Intraday Variability and Trading Volume: Evidence from National Stock Exchange

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Abstract

We investigate intraday patterns in returns, volumes, volatility and analyze the volume-return relationship using tick by tick data from the Indian market. Using descriptive measures and several regression frameworks, we document three important findings. Firstly, we report unusually high volatility, trading volume and number of trades during the opening and closing minutes depicting a 'U' shaped curve, implying high market activity during these periods. Secondly, while accounting for trading volume, we find that volatility is not significantly different between mid-day period and evening period as compared to the normal 'U' curve. Finally, we find significant positive relationship between intraday volume and price movements controlling for microstructure effects. The impact of positive returns on trading volume is higher than the impact of negative returns implying presence of return-volume asymmetry in the Indian market.

Keywords: Intraday Patterns, India, National Stock Exchange, Return-Volume Regressions

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Intraday Variability and Trading Volume: Evidence from National Stock Exchange[1]

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[1] The authors would like to thank Department of Management Studies, IIT Madras for supporting this research. Aravind Sampath was a Ph.D. student at IIT Madras and this research was carried out during his stay at IIT Madras.

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Introduction

The stimulus for trading in financial markets is predominantly attributed to two major factors - 'information' and 'liquidity' [Admati and Pfleiderer (1988)]. While the trades of informed traders are based on private information, liquidity traders on the other hand, trade on reasons other than the fundamentals or future payoffs of the underlying asset. The differences in motivation of these trades often results in information asymmetry that drives intraday patterns / anomalies in returns and volumes. Admati and Pfleiderer (1988) further theorized that when a group of informed traders are active, it tends to drive away liquidity traders resulting in high trading volume and return volatility. The empirical validity of this theory was first explored by Wood et al. (1985) who studied patterns in intraday returns of the New York Stock Exchange (NYSE). Using descriptive measures, the study documented presence of high variability in returns during opening and closing minutes of trade denoting a 'U' shaped curve. Similarly, Harris (1986), Jain and Joh (1988), McInish and Wood (1990), Ozenbas et al. (2002), Glezakos et al. (2011), Tse and Dong (2014) etc. also empirically examined intraday patterns in returns and volumes of developed markets including U.S. and European markets. These studies predominantly used descriptive measures to document presence of 'U' shaped intraday volatility curve indicating presence of unusually high means and dispersions of returns at the beginning and end of a trading day. The results of these empirical studies coupled with theoretical propositions suggest that the morning and evening periods in the market are characterized by information disclosure.

The existing theories and empirical results on intraday behavior have predominantly focused on developed markets that are mostly quote driven or contain floor trading [Wood et al. (1985), McInish and Wood (1990) etc.]. With the increased economic growth of emerging economies during the last decade, few studies have also attempted to investigate intraday price behavior of emerging markets. Bildik (2001) for instance studied the intraday returns of Turkish market and reported presence of 'U' shaped volatility. Copeland and Jones (2002) for the Korean market and, Tian and Guo (2007) for the Chinese market also provide similar evidence of high volatility during market opening and closing periods. However, a striking difference between the results of developed markets and some of the emerging markets like China, is the presence of 'W' shaped intraday patterns in prices and volumes. This is because of the fact that the institutional framework of financial markets in emerging economies is substantially different from that of developed markets. Some emerging markets have systemic trading break during middle period of the day (China). Therefore, when there is a trading halt, the volatility spike before and after mid-day break is reflected as 'W' shaped curve. Apart from studies on Turkey, Korea and China, very few studies have analyzed the emerging Indian market. Agarwalla et al. (2015) and, Sampath and Gopalaswamy (2015) were two such studies that explored intraday volatility patterns in the Indian market. The focus of Agarwalla et al. (2015) was to understand the impact of call auction on opening price volatility while also addressing the impact of block trades on market volatility. Sampath and Gopalaswamy (2015) on the other hand documented few intraday patterns using a longitudinal data set. However, studies that addressed the relationship between trading volume and returns in an Indian context have been very minimal.

Along with China, India is an important market in the Asia-Pacific region that has grown tremendously over the last decade. In contrast with other developed and few emerging markets, the Indian market is an electronic exchange without market makers, a mechanism that is expected to reduce trading (and adverse selection) costs. Therefore, examining intraday patterns on an emerging market like India not only adds to the existing literature, but also provides a new perspective as the structure and institutional framework of the Indian market is unique compared to the rest of the markets. Between the two major exchanges in India, despite the fact that larger number of firms are listed in Bombay Stock Exchange (5673 as of May 2015, source: BSE) compared to National Stock Exchange (1749 as of May 2015, source: NSE), the turnover in cash and Futures & Options (F&O) section of NSE is substantially higher as compared to BSE. Between January 2007 to July 2015, NSE's cash turnover was approximately \$3.98 trillion compared to \$1.21 trillion for BSE (sources: NSE and BSE). In the F&O section, NSE's turnover during the period was \$30.85 trillion compared to \$3.3 trillion for BSE. NSE's market capitalization has grown more than five times from \$0.26 trillion in 2004 to \$1.65 trillion as on January 2015. Despite the similarity in structure compared to other emerging markets (like China), the Indian market is still unique. NSE is a continuous market and does not have a trading halt like the Chinese and other Asian markets. For the data period under consideration, the trading period was between 09:55 hrs. To 15:30 hrs. The leading index of NSE is the NIFTY index which comprises of the top 50 securities based on free float market capitalization. The turnover of these 50 securities is expected to be greater than 60% of the overall market turnover (source: NSE database).

In this article, we empirically examine patterns in price changes (returns), volatility, trading volume and, the relationship between returns and volume of transaction stocks of National Stock Exchange (NSE) of India and document several important findings. Similar to other markets, the returns, trade patterns and volume patterns follow a distinct 'U' shaped curve depicting the unusual trading activity during opening and closing minutes. However, unlike other studies, we also attempt to understand intraday patterns further, by accounting for trading volume in estimating variability. The results indicate that opening minutes are volatile despite accounting for trading volume suggesting possible private information disclosure. On the other hand, contrary to the results documented in literature, while accounting for trading volume, the estimated variability for the evening and mid-day periods were not found to be significantly different. Finally, we also document presence of strong contemporaneous relationship between trading volume and absolute returns while controlling for period and day specific effects. The impact of positive returns on trading volumes is significantly higher as compared to negative returns, thus concurring with the asymmetric return-volume hypothesis proposed by Karpoff [1976, 1978].

