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# Stock returns and trading volume: does the size matter?

## Abstract

The main theme of the paper is to analyze whether the size has any effect on stock return-volume relationship. The study examines the dynamic relationship between returns and trading volume. The paper also examines the duration of impact of stock returns on trading volume and the trading volume on stock returns and the impact of size on stock returns volume relationship. Further, the study also looks at the role of the trading volume in predicting the returns and the role of returns in predicting the trading volume. The study has employed the VAR (Vector Auto Regression) framework for the analysis along with Granger Causality/Block Exogeneity Wald Tests, impulse response function and variance decomposition analysis. The study shows that the returns cause the trading volume. However, as size of the firm decreases, there is bidirectional causality between returns and volume. In the post subprime crisis period the causal relationship between returns and volume is almost nonexistent. The duration of impact is more prominent as the size of the firm becomes smaller. The study also shows that size of the firm does not have an impact on the information content of stock returns and trading volume. Stock returns dominate trading volume in term of information content. The information content of stock returns and trading volume increases during crisis period. The study also shows that Indian stock market is more efficient after the subprime crisis.

**Keywords:** trading volume, VAR (vector auto regression), GCBEW (Granger Causality/Block Exogeneity Wald tests), impulse response function and variance decomposition analysis.
**JEL Classification:** C32, C58, G12, G14.

## Introduction

Price-volume relationship has been widely debated among the academia and stock market practitioners. Karpov (1987) provides a detailed literature survey of price-volume relationship literature. The contribution is summarized as follows. First, the stock returns volatility-volume relationship depends upon the rate of information flow to the market, information dissemination, market size, and the existence of short sale constraints. Second, the price-volume relationship has implications for event studies. Third, the relationship throws light into the empirical distribution of speculative assets.

The price-volume dynamic relationship has also examined in various markets and mixed results are seen in the literature. Moosa and Al-Loughani (1995) focus on the price volume relationship in the emerging Asian stock markets and show that casual relationship exists between volume to price and not from price to volume. Basci et al. (1996) examine the price volume relationship on Istanbul stock exchange and suggests that there exists a long-term relationship or cointegration between price and trading volume. Hiemstra and Jones (1994) and Malliaris and Urrutia (1998), show a bidirectional lead-lag relation between returns and volume. Saatcioglu and Starks (1998) examines the stock price-volume relation in a set of Latin American markets using VAR model and find that trading volume lead stock returns which is contrary to the developed markets. Lee and Rui (2000) report that volume does not predict the next day's index returns on the Chinese A and B markets in Shanghai and Shenzhen. Lee and Swaminathan (2000) and Gervais et al. (2001) find that past trading volume contains valuable information about future stock returns. Chen et al. (2001) report no causal link between price and volume in France, Italy, Japan, the UK or the US. Lee and Rui (2002) examine the dynamic causal relationship between trading volume and stock returns in the US, Japan and the UK stock markets and find that trading volume does not Granger-cause stock market returns on each of the markets. Statman et al. (2006) use monthly data from the NYSE/AMEX and provide evidence that trading activity is positively related to lagged returns for many months. Xu et al. (2006) use a time-consistent VAR model to test the dynamic return volatility-volume relationship, and find that volatility and volume are persistent and highly correlated with past volatility and volume. Memcha and Sharma (2006) examine the link between price changes and trading volume in Indian stock market in the context of Economic liberalization and has identified that there is no significant relationship between trading volume and share prices changes. Pisedtasalasai and Gunasekarage (2007) investigate the casual and dynamic relationship among the stock returns, volatility and trading volume in five emerging stock market and find that returns can predict trading volume and trading volume has very limited impact in predicting stock returns. Rashid (2007) examine the relationship between daily stock index returns and trading volume changes in the Karachi Stock Exchange and find that volume has a significant nonlinear explanatory power for stock returns and the stock returns have linear explanatory power for trading volume. Griffin et al. (2007) find that the observation that large market-wide returns are followed by large market-wide trading volume is a global phenomenon. Kamath (2008) examines the price volume relationship in the Chilean stock market and show the clear evidence that returns Granger cause the trading volume. Chen (2008) examines the existence of linear and nonlinear casual relationship between price and volume in the Chinese market and find that there is a long-term relationship between the share price and trading volume. Kumar et al. (2009) investigate the nature of relationship between price and trading volume for Indian stock market and show that there is a weak dynamic relationship between stock returns and trading volume. Chuang et al. (2009) use quantile regressions to investigate the causal relations between stock return and volume, and show that causal effects of volume on return are usually heterogeneous across quantiles and those of return on volume are more stable. Chuang et al. (2012) identify the contemporaneous relationship between stock returns and trading volume and the causal relation from stock returns and trading volume are significant in major Asian stock markets.

The relationship between size and stock returns are also examined by number of studies. Banz (1981) first examines the impact of size on the returns of the stocks. The study shows that smaller firms have higher returns, on average, than larger firms. This size effect has led to the misspecification of capital asset pricing model. According to Campbell et al. (1997) large size stocks leads small size stocks in developed stock markets. Chordia and Swaminathan (2000) study the relationship between trading volume and predictability of short-term stock returns. They find that stock returns with high trading volume lead stock returns with low trading volume. They concluded that trading volume plays a significant role in the dissemination of market wide information. Poshakwale and Theobald (2004) study the lead lag relationship between large cap and small cap firms in an emerging market like India and find that large cap indices lead small cap indices. They find that thin trading effects and an interaction effect between thin trading and speeds of adjustment are found to make significant contributions to the lead/lag effect.

The recent global financial crisis shows that none of the emerging markets are insulated from in negative shocks. IMF (2008) argues that the global financial crisis could have a significantly larger impact on Asian economies than earlier global downturns, because of more extensive trade and financial integration with the United States. Furthermore, Hong et al. (2010) show that the earlier worldwide financial crises often had overwhelming impacts on the Asian economies. Moreover, Griffin et al. (2007) argue that the return- and volatility-volume relations should be stronger in less efficient markets such as emerging markets, where presumably information is incorporated in price more sluggishly.

In the literature there are studies on price-volume relationship. There are also studies on the relationship between size and stock returns. Few studies explore the lead lag relationship between large size and small size stocks. However, there is a research gap whether the size has any effect on price-volume relationship. The contribution of this paper is threefold. First, examine the role of size in the dynamic linkages between returns and trading volume. Second, analyze the role of size in the price-volume relationship in terms of market efficiency. Finally, the study examines the role of size in the price volume relationship in an emerging market like India during a crash period like subprime crisis. The remainder of this paper is organized as follows. Section 1 explains data and methodology. Section 2 discusses the results and the final section concludes the paper.

