Indian Institute of Management Calcutta
Working Paper Series
WPS No 863 /April, 2021

Impact of Bulk Trades on Price Discovery in Equity Market

Vivek Rajvanshi*
Associate Professor, Finance & Control Group,
IIM Calcutta, Joka, Kolkata 700104, India
Email: vivekr@iimcal.ac.in
*Corresponding Author

Indian Institute of Management Calcutta, Joka, D.H. Road, Kolkata 700104
URL: http://facultylive.iimcal.ac.in/workingpapers

Impact of Bulk Trades on Price Discovery in Equity Market

Vivek Rajvanshi[1]

Abstract

We investigate and find evidence of front-running and economic gains around the bulk deals of stocks traded at the National Stock Exchange (NSE), a leading and fast-growing stock exchange in India, from 2010 to 2019. We divide the bulk deals into Only Buy, Only Sell, Partial Buy, and Partial Sell trades. Further, we examine the price impact on share price if an individual investor or multiple investors initiate the deal. Our results show that the front-runners can achieve around 5-7% returns within a week around the event day. Excess returns before the deals are higher for 'Buy' deals than 'Sell' deals. We also examine the role of volume and delivery in explaining the cumulative abnormal returns (CAR) earned in the pre-event period. Results show that trading volume and delivery percentage increases significantly before the bulk deals. Lagged CAR and change in volume and change in delivery explain the abnormal returns (AR) on the event day. Our results are robust after controlling for Bullish and Bearish Periods and other control variables.

Keywords: Front running, price manipulation, abnormal returns, volume, delivery, bulk deal

---

[1] Associate Professor, Finance and Control Group, Email-vivekr@iimcal.ac.in
Acknowledgement: Author acknowledge research grant received under category-I project from IIM Calcutta (IBTPDEM/3737/2017-18).

Impact of Bulk Trades on Price Discovery in Equity Market

1. Introduction

Anecdotal evidence suggests that institutional investors are better informed about a stock's investment potential compared to their retail counterparts (Ali et al., 2008; Cai et al, 2010; Yan & Zhang, 2009). This information asymmetry often translates into stock price manipulation. For example, Comerton-Forde and Putnins (2014) find that stocks exhibiting higher information asymmetry and lower liquidity are most likely to be manipulated. This manipulation has an adverse impact on market efficiency and investors' confidence, which produces deadweight economic loss (Pirrong, 1995). Therefore, it's quite natural that regulators and investors are always concerned about such manipulation. One of the popular strategies of price manipulation is 'Pump and Dump', wherein few investors artificially try to inflate the price of an asset and then sell those cheaply bought assets at an inflated price (Huang & Cheng, 2015). When the 'dumping' of assets is exercised, the price correction takes place and by the time, investors incur a loss. These strategies are quite common with low priced stocks. 'Pump and Dump' in the US stock market has been deemed illegal by the U.S. Security Exchange Commission (SEC). Other forms of stock price manipulation, e.g. insider trading or revealing false information, are also prohibited by law. Allen and Gale (1992) identify another avenue to manipulate stock price, wherein uninformed investors will be unsure about the actual intention of large trades. According to them, if uninformed investors consider the stocks to be undervalued (overvalued), but the bulk buyers (sellers) trade to disguise them, a stock price manipulation can occur. This is termed as 'Trade based' manipulation.

Stock Price manipulation, although exists worldwide, could be of more concern for emerging economies. This is primarily due to poor institutional structure, concentrated ownership and weaker regulations prevailing in these countries. As mentioned earlier, in developed countries like US any form of price manipulation invites litigation risk. Despite that, Aggarwal and Wu (2006) reveal evidence of price manipulation in the US market. Therefore, it is imperative to delve deeper into the issues of stock price manipulation in emerging countries. For example, few studies have already identified the existence of pump and dump in emerging countries (Khwaja and Mian, 2005; Imisiker and Tas, 2013). Similarly, other studies document the existence of stock price manipulations in emerging market contexts (Laksomya et al, 2018; Ogut et al, 2009).