Literature Review

Copeland (1976), was one of the first to theoretically and empirically prove the presence of positive correlation between absolute price changes and trading volume. Copeland (1976) posited a model of sequential information arrival where the agents sequentially adjusted to arrival of new information, resulting in positive correlation between price changes and volumes. Later, Karpoff [1986, 1987] in his seminal articles outlined that positive associations exist between volumes and absolute values of price changes, adding that the quantum of positive changes impacts volume more than negative changes. However, Karpoff [1986, 1987] indicated that these findings are valid only in markets where short selling costs are higher than long positions. In terms of empirical validations, early studies used daily data to provide evidence on this positive correlation based on the U.S market. Crouch [1970a, 1970b] for instance documented positive correlations between absolute returns and volumes for both indices and stocks. Clark (1973) on the other hand found a similar relation, however using price change square and aggregated volume for the cotton futures market using daily data. The study by Wood et al. (1985) was a comprehensive investigation of intraday data based on New York Stock Exchange (NYSE) stocks. Using period specific means and standard deviations, the study documented presence of high variations in stock returns, trading volume and transactions during opening and closing periods. Further, at a transactional level, the study also crucially documented presence of positive relation between volume and quantum of price change. Harris (1986) further added to the evidence of positive correlation between volumes and price changes using 479 stocks of NYSE. Jain and Joh (1986) used aggregated hourly NYSE market data to report (a) presence of 'U' shaped returns and volumes curve, (b) day-of-the-week effects in terms of volumes and (c) strong association between trading volumes and absolute returns using regression frameworks. Most of the early studies in the 1970s and 80s used data from U.S market (mainly equity markets) to document presence of unusual means and volatilities in intraday returns and, crucially a strong linear association between absolute returns and volumes.

Bessembinder and Seguin (1993) studied the relations between volume, volatility and market depth using data from eight physical and financial futures markets (including two currencies, two metals, two agricultural commodities and two treasury bonds/bills). Using conditional estimates of returns and volatilities, the study indicated that volume shocks tended to have a greater impact on volatility. This relation was found to be asymmetric – positive shocks have a higher impact than negative shocks, thus in line with the theory posited by Karpoff [1986, 1987] and empirically validated by Jain and Joh (1986). Chen et al. (2001), studied the dynamic relations between returns and volumes of nine large and well-regulated stock market indices. Unlike any other study, this study allowed a linear and quadratic time trend to understand the dynamics between trading volume and time periods. With strong statistical validation of linear and non-linear trends, they de-trend the data to further study the relationship between returns and volumes. Using regression frameworks, the study reported positive correlation between returns and volumes (after de-trending the data). Unlike other studies, this was one of the first studies to not only de-trend data to provide more robust findings, but also apply it across multiple markets other than the U.S. market. In the emerging market front, studies like Bildik (2001) for Turkey, Tian and Guo (2007) for China provide empirical evidence of unusual market activity during opening and closing minutes based on intraday data. In the Indian context, Agarwalla et al. (2015) studied the impact of call auction on opening period volatility in the Indian market. The study provided evidence to suggest that call auction did not reduce the opening period volatility in the Indian market. Pati and Rajib (2011), used time series regressions to indicate return-volume relations between spot and futures strengthening the cost of carry model in an intraday set up. Jain et al. (2016) further added to the literature on intraday set up in the Indian market by analyzing the 50 stocks of Nifty Index. The study indicated the importance of trading volume in information transfer in the context of spot-future relationship.

Since 1980s, literature on empirically investigating dynamics of intraday data to draw implications have been aplenty. Several theories have been validated and established in the process. The presence of abnormal dispersions in returns and volumes have been well documented in most developed markets and a few emerging markets. Further, the relationship between absolute price changes (denoted as absolute returns) and trading volume have been important in understanding several facets of a market's functioning. In this context, though studies have provided evidence, most of it has been based on developed markets. The studies that have attempted to test these hypotheses to draw conclusions on emerging markets, especially that of India are few. The few studies based on India have also been context specific. Studies that have looked upon longitudinal data of the Indian market to validate intraday patterns and relationships have been few. This study is an attempt to narrate the intraday dynamics observed in the Indian market using tick by tick data of Nifty index for a long time period, using robust estimations.

Dataset

The data used in this study consists of tick by tick returns of the NIFTY index for the period August 2000 to September 2008 and transactions data of top 50 stocks[1] for the years 2002, 2004, 2007 and 2008 respectively. The data period is chosen because the period in study captures various macro-economic trends in the Indian market. In 2002, the market was predominantly flat (index values ranged from 1055-1095), while 2004 depicted a bullish trend (1910 to 2080). The year 2007 witnessed enormous proportions of trading activity in the Indian market, resulting in an extraordinary growth in the index from 4000 to 6100. Finally, the data pertaining to 2008 contains the impact of global economic recession where NIFTY fell sharply from 6100 to approximately 2960. Examining data during diverse market scenario was particularly chosen as it offers robustness in explaining the role of externalities on individual stock price behavior. Intraday index and individual firm data used in this study are part of a purchased database from NSE. The database provides time stamped values of index and, transaction data in terms of price and volume for each transaction on all trading days.