## 1. Data and methodology

**1.1. Data.** Data has been collected from National Stock Exchange of India (NSE) one of the premier stock exchange in India. The study has used S&P CNX Nifty, Nifty Junior and Nifty Midcap, indices as proxies for capturing the size effect. The closing price and volume data are considered for the analysis. Nifty and Nifty Junior indices data consists of 3778 daily observations from January 1997 to 2012 January. Nifty Midcap index data consists of 2028 observation from January 2004 to 2012. For testing the robustness of results, the entire data set is classified into three sub categories; period 1 (pre-crisis period), period 2 (crisis period), period 3 (post-crisis period). The pre-crisis period ranges from 01-01-1997 to 30-11-07, crisis period ranges from 03-12-07 to 29-05-09 and the post crisis period ranges from 01-06-09 to 17-02-12.

**1.2. Methodology.** The study has employed the VAR (vector auto regression) framework for the analysis. It helps to identify the dynamic structure of time series variable. It is considered to be more flexible and easy to generalize even though it provides little theoretical information about the relationship among the variable. This methodology was popularized by Sims (1980). The present study has used bivariate VAR, where there only two variables $y_{1t}$ and $y_{2t}$:

$$y_{1t} = \beta_{10} + \beta_{11} y_{1t-1} + ... + \beta_{1k} y_{1t-k} + \alpha_{11} y_{2t-1} + ... + \alpha_{1k} y_{2t} - k + u_{1t},$$
$$y_{2t} = \beta_{20} + \beta_{21} y_{2t-1} + ... + \beta_{2k} y_{2t-k} + \alpha_{21} y_{1t-1} + ... + \alpha_{2k} y_{1t} - k + u_{2t}, \quad (1)$$

where $u_{it}$ is a white noise disturbance term with $E(u_{it}) = 0$, $(i = 1,2)$, $E(u_{1t}\, u_{2t}) = 0$.

For the successful implementation of VAR system the concerned time series data should be stationary in nature. Otherwise it may bring out the spurious relationships among the variables and its relationships. Generally, data obtained from stock market is not stationary. So before precedes to any econometric analysis it essential to confirm the stationarity of the series. On the other hand, there are many tests to understand the stationarity of the series. The present study has used both Augmented Dickey Fuller test and Phillips-Perron test to determine the stationarity of the series.

**1.3. Augmented Dickey-Fuller test.** Augmented Dickey Fuller is a variant of Dickey-Fuller test which is used when $u_t$ is correlated. This test is conducted by adding the lagged values of the dependent variable $\Delta Y_t$ or it absorbs the possible serial correlation in the error term $u_t$.

$$\Delta Y_t = \beta_1 + \beta_2 t + \delta Y_{t-1} + \sum_{i=1}^{m} \alpha_i \Delta Y_{t-i} + \varepsilon_t, \quad (2)$$

where $\varepsilon_t$ is error term and $\Delta Y_{t-1} = (Y_{t-1} - Y_{t-2})$, $\Delta Y_{t-2} = (Y_{t-2} - Y_{t-3})$.

**1.4. Phillips-Perron test.** This test also examines the stationarity of the time series data. It examines the stationary without adding the lagged values of the variables. It uses non parametric statistical methods to capture serial correlation in the error terms.

The study also has used both sequential modified LR test statistic and information based criteria such as final prediction error (FPE), Akaike information criterion (AIC), Schwarz information criterion (SC), Hannan-Quinn information criterion (HQ) for the selection of optimal lag length. A model will be insignificant if the lag length is too small or too large.

**1.5. Granger Causality/Block Exogeneity Wald tests.** VAR Granger Causality/Block Exogeneity Wald Tests (GCBEW) examines whether the lags of excluded variable affects the endogenous variable. The present study contains two variables such as return and trading volume. The GCBEW test helps to investigate the causality between these two variables. It helps to identify whether the lags of one variable cause the lags of another variable in a VAR model. It never explains when the change will take place because of the change in the other lagged variable. It provides simple causality among the variable not the time of change or the effect of change.

**1.6. Impulse response and variance decomposition.** *1.6.1. Impulse response analysis.* Impulse response traces out the responsiveness of the dependent variable in the VAR to shocks to each of the variable (Brooks, 2008). It plots the response of a variable against the shock during a particular period of time. It identifies the response of other variable due to a shock during a particular period of time.

*1.6.2. Variance decomposition analysis.* Variance decomposition or forecast error variance decomposition shows the amount of information each variable contribute the other variable in a VAR model. Variance decomposition gives the proportion of movements in the dependent variables that are due to their own shock and shock to the other variables in the system (Brooks, 2008). The study also conducts the Hasbrouck (1995) information share to understand the proportional contribution of that market to price innovation variance

## 2. Results and discussion

**2.1. Unit root test.** The present study has used both Augmented Dickey-Fuller (ADF) test and Phillips-Perron (PP) test for the test of stationarity. Table 1 reports the stationary results of S&P CNX Nifty, Nifty Junior, CNX Nifty Midcap and its three sub periods. The test has included two variables such as stock price and trading volume. The test reveals that variable stock price is non stationary at 1% level. ADF tests show that the trading volume variables during the whole sample period and sub period 2 have shown non stationarity but during the sub period one and three, the variables have shown stationary results. However, PP test shows that stock price is non stationary and the trading volume stationary during the whole sample period and three of its sub periods. According to ADF and PP test the Nifty Junior price data has shown non stationarity at 1% level. However, both these tests have shown that the entire series of trading volume are stationary at levels. According to ADF and PP tests the CNX Nifty Midcap price has shown non stationarity at 1% level. It should be noted that the variable trading volume has shown stationarity at levels. Thus study has used first difference of stock prices (stock returns) to ensure the stationarity of the different price series. It should be noted that some of the series of trading volume has shown stationarity at levels itself except the subprime crisis.

Table 1. Unit root test – S&P CNX Nifty

| Series | Period | Augmented Dickey-Fuller test | | Phillips-Perron test | |
|---|---|---|---|---|---|
| | | Price | Trading volume | Price | Trading volume |
| Nifty | Whole sample | -0.500032 | -2.618161 | -0.465309 | -13.16296*** |
| | Period 1 | 3.136196 | -3.732829*** | 3.122994 | -17.30897*** |
| | Period 2 | -1.673517 | -1.248540 | -1.673465 | -5.980261*** |
| | Period 3 | -2.096950 | -4.61645*** | -2.130477 | -10.39487*** |
| Nifty Junior | Whole sample | -0.680230 | -11.34751*** | -0.607939 | -11.34751*** |
| | Period 1 | 2.212544 | -3.732829*** | 2.363913 | -8.620465*** |
| | Period 2 | -1.954717 | -6.082148*** | -1.892462 | -9.600985*** |
| | Period 3 | -2.205401 | -4.723452*** | -2.134024 | -8.071615*** |
| Nifty Midcap | Whole sample | -1.908587 | -3.558898*** | -1.898561 | -12.51584*** |
| | Period 1 | 1.769978 | -2.922416*** | 1.796970 | -17.30897*** |
| | Period 2 | -3.106545 | -3.307488*** | -2.875938 | -6.393274*** |
| | Period 3 | -1.785117 | -3.127088*** | -1.751239 | -8.632497*** |

Notes: *** Significant at 1% level; ** significant at 5% level; * significant at 10% level.

