigma^2_{t-j} \) is a forecasted variance of previous day, it is a GARCH term. We have added an dummy variable (D) in conditional variance equation, D is equal to 1 if squared residual term is lesser than zero, otherwise it was treated as zero. This was taken because if squared residual is lesser than zero than good news have greater impact on the conditional variance otherwise bad news have impact on the conditional variance equation. Although we were not interested in the leverage effect. The persistence
of volatility will be determined by the addition of ARCH and GARCH term. If the addition of $\beta_1$ and $\beta_2$ equals to one then shocks will remain long lasting in conditional future variance. If there addition is greater than one, than volatility will be explosive and if it is lesser than one, than shocks of news will be decayed with time.

We measured derivatives trading activity by open interest and volume for all players of the market either hedgers, or speculators or arbitrager. Hedgers and speculators also called informed and uninformed traders, respectively. The background for this approximation was found in the traders characteristic, that the vast majority of speculators are day-traders who do not hold open positions overnight. Hence, the data for open interest, which indicates the number of open contracts as of the end of a trading day, it reflects the derivatives trading activity primarily used for hedging. Thus, volume in combination with open interest was taken as the indication of trading activities of speculators. We have added the implications of the volume and open interest in our equation. We assumed that daily information arrival is serially correlated and formulated a model by adding volume and open interest in the conditional variance equation.

Mean Equation

$$Y_t = a_0 + a_1 X_t + \varepsilon_t, \quad \text{where, } \varepsilon_t \sim N(0, \sigma_t^2)$$

Variance equation

$$\sigma_t^2 = \beta_0 + \beta_1 \varepsilon_{t-1}^2 + \beta_2 \sigma_{t-1}^2 + \delta_0 \text{OI}_{t-1} + \delta_1 \text{VOL}_{t-1}$$

VOL$_{t-1}$, OI$_{t-1}$ is the trading volume and open interest respectively. In this study we tried to examine whether surprises in trading activity whether convey more information or not. If it convey, then there is larger effect on price than forecasting. Trading volume which is serially correlated then it is highly forecast-able. In an efficient market, the importance of unexpected activity in trading is greater. For this purpose we have applied ARMA (p,q) processes to divide the trading activity into expected and unexpected components.

$$\text{VOL}_t = \delta_0 + \delta_1 \text{VOL}_{t-1} + \delta_2 \varepsilon_{t-1} + \varepsilon_t$$

$$\text{OI}_t = \delta_0 + \delta_1 \text{OI}_{t-1} + \delta_2 \varepsilon_{t-1} + \varepsilon_t$$

With the actual and the unexpected values obtained for each variable, we have defined the expected volume and expected open interest as the difference between the two:

$$\text{EXVOL}_t = \text{VOL}_t - \text{UNEXVOL}_t$$

$$\text{EXOI}_t = \text{OI}_t - \text{UNEXOI}_t$$

Where, VOL$_t$ is the observed volume of future contract at time $t$; EXVOL$_t$ is the expected volume of future contract at time $t$; UNEXVOL$_t$ is the expected volume of future contract at time $t$.

The division into expected and unexpected trading activity of future contract gives us more convenience and more dimensions for the analysis. In the open interest, the expected portion means the open interest at the beginning of the trading day; while unexpected open interest reflects unanticipated changes in net open positions of future contracts at the end of the day. Generally expected open interest is almost equal to yesterday’s level, and unexpected open interest will be equal to the change in open interest during the trading day. By including expected and unexpected components of open interest and volume in the conditional variance equation, we try to capture responses of volatility towards new information arrival which was caused by different types of traders. This would not have been possible with only GARCH processes in the conditional mean equation. The final variance equation in ARMA-GARCH (1, 1) model is defined by following equations.

Variance equation

$$\sigma_t^2 = \beta_0 + \beta_1 \varepsilon_{t-1}^2 + \beta_2 \sigma_{t-1}^2 + \delta_2 \text{UNEXOI}_t + \delta_3 \text{EXOI}_t + \delta_4 \text{UNEXVOL}_t + \delta_5 \text{EXVOL}_t$$
Findings and Conclusion:

The findings are reported in Table 3 to Table 5. The R-square function is less than one which indicates that the GARCH model has been appropriately fitted to daily return behaviour of CNX nifty and it captures the temporal behaviour of return volatility. In Table 3 the results of GARCH (1,1) model is reported, without the trading volume and open interest. The coefficients for ARCH and GARCH term are statistically significant for CNX nifty at 5% level of significance. GARCH Coefficient is greater than ARCH coefficient which indicates, even if market surprises with bigger event then there is smaller revisions in future volatility. The persistence of the conditional volatility is measured by the addition of ARCH and GARCH term, which is smaller than one for CNX nifty. This indicates a high degree of persistence of the volatility shocks. Also it indicates that size of news is more important than the direction of market. GARCH coefficient is greater than zero confirms the stationary process was present and this implies that, we can predict the future volatility through given information.