Intraday patterns – Index and Stocks

<Insert Figure 1>

In order to investigate the intraday properties in the Indian market, we first examine the market index. Figure 1 depicts the average trades, volatility[2] and standard deviation of the NIFTY index aggregated for the time period under consideration. It is observed that the microstructure patterns documented across several markets [Wood et al. (1985), Harris (1986), Jain and Joh (1988), Bildik (2001), Tian and Guo (2007), Sampath and Gopalaswamy (2015)] are observed in the Indian market also. Intraday volatility follows a 'U' shaped pattern suggesting presence of information dissemination during opening and closing minutes of trade. In addition, it is also observed that the number of trades (proxy for transactions of index stocks) of the NIFTY index follows 'U' shaped pattern reinforcing presence of unusual market activity during opening and closing minutes of trade.

In order to statistically validate 'U' curve and for robustness of results, we go beyond the index by also analyzing individual stock returns. We define a regression framework to examine the relationship between volatility and time period for both the index and choice of stocks. In order to sample the data for analysis, the returns are categorized into 12 discrete time intervals (one five-minute interval and eleven 30 minute intervals) [3]. We compute the intraday returns are calculated as follows:

$$r_t = \ln(p_t/p_{t-1}) \qquad (1)$$

Where p_t is the price of the asset (index or stock) at time period t and r_t is the logarithmic return depicting continuous price change.

Given the observed intraday patterns in our dataset, we use the transformation suggested by Jain and Joh (1988), Copeland and Jones (2002) and Agarwalla et al. (2015) to account for the period and day specific effects. This approach accounts for the microstructure effects (period and day specific) and increases the statistical power of tests.

$$R_t = \frac{r_t - \check{r}_T}{\sigma_T} \quad (2)$$

Where r_t is the intraday return for the period t, $\check{r}_T$ is the mean return for the day T and σ_T is the standard deviation of returns for the day T[4]. Subsequently, the following regression framework is specified:

$$|R|_t = a + \beta_1 \times t + \beta_2 \times t^2 + \beta_3 \times t^3 + \varepsilon_T \quad (3)$$

where $|R_t|$ is the absolute value of transformed returns and t denotes the time period from 1 to 12.

<Insert Table 1>

<Insert Table 2?

The regression results presented in tables 1 and 2 strongly reinforces presence of intraday patterns (depicted by 'U' shaped curve) in NIFTY index and transactions data. The estimated coefficients illustrate two important conclusions. Firstly, it is observed that the direction of coefficients for variables t, t^2 and t^3 reverse continuously (negative, positive and negative). Secondly, with increased power of time variable, the absolute value of coefficient drops to almost zero (for t^3). The estimated coefficient of t is largest (in terms of absolute value) with negative sign implying that volatility is highest during the beginning of the day. This result reinforces the fact that return variability is higher during the earlier parts of the day (morning period variability) and reduces as the day progresses. The coefficient of t^2 is significant, but relatively lower (almost zero) compared to the coefficient of t. In addition, the positive sign of the coefficient is suggestive of the fact that variability is also higher during evening period, but relatively lower compared to morning period. This estimate also strongly suggests that the mid-day period has the lowest variability as unevenness during the middle periods are likely to be lower than that of evening periods. The coefficient of t^3 reverses (negative) strengthening the presence of 'U' shaped curve. However, the impact of this variable is very less as the coefficient value is very small (close to zero). However, this result of negative coefficient is a strong indication that the variability pattern is a crude 'U' shaped curve. The results of this regression setting essentially illustrates the time varying non-linearity of the 'U' shaped curve and provides statistical evidence on the observed intraday variability pattern. The results strongly suggest that the volatility during opening period is highest, followed by the closing period while the middle period is fairly stable.

Intraday variability accounting for trading volume

One of the disadvantages of examining intraday variability from the perspective of returns alone (index prices) is that it fails to capture the market depth effect. Trade price is normally accompanied by trading volume, which is equally important and completes the puzzle about the intent of trades, explaining investor/agent behavior holistically. Traditionally, studies that examined intraday patterns documented return characteristics and volume patterns separately. Comparing asset price volatility accounting for corresponding trade volumes would offer far richer explanations about investor behavior. As index prices (and returns) do not contain volumes, we shift our focus on examining individual stock prices and their corresponding trading volume. We define a new metric to compute intraday variability accounting for trading volume. In principle, this measure is similar to the common dispersion measures. However, instead of computing return dispersion from the mean (or any other benchmark), we estimate dispersion in price movements accounting for trading volume. In order to achieve that, we first compute Volume Weighted Average Price (VWAP) that accounts for each transaction price and volume thereby aggregating it for all the transactions for a particular sample period.

$$\text{VWAP} = \frac{\sum_{i=1}^{N} p_i \times v_i}{\sum_{i=1}^{N} v_i} \tag{4}$$

Where, for the particular time period, there are i =1 to N number of transactions, p is the tick price and v is the corresponding volume.

Further, to estimate the dispersion, the deviation of each tick price from VWAP is computed. In order to aggregate the measure, the deviations are weighted for the corresponding volume for the particular transaction and averaged for the total volume. Finally, as the number of transactions also follows a seasonal 'U' shaped pattern (as described earlier), this estimate is accounted for total transactions to correct any bias. This measure essentially captures the variability in price movements factoring with trading volume and transactions[5].

$$\text{V**} = \frac{\sum_{i=1}^{N} \left(\frac{p_i - VWAP_T}{VWAP_T}\right)^2 \times v_i / \sum_{i=1}^{N} v_i}{N} \tag{5}$$

where V** is the adjusted variability accounting for trading volume, i represents the particular tick, T is the sample period, t is the total number of transactions for the particular period, p and v are price and volume respectively. The variability is estimated for each stock for each trading day and aggregated to present the results.