**2.2. VAR Granger Causality/Block Exogeneity Wald tests.** VAR Granger Causality/Block Exogeneity Wald Tests examine the bidirectional causal relationship between trading volume and stock returns. Table 2 shows the GCBEW (Granger Causality/Block Exogeneity Wald test) for S&P CNX Nifty, Nifty Junior, Nifty Midcap and three of its sub periods. In the case of Nifty, the study has identified that during the whole sample period the trading volume does not affect the return but the return does affect the trading volume. During the pre-crisis period, volume causes return and during crisis period, return causes volume. Finally, post crisis, there is no causal relationship between returns and volume.

Table 2. VAR Granger Causality/Block Exogeneity Wald test – Nifty

| | Series | Depended variable | Excluded variable | Chi-square |
|---|---|---|---|---|
| Nifty | Whole sample | RETURN | VOLUME | 0.74564 |
| | | VOLUME | RETURN | 109.0052*** |
| | Period 1 | RETURN | VOLUME | 4.981976* |
| | | VOLUME | RETURN | 1.310019 |
| | Period 2 | RETURN | VOLUME | 0.222017 |
| | | VOLUME | RETURN | 46.41563*** |
| | Period 3 | RETURN | VOLUME | 1.347007 |
| | | VOLUME | RETURN | 0.054195 |
| Nifty Junior | Whole sample | RETURN | VOLUME | 5.281379* |
| | | VOLUME | RETURN | 62.76756*** |
| | Period 1 | RETURN | VOLUME | 4.677765* |
| | | VOLUME | RETURN | 5.980757* |
| | Period 2 | RETURN | VOLUME | 0.953480 |
| | | VOLUME | RETURN | 26.96603*** |
| | Period 3 | RETURN | VOLUME | 2.387904 |
| | | VOLUME | RETURN | 1.227076 |
| Nifty Midcap | Whole sample | RETURN | VOLUME | 20.89436*** |
| | | VOLUME | RETURN | 57.00623*** |
| | Period 1 | RETURN | VOLUME | 12.87808*** |
| | | VOLUME | RETURN | 9.015761** |
| | Period 2 | RETURN | VOLUME | 6.533687** |
| | | VOLUME | RETURN | 24.18280*** |
| | Period 3 | RETURN | VOLUME | 5.082183* |
| | | VOLUME | RETURN | 3.643902 |

Notes: *** Significant at 1% level; ** significant at 5% level; * significant at 10% level.

Nifty junior index shows that bidirectional causality exists between return and trading volume during the whole sample period and pre-crisis period. During the crisis period the return causes volume. However, there is no causal relationship between return and trading volume during post crisis period. Nifty Midcap index shows the existence of causal relationship between trading volume and stock returns during the whole sample period, pre-crisis and crisis period. However, during post crisis period, there is unidirectional causality from volume to return which is significant at 10% level.

VAR Granger Causality/Block Exogeneity Wald test has shown that, in most of the cases the significance of causal relationship increases when the size of the stock decreases. It should be noted that the size has an impact on price trading volume relationship. After the subprime crisis, the bidirectional causality has disappeared from the smaller sized stocks. During the pre crisis and crisis period, both the variables have shown causal relationship. This indicates that both the variables have relevant information content. Moreover, it is a sign of market inefficiency. However, post crisis period shows lack of causality and greater market efficiency. In order to get a detailed insight the study focuses on impulse response functions and variance decomposition analysis.

**2.3. Impulse response function.** Impulse response function identify the response of variables due shock in VAR system during a particular period of time. The horizontal axis shows the time frame and the vertical axis shows the percentage points or the impact of one variable over the other variable over time.

*2.3.1. S&P CNX Nifty. 2.3.1.1. S&P CNX Nifty – whole sample period.* Figure 1 to Figure 8 shows the impulse response function for S&P CNX Nifty and its sub periods. Figure 1 and Figure 2 show the impact of trading volume on return and return on trading volume respectively. Trading volume has a slight positive impact on the return and it is difficult to understand the period of impact. Figure 2 shows that return has positive influence trading volume but during the second day it shows a high impact and thereafter it decreases.

*2.3.1.2. S&P CNX Nifty – sub period 1.* Figure 3 and Figure 4 show impulse response result of Nifty for pre-crisis period. Figure 3 shows that volume has a positive impact on return and volume has significant impact on second day. However, Figure 4 shows that the returns have insignificant impact on trading volume.

*2.3.1.3. S&P CNX Nifty – sub period 2.* Figure 5 and Figure 6 show impulse response analysis result of Nifty for the crisis period. Figure 5 shows the impact of trading volume on return. It shows that volume has slight negative effect on return. Figure 6 shows that return has a positive impact on trading volume because impulse response is positive. The impact of return on volume is increasing and reaches maximum at second day and decreases after that.

*2.3.1.4. S&P CNX Nifty – sub period 3.* Figure 7 and Figure 8 show impulse response analysis result of Nifty for the post-crisis period. Figure 7 shows the impact of trading volume on return. It shows a negative tendency from the second day onwards and slowly goes up from the third day and then becomes insignificant. Figure 8 shows the impact of return on trading volume. It shows that the return does not have much impact on volume. The impulse response function shows that both volume and return have a high impact on each other for a short period of time and subsides thereafter.