Our study revolves around National Stock Exchange of India Limited (NSE), the leading stock exchange of India. As of April 2018, this is ranked 11th in size[2]. According to the estimate of Economic Times, a leading newspaper in India, 60 million retail investors invest in equity market either through direct investment or through mutual funds. If a trade includes more than 0.5% of a firm's equity under single client code, it's termed as bulk deal. Bulk deals are performed during regular trading hours and comprise single or multiple transactions.

Front-running is often associated with bulk deals as the front-runners with some unique private information trade in bulk ahead of others who don't have that information (Heidle and Li, 2003). The volume of bulk trades plays an important role in manipulating price and generating abnormal profit for front-runners. Chaturvedula et al. (2015) document the front-running behaviour of investors exploring bulk deals in the Indian stock market for 2004-2012. We extend the analysis of Chaturvedula et al. (2015) in several ways. First, we include two additional groups of trades, 'Partial Buy' and 'Partial Sell', where traders use a mixture of trades to disguise other uninformed investors but ultimately take a one-sided position. Second, we analyse both individual as well as multiple investors in a bulk trade to explore whether category of investors does matter in front running. Third, we empirically test the asymmetric market reaction between 'Buy' and 'Sell', as well as between 'Only Buy (Sell)' and 'Partial Buy (Sell)'. Fourth, we study the role of volume and delivery in bulk trades. Finally, our study period encompasses almost ten years of latest bulk deals. In a nutshell, our study explores the various characteristics associated with stock price manipulation focussing on NSE where stocks exhibit higher liquidity and are free from small size bias.

We employ an event study methodology to find the impact of bulk deal announcements. Our findings strongly support the evidence of front running in the Indian stock market. However, the market reactions between 'Buy' and 'Sell' as well as between 'Only Buy (Sell)' and 'Partial Buy (Sell)' are asymmetric. Among other factors, trading volume and delivery positions play a crucial role in explaining stock price manipulations. Cumulative abnormal returns with changes in volume and delivery before the event date explain the abnormal returns on the event date. We believe that our study would significantly contribute to the existing literature by bringing these new insights.

[2] https://en.wikipedia.org/wiki/National_Stock_Exchange_of_India

The rest of the paper is structured as follows: Section 2 lists the relevant literature and discusses the institutional background. Section 3 explains the development of hypotheses. Section 4 deals with the methodology and section 5 describes the data. Section 6 analyzes the discuss the empirical findings. Finally, section 7 concludes the study with possible implications and future scope of the study.

2. Literature Review and Institutional Background

2.1 Literature Review

Occurrence of block trades often results in movement of stock prices created by asymmetric information (Mikkelson & Partch, 1985). These price movements can be temporary or permanent based on the nature of block deals. Liquidity cost theory and price pressure hypothesis explains the temporary impact caused on stock prices due to huge impact cost (Holthausen et al., 1987; Shleifer, 1986). On the other hand, information effect (Chan & Lakonishok, 1993) and substitution effect (Scholes, 1972) explains the permanent impact on price movement due to block trades. Anecdotal evidence suggest that this price impact is significantly higher for bulk 'Buy' than bulk 'Sell' (Aitken & Frino, 1996; Gemmill, 1996; Keim & Madhavan, 1995, 1996, 1997). One plausible explanation may be that bulk 'Buy's carry more information than bulk 'Sell's. Further, few studies observe a continued price increase following bulk purchase and price reversal after bulk sales (Chan & Lakonishok, 1993, 1995; Frino et al., 2005; Holthausen et al., 1987, 1990). However, existing literature is silent on whether this asymmetry in price reaction pertains to only one-sided trades (e.g. Only Buy or Only Sell) or it's evident in partial trades (e.g. Partial Buy or Partial Sell) as well.

Few studies that large trades enhance shareholders' value (Ball & Finn, 1989; Barclay & Holderness, 1991; Mikkelson & Partch, 1985; Sudarsanam, 1996). Among these studies, Sudarsanam (1996) reports cumulative average abnormal returns of approximately 13% within an event window of [-5,5], i.e. 11 days. Banerjee et al. (1997) infer that value creation is not always a result of block trades. Rather, it depends on the identity of traders. In any case, presence of abnormal returns on or before the event day (i.e. day 0) indicates the leakage of private information and front-running behaviour by informed investors. Chaturvedula et al

(2015) provide the evidence of front-running and report the existence of same predominantly on ‘Buy’ sides.