<Insert Table 3>

Table 3 presents the results of intraday variability adjusted for trading volume. Estimates illustrated in the table represent the mean and median values of variability across the stocks and averaged for each year. Unlike the results described earlier ('U' shaped volatility curve), volatility while accounting for trading volume does not follow 'U' shape. Firstly, despite accounting for trading volume, the morning period is characterized by extreme variability in returns. High variability despite accounting for volume strongly indicates that information dissemination is highest during the opening minutes. Coupled with earlier results, this strongly indicates that morning period of the Indian market is characterized by both organic [security specific] and inorganic [non-security based] information distribution. Both the 'U' shaped volatility from earlier result and high volatility accounting for volume are indications that this period (thick market) is likely when informed investors mask their trades. Informed agents are likely to trade in a period where there is generic price movements due to overnight information bunching, reactions due to other market movements etc. The results confirm with Admati and Pfleiderer's (1988) hypothesis that the thick trading hours would be accompanied with high volatility and volume. In addition, it is observed that this result is uniform regardless of the industry (or index) association of the stocks, also implying that price formation during this period may not reflect the fundamentals of a security implying lack of efficiency[6].

Secondly, the results also suggest that mid-day and evening period variability are not different while accounting for trading volume. Normally, the impact of intraday traders squaring off positions is likely reflected as evening period volatility of returns. But, the contrary results observed while accounting for trading volume (the difference in price changes are not significant between evening and mid-day periods) poses further questions about the relationship between intraday prices and trading volume.

Intraday Volume Patterns

The earlier results strongly indicate that trading volumes are imperative in explaining price movements in the Indian market. Therefore, we explore the presence of patterns / anomalies in trading volumes. Figures 2 to 5 summarize the patterns of intraday volumes within a day and throughout a week. From the illustrations of figures 2 to 5, it is evident that the volume patterns in Indian market also follow a crude 'U' shaped curve. It is observed that the last half hour interval (15:00hrs to 15:30hrs) has the highest volume traded in the Indian market ranging between 13% - 20% of total volume on any given day. The second period (10:00hrs to 10:30hrs) contains the second highest volume traded, ranging between 8% - 18%. Trading volume picks up in the second period and flattens out from the third period till the tenth period (14:30hrs to 15:00hrs). The volume subsequently begins to increase from the eleventh period and is the highest at the twelfth trading period. This pattern is visible regardless of the security or firm year under consideration. However, the volume traded during the middle period is evenly spread between 6% - 10%.

The results of volume variations in addition to earlier results indicate important implications about intraday investor behavior. The fact that return volatility, volatility adjusting for volume and volume are all high during the opening minutes is a strong indication of information bunching in the market. Enhanced volume in the opening minutes coupled with price variability indicates the market's adjustment to arrival of new information. In this aspect, the Indian market is similar to the U.S (and other) markets. However, it is also observed that volume trading is highest during evening period, while price variability is relatively low during this period compared to morning period. This result is contrary to the results of the developed U.S market. The likely explanation for this pattern is the impact of intraday trading effects on price changes. The increase in volumes (coupled with increase in variability) is an indication that intraday market agents are forced to square off positions, (thus revealing their positions) resulting in enhanced volumes during market close. The anticipation for new information for the next day coupled with idiosyncratic information is revealed through the volumes and price variability increase.

To investigate the volume patterns further, day-of-the-week effect on trading volume is also described in figures 2 to 5. The results of the Indian market are contrary to the results obtained by Jain and Joh (1988) for the U.S market. Firstly, unlike the U.S market where highest amount of volume is witnessed during opening period for NYSE, the NSE witnessed high volumes during the closing period. Secondly, the volumes traded across days does not prove the significance of differences for most of the periods barring the 12th period. However, it is observed that during the 12th period (15:00hrs to 15:30hrs) on Thursdays, the trading volume is significantly higher compared to the rest of the days in the week. This pattern is visible for 2004, 2007 and 2008. For the year 2002, 12^{th} period volume on Friday is high in addition to the high volume on Thursday. The possible explanation for the volume spike is the fact that derivatives settlement in NSE happens during the last Thursday of every month. Therefore, the volumes towards end of the day on Thursdays are expected be significantly high reflecting investor expectations. As a result, the averaged values for Thursdays are skewed.

Volume-Return Relationship

Given the fact that intraday returns and volumes conform to 'U' shaped curve, we finally focus on understanding the relationship between returns and volumes. We define three regression settings similar to Jain and Joh (1988) to analyze this relationship. These regressions are used to understand the relationship between intraday volumes and absolute returns. The regressions between volume and absolute returns do not merely capture the return-volume relationship, but also explain the relationship between variability and volume. The first regression is a plain vanilla regression that measures the association between returns and volumes, with a particular emphasis on the impact of positive and negative returns on volumes. In the second regression, the same relationship is tested controlling for period specific and day specific effects owing to the seasonality observed in the earlier analysis. Finally, the third regression adds additional control variables controlling for the positive-negative return impact on day and period specific effects. We use the Cochrane-orcutt method of estimation to estimate the regression coefficients as the error terms follow an AR(1) process[8]. The regression settings are defined as follows:

$$V_t = a + b|ret|_t + c(D_t \times |ret|_t) + u_t \tag{6}$$

$$V_t = a + b|ret|_t + c(D_t \times |ret|_t) + \sum_{i=1}^{15} e_i \times DD_{it} + u_t \qquad (7)$$

$$V_t = a + b|ret|_t + c(D_t \times |ret|_t) + \sum_{i=1}^{15} e_i \times DD_{it} + \sum_{i=1}^{15} f_i \times DD_{it} \times |ret|_t + \sum_{i=1}^{15} g_i \times DD_{it} \times |ret|_t \times D_t + u_t \qquad (8)$$

where,

V_t signifies the volume traded at period t

$|ret|_t$ is the absolute value of holding period returns for the particular period t. This represents price variability for the particular period

D_t is a dummy variable whose value is 0 when the returns for the particular period is positive and 1 otherwise

DD_{it} are a vector of dummy variables (i = 1 to 15) that account for day-of-the-week effects and period effects (11 for period and 4 for day-of-the-week)

u_t is a random error term

The variables a, b, c, e_i, f_i, g_i are unknown parameters to be estimated.