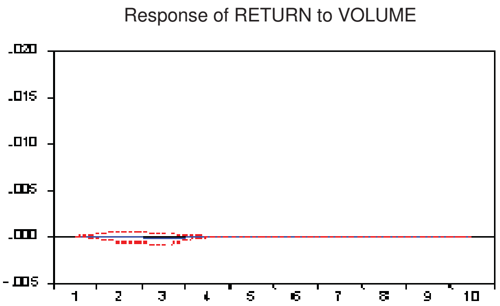


**Fig. 1. Impulse response to Cholesky one S.D. innovations ± 2S.E in volume on return**

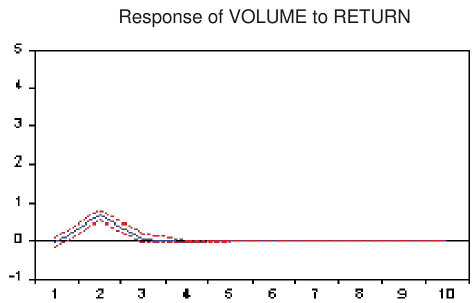


**Fig. 2. Impulse response to Cholesky one S.D. innovations ± 2S.E in return on volume**

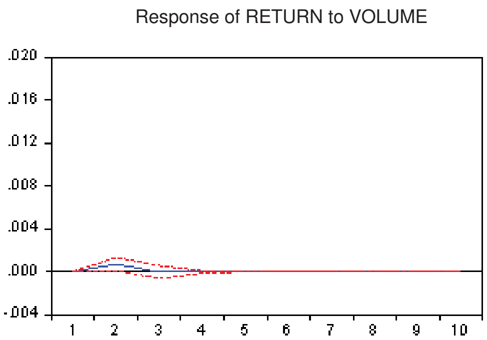


**Fig. 3. Impulse response to Cholesky one S.D. innovations ± 2S.E in volume on return**

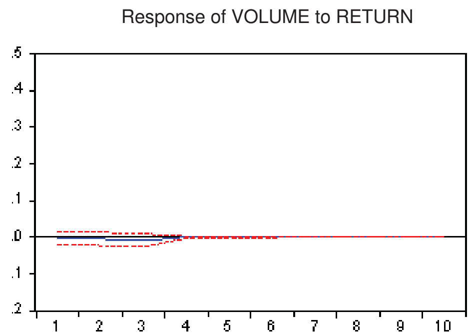


**Fig. 4. Impulse response to Cholesky one S.D. innovations ± 2S.E in return on volume**

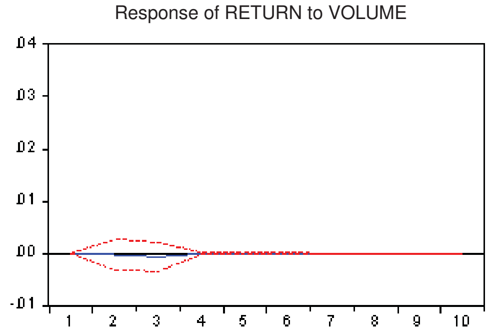


**Fig. 5. Impulse response to Cholesky one S.D. innovations ± 2S.E in volume on return**

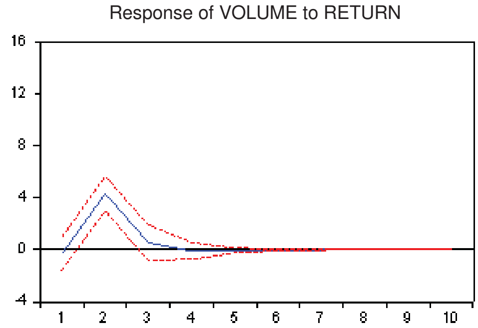


**Fig. 6. Impulse response to Cholesky one S.D. innovations ± 2S.E in return on volume**

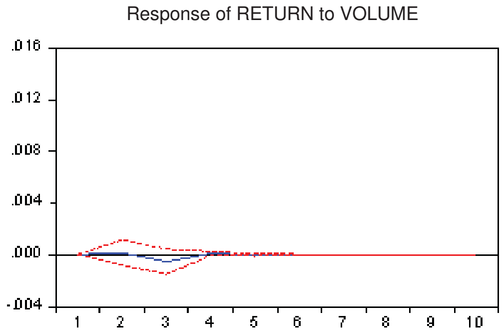


**Fig. 7. Impulse response to Cholesky one S.D. innovations ± 2S.E in volume on return volume**

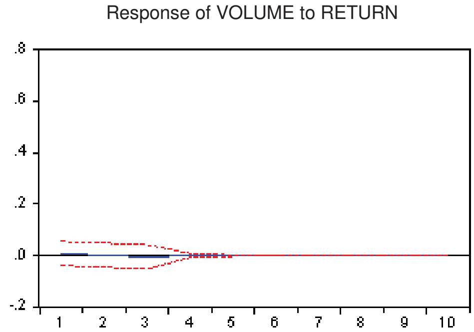


**Fig. 8. Impulse response to Cholesky one S.D. innovations ± 2S.E in return on**

*2.3.2. CNX Nifty Junior. 2.3.2.1. CNX Nifty Junior – whole sample period.* Figure 9 to Figure 16 show the impulse response function for Nifty Junior and its sub periods. Figure 9 and Figure 10 show the impulse response function analysis for the whole sample period of Nifty Junior. Figure 9 shows impact on trading volume on return. The response shows that trading volume has a positive impact on return. Day two shows the significant impact on return and gradually it decreases. Figure 10 shows that during day two the return has a substantial influence on trading volume but thereafter it decreases.

*2.3.2.2. CNX Nifty Junior – sub period 1.* Figure 11 and Figure 12 show the impulse response function analysis for the pre-crisis period of Nifty Junior. Figure 11 shows the impact of trading volume on return. It shows that trading volume has a slight positive impact on return. Figure 12 shows that the return has a slight positive impact on trading volume till the second day and subsequently decreases to negative.

*2.3.2.3. CNX Nifty Junior– sub period 2.* Figure 13 and Figure 14 show the impulse response function analysis for the crisis period of Nifty Junior. Figure 13 shows the impact of trading volume on return. Figure 13 explains that after initial day of the shock the trading volume has significant impact on return then decreases to zero. Figure 14 shows that return has a positive impact on trading volume

*2.3.2.4. CNX Nifty Junior – sub period 3.* Figure 15 and Figure 16 show the impulse response function analysis for the post crisis period of Nifty Junior. Figure 15 shows the impact of trading volume on return. It shows that trading volume has a positive impact on return for two days and after that the impact subsides. Figure 16 shows that return have an insignificant impact on trading volume. The return shock produces an insignificant positive impact on trading volume during the initial stage and thereafter drives down below zero.