A persistent and significant rise in trading volume before the event indicates the presence of front-runners. Manahov (2016) discusses the correlation between front-running and trading volume and argues that the stock price volatility created by front-runners’ trades may influence the trading volume. Chen (2012) explores bear stock markets and establishes a negative correlation between trading volume and stock returns. Few studies also examine the association between front-running and stock delivery (Cai, 2003; Markham, 1988). Markham (1988) shows that delivery options often explain the abnormal stock price movement caused by front-running.

Another pool of literature explores the potential factors that may explain the abnormal returns associated with block trades. For instance, Grier and Albin (1973) find that ‘monopolistic information’ obtained by the traders may influence the stock prices. Holthausen et al. (1990) show that stock prices' movement depends on the block size. On the other hand, Keim and Madhavan (1996) report that the impact of large trades on stock prices is higher for small-size firms. Gemmill (1996) and Holthausen et al. (1990) explore the impact of volatility on price movement due to block trades. Madhavan and Cheng (1997) argue that block trades are often guided by liquidity. Brockman et al (2009) state that block deals adversely impact liquidity trading. In addition, some studies have included various macroeconomic measures, such as GDP, Interest rate, or business cycle in explaining abnormal returns earned due to large trades (Aggarwal & Wu, 2003; Chaturvedula et al., 2015).

2.2 Institutional Background

Before developing relevant hypotheses from the existing literature, it is imperative to understand the institutional background of the study. The Securities and Exchange Board of India (SEBI), the regulator of India's securities and commodity market, provides the framework to identify and disclose trade details of bulk deals. Brokers inform the exchange about all transactions in a scrip where parties trade more than 0.5% of the company's total shares on the exchange. Such trades are known as bulk trades. On the same day, after market hours, the exchange disseminates the information about bulk trades to the public.[3] These transactions occur in the equity cash segment and cannot be squared off during the same day.

SEBI also allows Indian exchanges to provide a 35-minute trading window (9:15 am to 9:50 am) on exchange working days for Block deals. A minimum of 500,000 shares or Rs. Fifty million transactions form a block deal. There should not be a price difference of more than one percent (higher/lower) from the last price traded in the regular trading window. Block deals are placed through the limit orders and executed if the opposite party is ready to transact at the same price and exact quantity. Usually, dealers/brokers facilitate the deals. Block order remains valid only for 90 seconds, and it gets automatically cancelled if not executed. As both parties deal with higher value trade, it is difficult to suspect that deals attract any private information, and therefore any price reaction before such events is not expected. Unlike the block deal, there is no such price restriction on the bulk deal, and traders may split large orders into any number of small orders and trade in a standard trading window. In this study, we have focused only on bulk deals. Such deals provide an opportunity to the brokers and other participants to front run and generate economic gains based on the information leakage.

3. Hypothesis Development

A large number of studies on market microstructure investigate whether informed traders, such as insiders or strategic entities, can trade profitably with prior information (Easley & O'hara, 1987; Glosten & Milgrom, 1985; Kyle, 1985, 1989). In contrast, Van Bommel (2003) suggests that sometimes an informed trader would prefer not to trade even based on her own information. On the other hand, Allen and Gale (1992) report that a trader can manipulate the price simply by buying and selling in bulks and without releasing information about the firms. Such price manipulation increases market inefficiency and triggers front-running before larger trades (Chaturvedula et al., 2015). Aktas and Kryzanowski (2014) also show that informed trading often results in larger trades. However, these larger trades can exhibit asymmetric impact of buy and sell (Alzahrani et al., 2012). Frino, Mollica and Romano (2012) also affirm that informed purchase is more evident in a stock compared to informed sale. Further, few studies argue that traders are often uncertain about the fact that the bulk traders actually have the correct information (Aggarwal & Wu, 2006). This uncertainty makes price manipulation profitable. In contrast, bulk traders may also disguise other investors by simultaneous purchasing and selling, but holding a net position at the end of the period. This type of trading

[3] Refer Master Circular For Stock Exchanges on Trading Part I on www.sebi.gov.in/circulars/2010/anncir1.pdf.

behaviour may weaken the evidence of front-running behaviour. Based on these factors, we posit the following hypotheses:

H1a: Average abnormal returns (AAR) earned by investors in the pre-event period, i.e. just before bulk buy (sale) are positive (negative) and significant
H1b: Average abnormal returns (AAR) earned by buyers of bulk deal in the pre-event period are significantly higher than that of sellers of bulk deal
H1c: Average abnormal returns (AAR) earned in the pre-event period are lower for Partial Buy and Partial Sell compared to Only Buy and Only Sell, respectively

One crucial and complementary indicator of the front running behaviour is a significant and persistent increase in trading volume in the pre-event period. Unlike abnormal returns, the abnormal trading volume does not require any benchmark model to estimate. Thus, the increase in trading volume indicates the presence of high volatility which may be caused due to information leakage or more uncertainty around bulk trades. Front runners who hold positions much before the event to get the benefit of price movement can trade as intraday traders or opt for physical delivery. Whereas intraday traders square off their positions on the same day, other group of traders go for physical settlement and delivery. As days approach the event, more information gets revealed and there is a risk of gap up or gap down openings in the stock price of the next day. Therefore, investors who have information about the expected bulk deal may be interested to take deliveries to avoid risk of gap up or gap down opening. One may invariably argue that if there is a significant increase in trading volume in the pre-event period, it can simply be an artefact of liquidity of the stocks. The front-running behaviour thus may cause higher liquidity as well. Therefore, we postulate the following hypotheses:

H2a: Due to front-running trading volume in the pre-event period increases significantly
H2b: Due to front-running delivery in the pre-event period increases significantly
H2c: Due to front-running liquidity in the pre-event period increases significantly

Chen (2012) explores the relationship between price movement and trading volume and reports a negative association in falling stock markets. Panic overselling or leakage of information about the bulk deals can explain such low price-high volume relationship. Therefore, it’s not surprising that the trading volume of pre-event period explains the cumulative abnormal returns (CAR) earned by the stocks in this period. On a similar ground, physical delivery agreement and liquidity of stocks may explain the stock price movement in the pre-event period effectively (Chaturvedula et al., 2015). Based on these arguments, we propose the following hypotheses:

H3a: Cumulative abnormal returns in the pre-event period can be explained significantly by the increasing trading volume
H3b: Cumulative abnormal returns in the pre-event period is significantly explained by change in delivery positions
H3c: Cumulative abnormal returns in the pre-event period is significantly explained by change in liquidity.

Finally, to establish the impact of front-running, it is imperative to explore the association between pre-event period cumulative abnormal return and the abnormal return earned on the event day. If front-runners are active before bulk deals, we may expect a positive and significant association between the pre-event cumulative abnormal returns and abnormal returns on the event date. Hence, we build our final hypothesis as:

H4: Abnormal returns earned on the event day can be explained by the cumulative abnormal returns earned in the pre-event period.

4. Methodology

4.1 Event Study

We employ an event study methodology to estimate average abnormal returns (AAR) around the bulk deal date for different securities. In the following sub-sections, we would first discuss the return event study and then the estimation of abnormal volume.

4.1.1. Return Event Study

The date of the bulk deal is considered as event date and has been marked as day 0. The event window notation [-p, +q] corresponds to an $(p + q + 1)$ −day period, from p trading days before the event date to q trading days after the event date. The daily abnormal return for stock k is calculated as the difference stock return on day t, $R_{k,t}$, and the expected stock return on day t, $E(R_{k,t})$, estimated using a particular expected returns model.

$$AR_{k,t} = R_{k,t} - E(R_{k,t}) \tag{1}$$

The AAR over the event window $[-p, q]$ is estimated as follows

$$AAR_{-p,q} = 1/N \sum_{k=1}^{N} AR_{k,t} \tag{2}$$

Where N is the total number of firms, and $1/N \sum_{k=1}^{N} AR_{k,t}$ is the average abnormal return on day *t*.

To ensure that our AAR estimates are not sensitive to the specification of the expected return model, we estimate abnormal returns using the market model[4].