Table 4 illustrates the aggregated volume-return regression results for the years 2002, 2004, 2007 and 2008 respectively[7]. The table summarizes the estimates for the three regression settings. The estimates for the first regression setting clearly indicate that the association between trading volume and absolute value of returns is significantly positive. The first slope coefficient in this regression represents the strength of the association between absolute returns and volume. The positive sign of the slope coupled with strong significance (less than 1%)

indicates that variability of price changes (measured by absolute returns) explains increase in trading volume. This slope coefficient represents the absolute return-volume relation without bounds on the direction of trade. This result is consistent for all the four firm years examined in the study.

The second coefficient (for the variable |ret|.D) in this regression setting signifies the difference between the slope of volume-returns association, specifically between positive and negative returns. The coefficient estimate is found to be significantly negative for all the four years indicating that price variability due to negative price movements also explains increase in trading volume. On further examination, it is observed that the absolute values of slope coefficients for positive returns is higher than that of negative returns for all the years[9]. These results observed for the Indian market are similar to the hypothesis by Karpoff (1987) about asymmetric volume-price change behavior indicating that positive changes impact volumes greater compared to negative changes. Examining the coefficients further, it is observed that the slope for the negative price changes is negative which signifies the fact that trading costs for short sales are higher compared to long positions [Karpoff (1986)].

Unlike regression setting 1 where coefficients indicate the average slope values across all days and hours, regression setting 2 and 3 accounts for the day and period specific effects. It is observed that the results of regression settings 2 and 3 do not alter the results of regression setting 1. Controlling for day-of-the-week and period specific effects on return-volume association still indicates significant relationship between return-volume.

Results of regression settings 2 strongly signify the relationship between trading period, returns and volume. It is observed that the control variables for day-of-the-week effect are insignificant. This reiterates the fact that unlike U.S market, day-of-the-week does not impact trading volume in the Indian market. On the other hand, period specific effects are found to be significantly related to trading volume. The impact of middle period (period 4 to 11) on volume traded is observed to be weaker. The coefficients for the middle period (periods 4 to 11) ranged between 0.7 and 0.9 for the entire sample compared to higher coefficients during morning and evening periods. The results of this regression setting offers statistical significance to the observed 'U' shaped patterns in the earlier part of the study. The trading volume is highest during the opening and closing hours signifying enhanced market activity compared to the middle period.

Results of regression settings 3 indicate that the relationship between return (price change) and volumes are significant in controlling for the direction, day-of-the-week and period specific effects. However, coefficients of the dummy variables controlling for day-of-the-week effects are found to be insignificant while considering the effects of returns on volumes[10]. This further indicates that intraday volumes in the Indian market are not explained by day-of-the-week effects. Examining the coefficients of returns controlling for period specific and direction effects provides new insights. For all the four firm years, for most of the periods, the relationship between returns and volumes controlling for period and direction is found to be significant. In addition, the impact of positive half hourly price movements on volumes is significantly higher than negative price movements during all the periods for all the firm years. This volume-return asymmetry significance during all periods reinforces the fact that short selling costs for traders is higher in the Indian market compared to outright purchase of securities.

V Conclusion

Investigation the properties of intraday prices and volumes is important to understand many facets of a market's efficiency. Traditionally, in quote driven markets, the adverse selection cost of a market maker is an important component in price formation. The market maker knows only the cumulative quantity that an informed and uninformed trader might want to trade at any point [Kyle (1985)]. The adverse selection cost (and trading cost) is finally factored into the prices set by the market maker. Contrarily, in an order driven market where there is no market maker, trading cost and the adverse selection cost are expected to be low. Therefore, understanding the properties of stock returns in an order driven market, whether similar or different to its quote-driven counterpart, is imperative in a broader understanding of agent behavior.

In this context, the results of this study offer some important implications. The fact that 'U' shaped intraday return volatility and volume patterns are similar to developed markets indicates that market structure does not influence trade behavior. The results of this study indicate that the possibility of information asymmetry is at its highest during the opening period due to the observed extreme volatility and price-volume patterns. Therefore, the price formation in the Indian market is also at its weakest during the opening 30 minutes. However, unlike the quote driven markets, the results of evening period volatility and price-volume behavior is observed to be different in the Indian market. The price variations and trading volume are strongly related explaining the spike in volatility during the closing period. When intraday agents are forced to reveal their positions by end of the day, there is a spike in trading activity, volume and consequently volatility. However, the quantum of information asymmetry during the closing minutes of the market is much lower than the opening period. This is evidenced by the lower return volatility and insignificant return volatility accounting for trade volume. The impact of negative returns on trading volume though significant is lower than that of positive returns. The presence of asymmetry within intraday-volume dynamics is a further indication that short selling costs are higher in the market despite a different market structure.

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Figure 1: Normalized Intraday Patterns of NIFTY Index