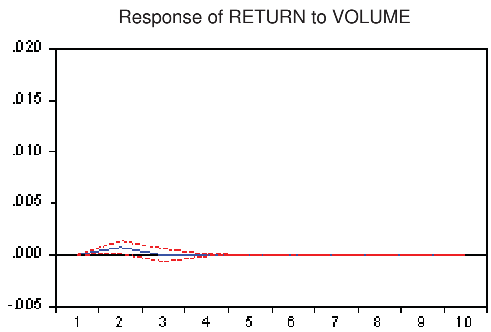


**Fig. 9. Impulse response to Cholesky one S.D. innovations ± 2S.E in volume on retur**

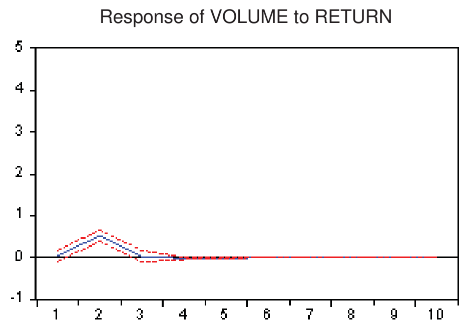


**Fig. 10. Impulse response to Cholesky one S.D. innovations ± 2S.E in return on volume**

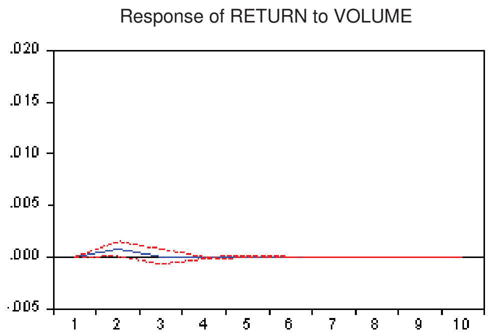


**Fig. 11. Impulse response to Cholesky one S.D. innovations ± 2S.E in volume on return**

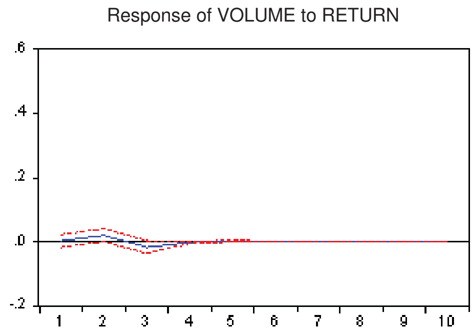


**Fig. 12. Impulse response to Cholesky one S.D. innovations ± 2S.E in return on volume**

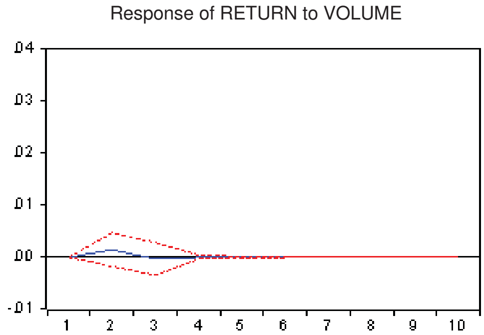


**Fig. 13. Impulse response to Cholesky one S.D. innovations ± 2S.E in volume on return**

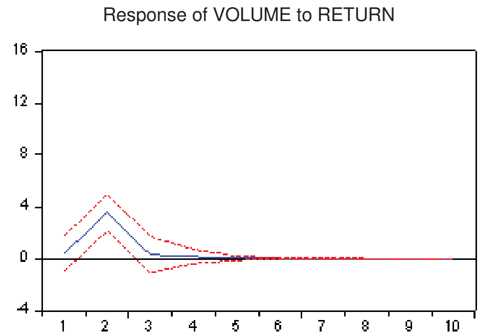


**Fig. 14. Impulse response to Cholesky one S.D. innovations ± 2S.E in return on volume**

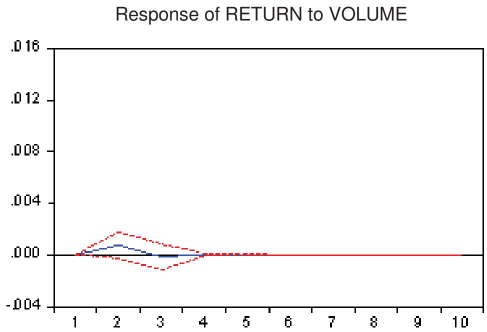


**Fig. 15. Impulse response to Cholesky one S.D. innovations ± 2S.E in volume on return**

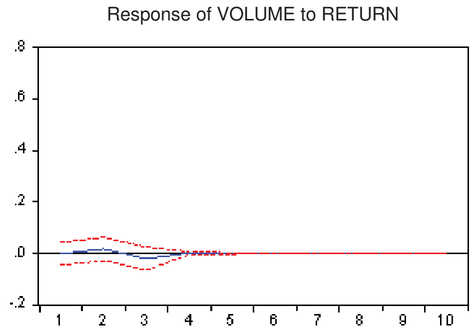


**Fig. 16. Impulse response to Cholesky one S.D. innovations ± 2S.E in return on volume**

*2.3.3. Nifty Midcap. 2.3.3.1. Nifty Midcap – whole sample period.* Figure 17 to Figure 24 show the impulse response function for Nifty midcap and its sub periods. Figure 17 and Figure 18 show the impulse response function analysis for the whole sample period of Nifty Midcap. Figure 17 shows the impact of trading volume on return. Figure 18 shows that trading volume shock has positive impact return till two days thereafter it reduces to zero. Figure 18 shows that the shock in return shows a positive impact on trading volume and gradually decreases to zero.

*2.3.3.2. Nifty Midcap – sub period 1.* Figure 19 and Figure 20 show the impulse response function analysis for the pre-crisis period of Nifty Midcap. Figure 19 shows the impact of trading volume on return. Figures 19 and 20 show that shock in both the variable have a significant impact on each other till two days thereafter it shows a negative impact on each other.

*2.3.3.3. Nifty Midcap – sub period 2*. Figure 21 and Figure 22 show the impulse response function analysis for the crisis period of Nifty Midcap. Figure 21 shows the impact of trading volume on return. It shows that the shock in trading volume results positive impact on return during the initial days of the shock and gradually that reduces to zero. Figure 22 shows that shock in return results a positive impact on trading volume and it decreases thereafter.

*2.3.3.4. Nifty Midcap – sub period 3*. Figure 23 and Figure 24 show the impulse response function analysis for the post crisis period of Nifty Midcap. Figure 23 shows the impact of trading volume on return. Figure 23 and Figure 24 show that both trading volume and return have a positive impact on each other as result of shock in both variable during the initial days and gradually decreases to negative.