The study then explores the effect of information flow by using open interest and trading volume of future contract as a proxy. In table 4 results of conditional variance along with trading volume and open interest are reported. Positive coefficient of trading volume and open interest leads to smaller coefficient of ARCH and GARCH. Both ARCH and GARCH terms are statically significant for CNX nifty at 5% level of significance. The persistence of the conditional volatility is measured by the addition of ARCH and GARCH term, which is smaller than one. The addition of ARCH and GARCH term is smaller with the inclusion of trading volume and open interest, than without trading volume and open interest.

Finally, we decomposed the trading volume and open interest into expected and unexpected components and investigate that, which activity (Unexpected or expected) is more important for the determination of the volatility. We decomposed trading volume and open interest into the expected and unexpected components by using an ARIMA (p,q) framework specific to each series. The proper values of this model was treated as the expected component, while the errors was used as the unexpected component.

In Table 5, the results of estimating Equation 7 are reported. First of all, the coefficient of estimates of expected volume and expected open interest are positive and statically significant and all statistically significant estimates of unexpected volume and open interest are also positive. Further, the estimated coefficients for ARCH and GARCH term are statistically significant. Further, the GARCH coefficient is still larger than ARCH implies that bigger event in market leads to smaller revisions in future volatility. Further, the results for the persistence of the conditional volatility, measured by addition of ARCH and GARCH term, is lower than one. Also it is lower than the without volume and open interest inclusion in conditional variance. The leverage coefficient is statistically significant confirming that size of the news is more important than its direction.

Regarding expected versus unexpected components of trading volume, it appears that both unexpected and expected portion is equally important. This result suggests that surprising movement in trading volume and open interest do not convey all the information related to trading volume and open interest is predictable in most of the cases. Unexpected news does not affect volatility significantly. The relationship between the expected volume, open interest and volatility was found positive, which indicates that with increase of trading activity prices may not be adjusted through speculative trading. If trading volume in the market increases, than we can expect that more information will be available in the market which, in turn, improves market efficiency and reduces uncertainty and the market volatility.

Finally, the findings of this confirm that the GARCH model is an appropriate model which imitates the conditionality of the second moments. The study also confirms that the persistency of conditional volatility is present and it is lesser than the unity, which indicates that the current information can be used to predict future volatility.
REFERENCES:


WEBSITES:
1. www.nseindia.com
2. www.moneycontrol.com
3. www.bloomberg.com
**ANNEXURES: TABLES**

**TABLE 1:**

<table>
<thead>
<tr>
<th>Company</th>
<th>Period (Count)</th>
<th>Mean</th>
<th>SD</th>
<th>Skew</th>
<th>Kurt</th>
<th>JB</th>
</tr>
</thead>
<tbody>
<tr>
<td>Nifty</td>
<td>3254</td>
<td>0.050817</td>
<td>1.729893</td>
<td>-0.22826</td>
<td>6.378880</td>
<td>1576.18936</td>
</tr>
</tbody>
</table>

Based on the data taken from NSE’s official website  
**Note:** JB Test at 5% level of significance is 7.88

**TABLE 2: Test of Stationarity with Augmented Dickey Fuller Test**

*based on the data taken from NSE’s official website

<table>
<thead>
<tr>
<th>ADF Levelled</th>
<th>ADF 1st Difference</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Lag Length</td>
</tr>
<tr>
<td>Nifty</td>
<td>6</td>
</tr>
</tbody>
</table>

**Notes:** for t-stat: at 1% level; 5% level, at 10% level,  
For p value: at 1% level is 0.01; 5% level is 0.05, at 10% level is 0.1

**TABLE 3 ESTIMATES OF GARCH (1, 1) MODEL WITH FUTURE DUMMY**

<table>
<thead>
<tr>
<th>Mean Equation</th>
<th>Variance Equation</th>
</tr>
</thead>
<tbody>
<tr>
<td>α₀</td>
<td>α₁</td>
</tr>
<tr>
<td>- 0.00119</td>
<td>0.65888 (55.633)</td>
</tr>
</tbody>
</table>

**TABLE 4 ESTIMATES OF GARCH (1, 1) MODEL WITH FUTURE VOLUME AND OPEN INTREST**

<table>
<thead>
<tr>
<th>Mean Equation</th>
<th>Variance Equation</th>
</tr>
</thead>
<tbody>
<tr>
<td>α₀</td>
<td>α₁</td>
</tr>
<tr>
<td>- 0.00099</td>
<td>0.3913 (49.67)</td>
</tr>
</tbody>
</table>

**TABLE 5 ESTIMATES OF GARCH (1, 1) MODEL WITH FUTURE VOLUME AND OPEN INTREST UNEXPECTED AND EXPECTED COMPONENTS**

<table>
<thead>
<tr>
<th>Mean Equation</th>
<th>Variance Equation</th>
</tr>
</thead>
<tbody>
<tr>
<td>α₀</td>
<td>α₁</td>
</tr>
<tr>
<td>- 0.00122</td>
<td>0.60414 (22.158)</td>
</tr>
</tbody>
</table>