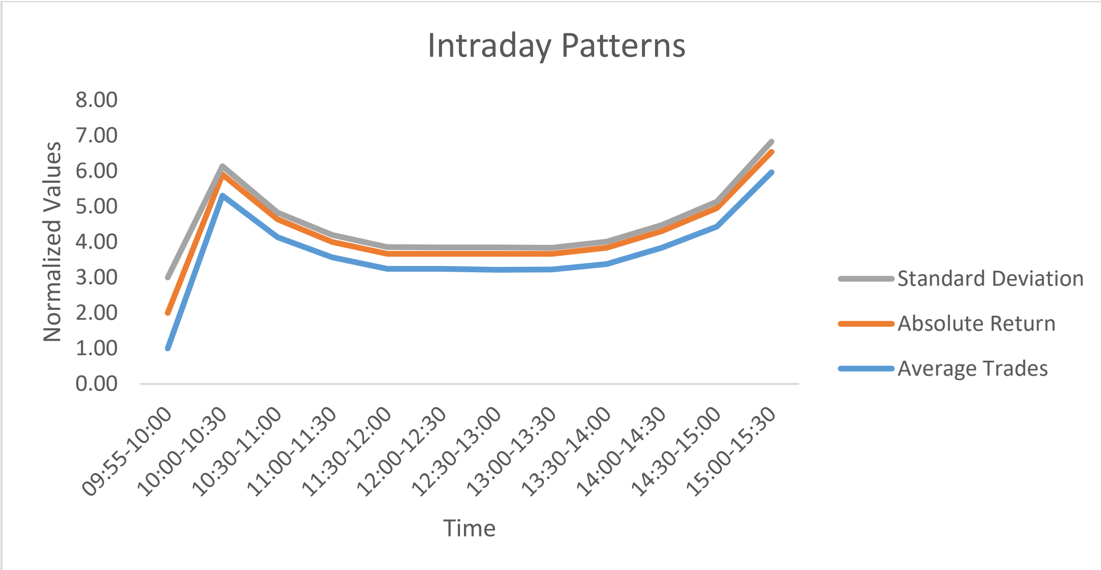

Figure 2: Volume Patterns for the year 2002

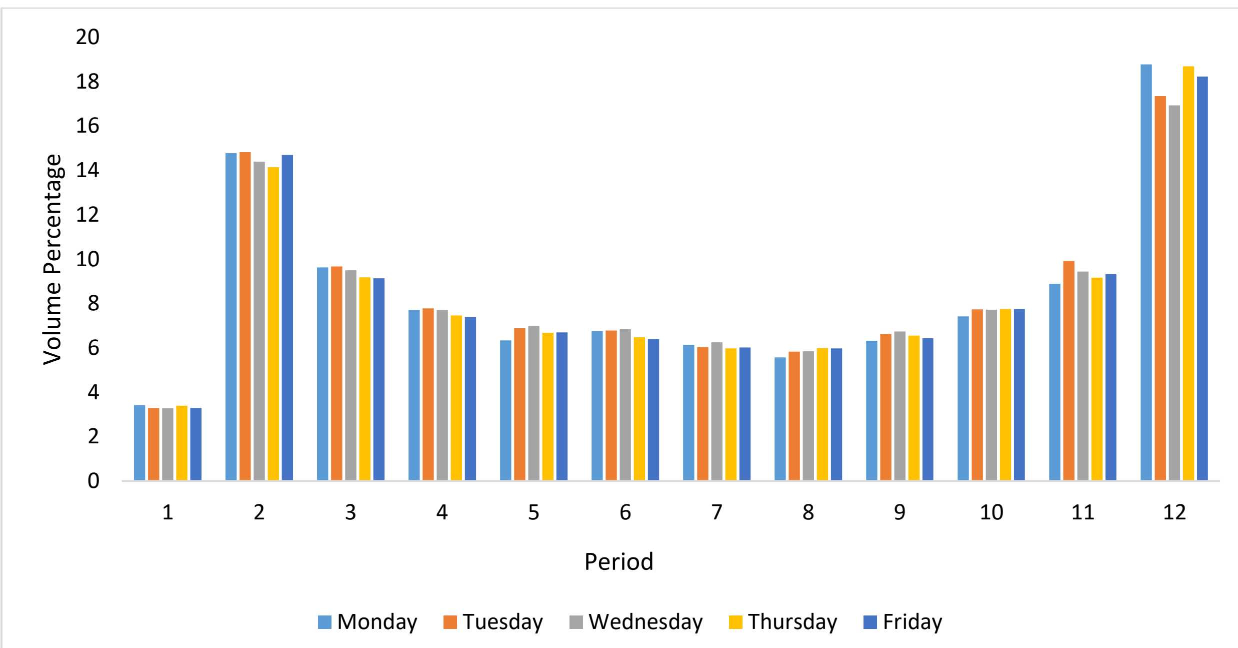

Figure 3: Volume Patterns for the year 2004

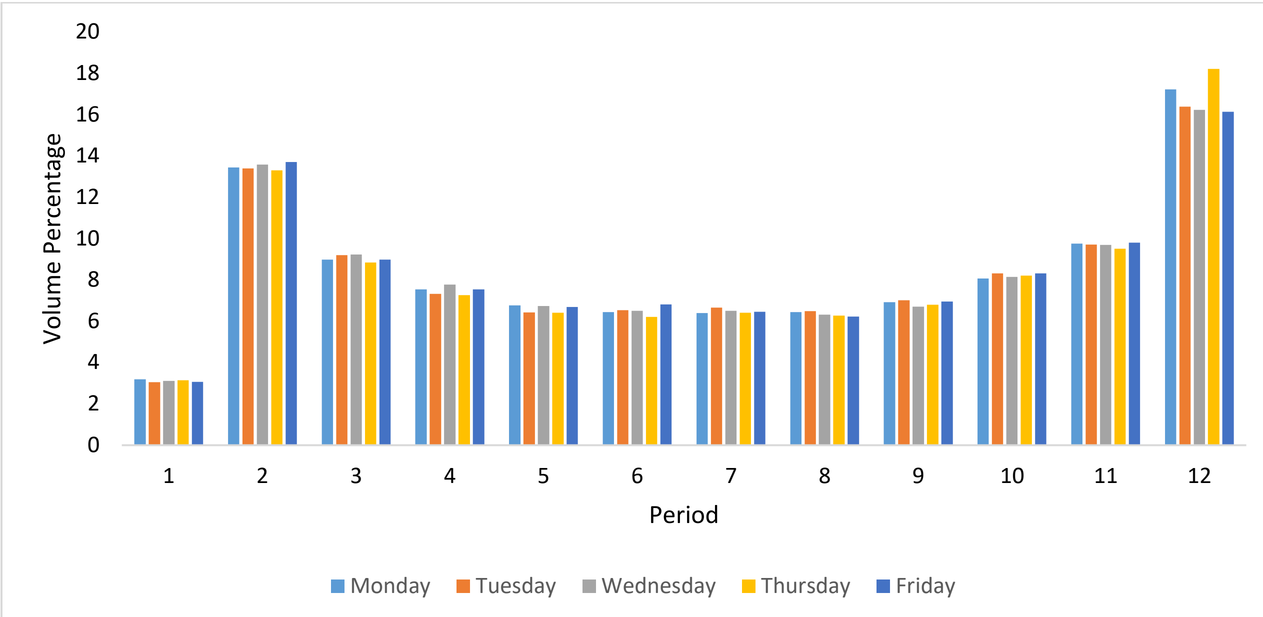

Figure 4: Volume Patterns for the year 2007

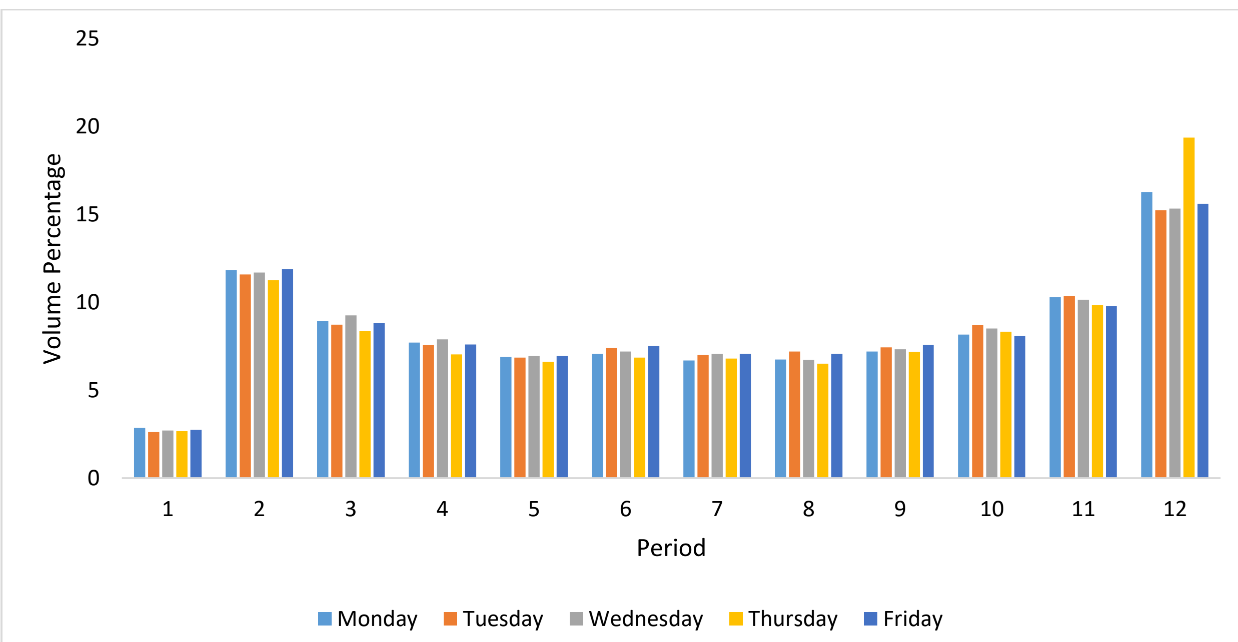