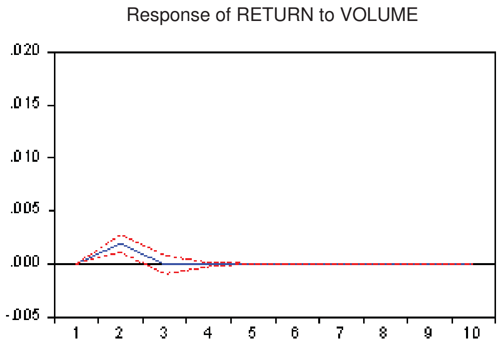


**Fig. 17. Impulse response to Cholesky one S.D. innovations ± 2S.E in volume on return**

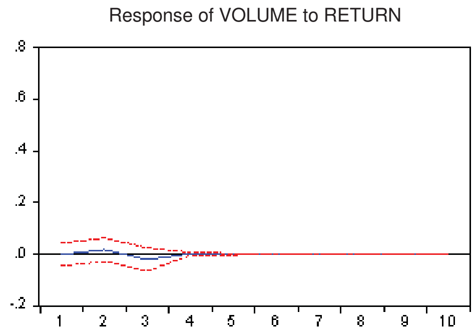


**Fig. 18. Impulse response to Cholesky one S.D. innovations ± 2S.E in return on volume**

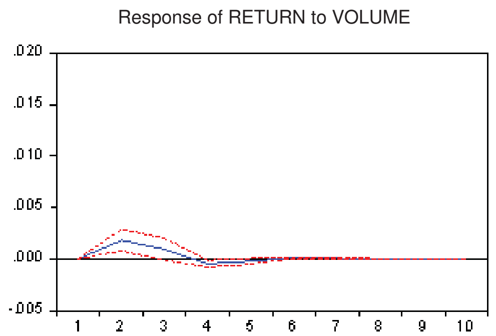


**Fig. 19. Impulse response to Cholesky one S.D. innovations ± 2S.E in volume on return**

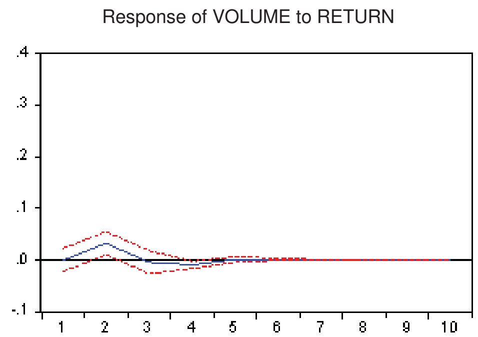


**Fig. 20. Impulse response to Cholesky one S.D. innovations ± 2S.E in return on volume**

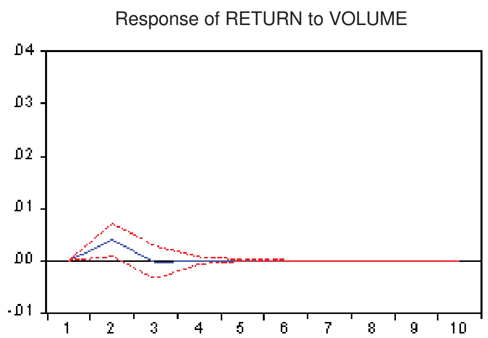


**Fig. 21. Impulse response to Cholesky one S.D. innovations ± 2S.E in volume on return**

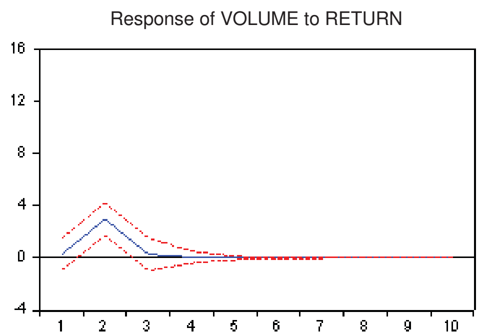


**Fig. 22. Impulse response to Cholesky one S.D. innovations ± 2S.E in return on volume**

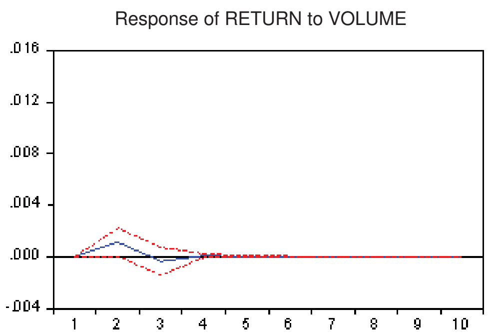


**Fig. 23. Impulse response to Cholesky one S.D. innovations ± 2S.E in volume on return**

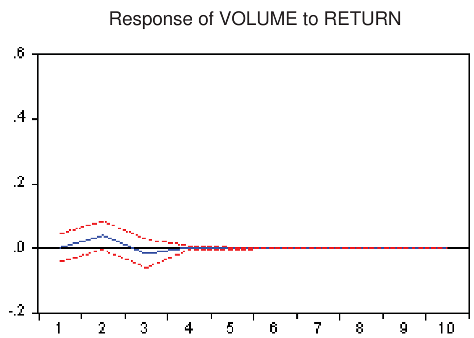


**Fig. 24. Impulse response to Cholesky one S.D. innovations ± 2S.E in return on volume**

The impulse response analysis shows that high impact of trading volume on return and return's impact on trading volume exist for a short period.

**2.4. Variance decomposition.** Variance decomposition or forecast error variance decomposition shows the amount of information each variable contribute the other variable in a VAR model. Variance decomposition gives the proportion of movements in the depended variables that are due their own shock, versus shock to the other variable (Brooks, 2008). Tables 3 to 6 show the variance decomposition analysis of the Nifty series.

*2.4.1. S&P CNX Nifty. 2.4.1.1. S&P CNX Nifty – whole sample.* Table 3 shows that the proportion of return's contribution attributed to return decreases from 100% to 99.98% and trading volume is increasing 0.00% to 0.019% during lag 1 to 5. The proportion of return's contribution to trading volume is increasing from 0.015% to 2.82% and volume's contribution to volume decreases from 99.98% to 97.17% from lag 1 to 5. According to Hasbrouck information share the average information share from the return is 51.40% and trading volume is 48.59%. The study confirms that during the whole sample period of Nifty return enjoys a dominant role than trading volume in the contribution towards other variable.

Table 3. Results of variance decomposition analysis

| Lag | Return attributed to | | Volume attributed to | |
|---|---|---|---|---|
| | Return | Volume | Return | Volume |
| 1 | 100.0000 | 0.000000 | 0.015128 | 99.98487 |
| 2 | 99.99987 | 0.000126 | 2.783633 | 97.21637 |
| 3 | 99.98105 | 0.018950 | 2.818766 | 97.18123 |
| 4 | 99.98100 | 0.019001 | 2.822115 | 97.17789 |
| 5 | 99.98097 | 0.019029 | 2.822337 | 97.17766 |

*3.4.1.2. S&P CNX Nifty – period 1.* Table 4 shows the proportion of return's contribution to return decreases from 100% to 99.82% and trading volume is increasing 0.00% to 0.017% during lag 1 to 5. Further the proportion of return's contribution to volume is increasing from 0.002% to 0.04% and volume's contribution to volume decreases from 99.99% to 99.95% from the lag 1 to 5. According to Hasbrouck information share the average information share from the return is 49.93% and trading volume is 50.06%. The study confirms that during the pre-crisis period trading volume enjoys a dominant role than return in contributing towards the other variable.

Table 4. Results of variance decomposition analysis

| Lag | Return attributed to | | Volume attributed to | |
|---|---|---|---|---|
| | Return | Volume | Return | Volume |
| 1 | 100.0000 | 0.000000 | 0.002320 | 99.99768 |
| 2 | 99.82318 | 0.176816 | 0.009245 | 99.99076 |
| 3 | 99.82203 | 0.177966 | 0.040627 | 99.95937 |
| 4 | 99.82035 | 0.179651 | 0.041482 | 99.95852 |
| 5 | 99.82031 | 0.179685 | 0.041765 | 99.95823 |

*2.4.1.3. S&P CNX Nifty – period 2.* Table 5 explains the variance decomposition analysis of crisis period. The test shows the proportion of return's contribution to return decreases from 100% to 99.94% and trading volume is increasing 0.00% to 0.05% during lag 1 to 5. Further the proportion of return's contribution to volume is increasing from 0.053% to 11.66% and volume's contribution to volume decreases from 99.94% to 88.33% from the lag 1 to 5. According to Hasbrouck information share the average information share from the return is 55.80% and trading volume is 44.19%. The study confirms that during the crisis period, the return enjoys a dominant role trading volume in terms of information content.

Table 5. Results of variance decomposition analysis

| Lag | Return attributed to | | Volume attributed to | |
|---|---|---|---|---|
| | Return | Volume | Return | Volume |
| 1 | 100.0000 | 0.000000 | 0.053152 | 99.94685 |
| 2 | 99.99290 | 0.007098 | 11.48843 | 88.51157 |
| 3 | 99.94202 | 0.057983 | 11.65686 | 88.34314 |
| 4 | 99.94197 | 0.058027 | 11.65995 | 88.34005 |
| 5 | 99.94194 | 0.058065 | 11.66160 | 88.33840 |

*2.4.1.4. S&P CNX Nifty – period 3.* Table 6 explains the variance decomposition analysis of post crisis period. The test shows that the proportion of return's contribution to return decreases from 100% to 99.80% and trading volume's contribution is increasing 0.00% to 0.19% during lag 1 to 5. Further the proportion of return's contribution to trading volume is increasing from 0.017% to 0.024% and volume's contribution to volume decreases from 99.98% to 99.97% from the lag 1 to 5. According to Hasbrouck information share the average information share from the return is 49.91% and trading volume is 50.08%. The study confirms that during the crisis period trading volume enjoys a slightly dominant role than return.

Table 6. Results of variance decomposition analysis

| Lag | Return attributed to | | Volume attributed to | |
|---|---|---|---|---|
| | Return | Volume | Return | Volume |
| 1 | 100.0000 | 0.000000 | 0.017421 | 99.98258 |
| 2 | 99.98730 | 0.012699 | 0.017544 | 99.98246 |
| 3 | 99.80893 | 0.191070 | 0.024004 | 99.97600 |
| 4 | 99.80492 | 0.195079 | 0.024176 | 99.97582 |
| 5 | 99.80443 | 0.195567 | 0.024194 | 99.97581 |

The variance decomposition analysis of Nifty shows that during the whole sample period and crisis period, return enjoys dominant role. However, during sub period one and three volume enjoys a dominant role than return in terms of information content.

*2.4.2. CNX Nifty Junior. 2.4.2.1. CNX Nifty Junior – whole sample.* Tables 7 to 10 show the variance decomposition analysis of the Nifty Junior series. Table 7 explains the variance decomposition analysis of Junior Nifty for whole sample period. The test shows the proportion of return's contribution to return decreases from 100% to 99.86% and trading volume's contribution is increasing 0.00% to 0.13% from lag 1 to 5. Further the proportion of return's contribution to trading volume is increasing from 0.012% to 1.64 % and volume's contribution to volume decreases from 99.98% to 98.35% from the lag 1 to 5.

Table 7. Results of variance decomposition analysis

| Lag | Return attributed to | | Volume attributed to | |
|---|---|---|---|---|
| | Return | Volume | Return | Volume |
| 1 | 100.0000 | 0.000000 | 0.012718 | 99.98728 |
| 2 | 99.86910 | 0.130904 | 1.639257 | 98.36074 |
| 3 | 99.86831 | 0.131693 | 1.644148 | 98.35585 |
| 4 | 99.86805 | 0.131950 | 1.645395 | 98.35461 |
| 5 | 99.86805 | 0.131952 | 1.645459 | 98.35454 |

According to Hasbrouck information share the average information share from the return is 50.75% and trading volume is 49.24%. The study confirms that during the whole sample period of Nifty Junior return enjoys a dominant role than trading volume.

*2.4.2.2. CNX Nifty Junior – sub period 1.* Table 8 explains the variance decomposition analysis of pre-crisis period. The test shows the proportion of return's contribution to return decreases from 100% to 99.83% and trading volume's contribution is increasing 0.00% to 0.16% during lag 1 to 5. Further the proportion of return's contribution to trading volume is increasing from 0.013% to 0.24% and volume's contribution to volume decreases from 99.99% to 99.75% from the lag 1 to 5. According to Hasbrouck information share the average information share from the return is 50.03% and trading volume is 49.96%. The study confirms that from the period 1 of Nifty Junior return enjoys a dominant role than trading volume in the market.

Table 8. Results of variance decomposition analysis

| Lag | Return attributed to | | Volume attributed to | |
|---|---|---|---|---|
| | Return | Volume | Return | Volume |
| 1 | 100.0000 | 0.000000 | 0.003145 | 99.99686 |
| 2 | 99.83619 | 0.163814 | 0.144258 | 99.85574 |
| 3 | 99.83648 | 0.163523 | 0.242662 | 99.75734 |
| 4 | 99.83391 | 0.166091 | 0.244121 | 99.75588 |
| 5 | 99.83391 | 0.166091 | 0.245737 | 99.75426 |

*2.4.2.3. CNX Nifty Junior – sub period 2.* Table 9 explains the variance decomposition analysis of crisis period. The test shows the proportion of return's contribution to return decreases from 100% to 99.75% and trading volume's contribution is increasing 0.00% to 0.24% during lag 1 to 5. Further the proportion of return's contribution to trading volume is increasing from 0.08% to 7.12% and volume's contribution to volume decreases from 99.91% to 92.87% from the lag 1 to 5.

Table 9. Results of variance decomposition analysis

| Lag | Return attributed to | | Volume attributed to | |
|---|---|---|---|---|
| | Return | Volume | Return | Volume |
| 1 | 100.0000 | 0.000000 | 0.081236 | 99.91876 |
| 2 | 99.76449 | 0.235508 | 7.065065 | 92.93494 |
| 3 | 99.75520 | 0.244801 | 7.110815 | 92.88918 |
| 4 | 99.75518 | 0.244815 | 7.123647 | 92.87635 |
| 5 | 99.75518 | 0.244821 | 7.123965 | 92.87603 |

According to Hasbrouck information share the average information share from the return is 53.43% and trading volume is 46.56%. The study confirms that during the period 2 of Nifty Junior return enjoys a dominant role trading volume.

*2.4.2.4. CNX Nifty Junior – sub period 3.* Table 10 explains the variance decomposition analysis of post crisis period. The test shows the proportion of return's contribution to return decreases from 100% to 99.66% and trading volume's contribution is increasing 0.00% to 0.33% from the lag 1 to 5. Further the proportion of return's contribution to trading volume is increasing from 0.00% to 0.21% and volume's contribution to volume decreases from 99.99% to 99.78% from the lag 1 to 5. According to Hasbrouck information share the average information share from the return is 49.93% and trading volume is 50.06%. The study confirms that during the post crisis period of nifty junior trading volume enjoys a slightly dominant role than return.

Table 10. Results of variance decomposition analysis

| Lag | Return attributed to | | Volume attributed to | |
|---|---|---|---|---|
| | Return | Volume | Return | Volume |
| 1 | 100.0000 | 0.000000 | 0.000409 | 99.99959 |
| 2 | 99.68362 | 0.316384 | 0.087165 | 99.91283 |
| 3 | 99.66691 | 0.333093 | 0.210335 | 99.78966 |
| 4 | 99.66672 | 0.333277 | 0.211175 | 99.78883 |
| 5 | 99.66672 | 0.333277 | 0.211184 | 99.78882 |

The variance decomposition analysis of Nifty Junior shows that during the whole sample period, pre-crisis and crisis period, return enjoys dominant role. However, during post crisis period three trading volume enjoys a dominant role than return.