Figure 5: Volume Patterns for the year 2008

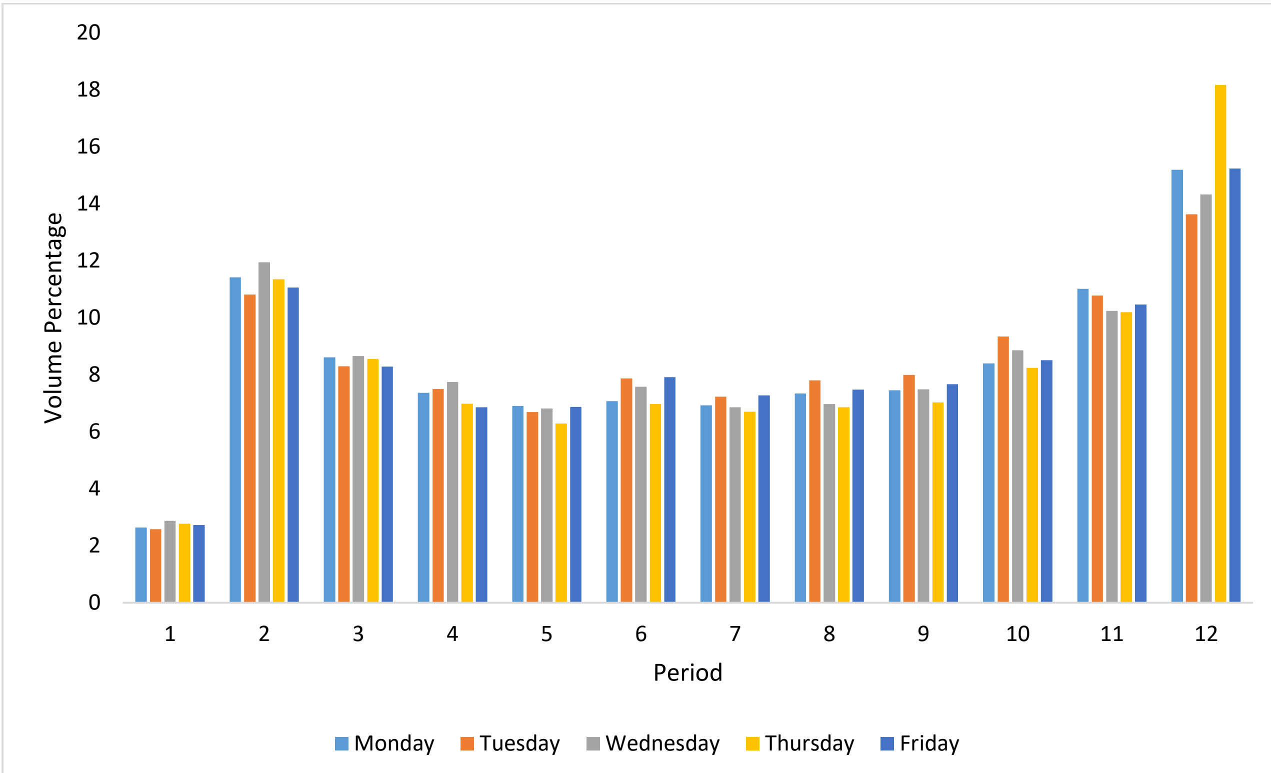

Table 1: Regression Results of Variability against Time for NIFTY Index

Variable	Estimate	t-statistic
Intercept	0.47	22.98***
t	-0.10	-25.69***
t^2	0.004	23.51***
t^3	-0.00	-20.30***
Adjusted R^2	3.13%	

Table 2: Regression Results of Variability against Time for Transactions Data

Variable	Estimate	t-statistic
Intercept	0.95	35.09***
t	-0.37	-21.09***
t^2	0.03	9.66***
t^3	-0.00	-2.04*
Adjusted R^2	0.59%	

***indicates significance at 0.1% (extremely significant), *indicates significance at 5%

Table 3: Variability Accounting for Trading Volume

Year	Mean			Median		
	Morning	Mid-Day	Evening	Morning	Mid-Day	Evening
2002	92.84	34.39	37.94	29.48	14.45	16.19
2004	26.85	11.07	22.13	17.51	8.31	10.38
2007	84.87	5.75	20.16	56.64	4.20	3.92
2008	3.10	0.12	0.22	0.91	0.06	0.06

The estimates were computed for each stock for each day. The table values presented contain mean and median of the aggregated results of the 50 stocks for each year for ease of interpretation. The values are normalized for ease of interpretation. Actual values to be multiplied by 10^{-9}.

Table 4: Volume-Returns Regression

Independent Variables	Setting 1	t-statistic	Setting 2	t-statistic	Setting 3	t-statistic
Intercept	0.004	3.2**	-1.045	-227.772***	-1.018	-207.443***
|Ret|	0.058	59.71***	0.064	85.129***	0.072	15.16***
|Ret|.D	-0.034	-23.47***	-0.023	-20.537***	-0.087	-13.851***
Mon			0.003	0.733	0.007	1.666.
Wed			0.001	0.127	0.004	0.977
Thu			0.005	1.182	0.004	1.077
Fri			-0.002	-0.39	0.000	-0.062
P2			1.868	381.09***	1.837	357.166***
P3			1.182	222.592***	1.176	208.778***
P4			0.914	170.321***	0.888	157.789***
P5			0.774	142.825***	0.757	133.284***
P6			0.784	144.066***	0.754	132.546***
P7			0.756	140.771***	0.728	129.263***
P8			0.744	138.468***	0.718	127.43***
P9			0.825	153.687***	0.797	141.534***
P10			1.022	190.845***	0.988	175.856***
P11			1.294	245.284***	1.267	228.998***
P12			2.440	494.023***	2.384	453.596***
|Ret|.Mon					-0.066	-21.061***
|Ret|.Wed					-0.068	-21.649***
|Ret|.Thu					0.000	0.05
|Ret|.Fri					-0.051	-15.102***
|Ret|.P2					0.054	10.45***
|Ret|.P3					0.112	20.728***
|Ret|.P4					0.014	2.997**
|Ret|.P5					0.181	29.646***
|Ret|.P6					0.033	6.715***
|Ret|.P7					0.176	27.781***
|Ret|.P8					0.121	18.666***
|Ret|.P9					0.017	3.645***
|Ret|.P10					0.154	24.845***

|Ret|.P11			0.012	2.487*
|Ret|.P12			0.130	23.397***
|Ret|.D.Mon			0.043	9.786***
|Ret|.D.Wed			0.071	14.779***
|Ret|.D.Thu			0.005	1.028
|Ret|.D.Fri			0.047	9.496***
|Ret|.D.P2			-0.017	-2.651**
|Ret|.D.P3			-0.016	-2.224*
|Ret|.D.P4			0.083	11.955***
|Ret|.D.P5			-0.057	-6.912***
|Ret|.D.P6			0.018	2.838**
|Ret|.D.P7			-0.039	-4.616***
|Ret|.D.P8			-0.019	-2.237*
|Ret|.D.P9			0.084	11.25***
|Ret|.D.P10			-0.042	-5.053***
|Ret|.D.P11			0.039	6.177***
|Ret|.D.P12			0.010	1.329
Adjusted R square	0.0078	0.399	0.412	

List of footnotes:

1. For each year, cumulative turnover is computed for every stock traded for every trading day. Subsequently, the data is arranged based on descending order based on cumulative turnover and averaged across days for the year. The top 50 stocks are finally chosen as the sample for analysis. The top 50 stocks accounted for more than 70% of the market's turnover for each year.
2. Based on broad consensus from literature, absolute returns are considered as a proxy for market volatility.
3. There are 335 trading minutes in a day. Therefore, splitting into equal 30 minute intervals is not possible. The first five minutes were chosen as a standalone period due to high market activity. The periods between 10:00 hrs and 15:30 hrs are split into equal 30 minute intervals. The choice of 30 minute intervals was based on an exploratory analysis and literature support, results of which are available upon request.
4. Each day is divided into 12 periods. The mean and standard deviation for the 12 periods are computed and used to transform the returns.
5. Following Sampath and Gopalaswamy (2015), morning, mid-day and evening periods are defined to compute volume adjusted variability over the course of a trading day.
6. The stocks were classified based on their industry/index affiliation but results are not reported in this study. Results indicated that the stocks for each year were heterogenic (no particular industry was dominant).
7. We ran the regressions separately for each firm year i.e. for 50 stocks for each year under consideration. We also ran the regression for all the stocks for all the years. The results

were mostly similar, so we only report the aggregated results. However, the overall results are available upon request.

8. We first estimated a normal OLS regression and tested for the diagnostics. For all the regressions used, we found AR(1) process in error term, so as suggested in literature and by Jain and Joh (1988), we used cochrane-orcutt estimation technique for coefficient estimates for robustness of results.
9. When we ran the regressions individually, we found that for all the three settings, for all the 4 years, positive returns had higher value than negative. The slight deviation as presented in the table is the result of aggregation, overall the results are concurrent.
10. This was observed uniformly when all the four firm years were analyzed separately, the aggregated results indicate small differences.