*2.4.3. Nifty Midcap. 2.4.3.1. Nifty Midcap – whole sample period.* Tables 11 to 14 show the variance decomposition analysis of the Nifty Midcap series. Table 11 explains the variance decomposition analysis of Nifty Midcap for whole sample period. The test shows the proportion of return's contribution to return decreases from 100% to 99.04% and trading volume's contribution is increasing 0.00% to 0.95% from the lag 1 to 5. Further the proportion of return's contribution to trading volume is increasing from 0.009% to 2.74 % and volume's contribution to volume decreases from 99.99% to 97.25% from the lag 1 to 5. According to Hasbrouck information share the average information share from the return is 50.89% and trading volume is 49.10%. The study confirms that during the whole sample period of Nifty Midcap return enjoys a dominant role than trading volume.

Table 11. Results of variance decomposition analysis

| Lag | Return attributed to | | Volume attributed to | |
|---|---|---|---|---|
| | Return | Volume | Return | Volume |
| 1 | 100.0000 | 0.000000 | 0.009037 | 99.99096 |
| 2 | 99.04856 | 0.951436 | 2.722863 | 97.27714 |
| 3 | 99.04585 | 0.954148 | 2.743370 | 97.25663 |
| 4 | 99.04348 | 0.956524 | 2.745705 | 97.25430 |
| 5 | 99.04343 | 0.956571 | 2.745986 | 97.25401 |

*2.4.3.2. Nifty Midcap – sub period 1.* Table 12 explains the variance decomposition analysis of pre-crisis period. The test shows the proportion of return's contribution to return decreases from 100% to 98.57% and trading volume's contribution is increasing 0.00% to 1.42% during lag 1 to 5. Further the proportion of return's contribution to trading volume is decreasing from 6.73% to 0.86% and volume's contribution to volume decreases from 100.00% to 99.03% from the lag 1 to 5. According to Hasbrouck information share the average information share from the return is 49.73% and trading volume is 50.27%. The study confirms that during the period 1 of Nifty Midcap trading volume enjoys a dominant role than return.

Table 12. Results of variance decomposition analysis

| Lag | Return attributed to | | Volume attributed to | |
|---|---|---|---|---|
| | Return | Volume | Return | Volume |
| 1 | 100.0000 | 0.000000 | 6.73E-10 | 100.0000 |
| 2 | 98.92609 | 1.073910 | 0.797532 | 99.20247 |
| 3 | 98.66613 | 1.333875 | 0.809459 | 99.19054 |
| 4 | 98.59274 | 1.407260 | 0.867557 | 99.13244 |
| 5 | 98.57154 | 1.428463 | 0.869034 | 99.13097 |

*2.4.3.3. Nifty Midcap – sub period 2.* Table 13 explains the variance decomposition analysis of crisis period. The test shows the proportion of return's contribution to return decreases from 100% to 98.32% and trading volume's contribution is increasing 0.00% to 1.57% from the lag 1 to 5. Further the proportion of return's contribution to trading volume is increasing from 0.06% to 6.51% and volume's contribution to volume decreases from 99.93% to 93.48% from the lag 1 to 5. According to Hasbrouck information share the average information share from the return is 52.46% and trading volume is 47.53%. The study confirms that during the crisis period, return enjoys a dominant role than the trading volume.

Table 13. Results of variance decomposition analysis

| Lag | Return attributed to | | Volume attributed to | |
|---|---|---|---|---|
| | Return | Volume | Return | Volume |
| 1 | 100.0000 | 0.000000 | 0.061279 | 99.93872 |
| 2 | 98.41267 | 1.587331 | 6.453096 | 93.54690 |
| 3 | 98.40470 | 1.595303 | 6.509321 | 93.49068 |
| 4 | 98.40449 | 1.595506 | 6.518430 | 93.48157 |
| 5 | 98.40452 | 1.595482 | 6.518616 | 93.48138 |

*2.4.3.4. Nifty Midcap – sub period 3.* Table 14 explains the variance decomposition analysis of post-crisis period. The test shows the proportion of return's contribution to return decreases from 100% to 99.18% and trading volume's contribution is increasing 0.00% to 0.81% from the lag 1 to 5. Further the proportion of return's contribution to trading volume is increasing from 0.006% to 0.58% and volume's contribution to volume decreases from 99.99% to 99.50% from the lag 1 to 5. According to Hasbrouck information share the average information share from the return is 49.83% and trading volume is 50.16%. The study confirms that during the post crisis period the trading volume enjoys a dominant role than return.

Table 14. Results of variance decomposition analysis

| Lag | Return attributed to | | Volume attributed to | |
|---|---|---|---|---|
| | Return | Volume | Return | Volume |
| 1 | 100.0000 | 0.000000 | 0.006382 | 99.99362 |
| 2 | 99.30752 | 0.692480 | 0.407273 | 99.59273 |
| 3 | 99.18272 | 0.817277 | 0.491760 | 99.50824 |
| 4 | 99.18120 | 0.818796 | 0.492763 | 99.50724 |
| 5 | 99.18120 | 0.818797 | 0.492772 | 99.50723 |

The variance decomposition analysis of Nifty Midcap shows that during the whole sample period the contribution of return to volume is more than from volume to return. However, during pre-crisis period, volume plays a dominant role, during crisis period, returns plays a dominant roles and during post-crisis period neither volume or returns plays a dominant role in terms of information content. It should be noted that irrespective of indices, during the whole sample period and crisis period return enjoyed a dominant role in terms of information content. However, post-crisis period has shown that neither returns nor trading volume has dominant information content. Our key findings can be summarized as follows: size has an impact on price-volume relationship. However, the results show that information efficiency has increased across stocks of different sizes after the subprime crisis.

## Conclusion

Price-volume relationship can be a critical input for various market players. The academicians and market practitioners need to understand the importance of market size in the price volume relationship. The size provides more insight about the nature of price volume relationship. It is also vital to understand the price volume dynamics in detail since it contributes to the efficiency of the market. In the financial market, price and trading volume are closely related and trading volume plays a crucial role in analyzing the market. The main objective of the paper is to analyze whether the size have any impact on price trading volume relationship. The study has identified that the size has a considerable impact on price-trading volume relationship. Nifty and Nifty Junior have shown a unidirectional causality from returns to volume. As size decreases there is bidirectional causality between returns and trading volume. This indicates that the size is a determinant of price trading volume relationship. However, the causal relationships cease to exist post subprime crisis. The duration of impact is prominent when the size decreases and for large cap stocks it is insignificant. The information content from Hasbrouck's information share shows that stock returns and trading volume show predictive elements during the subprime crisis period. The study also shows that size is not an important factor in determining information content. The study also shows that, after the subprime crisis Indian stock markets are showing more efficiency. In other words, Indian stock market has become less predictable after the crisis.

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