4.1.2. Abnormal Trading Volume

For each firm *k*, we take dollar traded volume on trading day *t*. The raw measures of daily trading volume, such as dollar traded volume, usually display a significant positive skew. However, a log-transformation yields trading volume measures that are approximately normally distributed (see, for example, Ajinkya & Jain, 1989; Cready & Ramanan, 1991). We estimate a daily measure of log-transformed dollar volume, V_{kt} (hereafter referred to as volume for brevity), as follows

$$V_{kt} = \log(Volume_{kt}) \tag{3}$$

We use the mean-adjusted daily volume as the measure of abnormal volume, AV_{kt}.

$$AV_{kt} = V_{kt} - \overline{V_k} \tag{4}$$

where $\overline{V_k}$ is the mean trading volume, calculated as the daily average of trading volume V_{kt} estimated over the pre-event window [-(30+p), -(p+1)] where the event window is [-*p*,*q*]

4.2 Cross-sectional Regression

Event study method is effective in understanding whether investors are earning any abnormal returns within different event windows. If there is a leakage of information about a bulk deal, investors with prior information try to front-run others. This practice of front-running is evident in pre-event period as well as on the event day. To identify whether such front-running exists in our sample, we have performed a cross-sectional regression analysis. The regression model adopted in this study can be expressed as:

---

[4] "*The market model is the most frequently used expected return model. It builds on the actual returns of a reference market and the correlation of the firm's stock with the reference market*." – https://www.eventstudytools.com/introduction-event-study-methodology

$$CAR_{[-p,-1]} = \gamma_0 + \gamma_1.PctChg\_TrdVol + \gamma_2.PctChg\_Del + \gamma_3.ChgLiq + \gamma_{4.}AmihudM8\_37 + \gamma_5.LogMktCap + \gamma_6.Bullish + \gamma_7.Bearish + \gamma_8.SD\_last30dys + \gamma_9.Yield10yr + \gamma_{10}.DPartialBuy + \varepsilon \quad (5)$$

$$CAR_{[-p,-1]} = \gamma_0 + \gamma_1.PctChg\_TrdVol + \gamma_2.PctChg\_Del + \gamma_3.ChgLiq + \gamma_{4.}AmihudM8\_37 + \gamma_5.LogMktCap + \gamma_6.Bullish + \gamma_7.Bearish + \gamma_8.SD\_last30dys + \gamma_9.Yield10yr + \gamma_{10}.DPartialSell + \varepsilon \quad (6)$$

where, the dependent variable $CAR_{[-p,-1]}$ denotes the cumulative abnormal returns earned by individual stocks for the pre-event window *[-p, -1]*. *CAR* for stock *k* can be computed as:

$$CAR_{-p,-1} = \sum_{t=-p}^{-1} AR_{k,t} \quad (7)$$

The main explanatory variables used in these equations are:

PctChg_TrdVol: percentage change in trading volume from the average 30 days volume *[-37,-8]* to volume on day *-1*

PctChg_Del: percentage change in delivery positions from the average 30 days positions *[-37,-8]* to positions on day *-1*

Other variables used in the regression as control variables are listed below:

ChgLiq**:** percentage change in liquidity as per Amihud (2002) from the average 30 days liquidity *[-37,-8]* to liquidity on day *-1*

AmihudLiq[-37 , -8]**:** measure of liquidity computed for 30 days *[-37,-8]* using Amihud (2002)

LogMktCap**:** proxy for size of firm computed by Logarithm of average Market Capitalization over *[-37,-8]* period

Bullish**:** a dummy variable with value 1 when the market state is bullish as per Pagan and Sossounov (2003), 0 otherwise

Bearish**:** a dummy variable with value 1 when the market state is bearish as per Pagan and Sossounov (2003), 0 otherwise

SD_last30Dys**:** Standard deviation of daily returns computed for *[-37,-8]* period is used as proxy for volatility of the stock price

Yield10yr: yield on Government 10-Year Bond used as proxy for risk-free rate

DPartialBuy**:** a dummy variable with value 1 if the deal is Partial Buy (both 'Buy' and 'Sell' trades happened on the event date, but 'Buy' dominates 'Sell' at the end of the day), 0 otherwise

DPartialSell: a dummy variable with value 1 if the deal is Partial Sell (both 'Buy' and 'Sell' trades happened on the event date, but 'Sell' dominates 'Buy' at the end of the day), 0 otherwise

In addition to *CAR*, it is also important to identify the factors that may explain the abnormal returns earned on the event day. Therefore, using *AR,* computed as per Eq (1), as a dependent variable following regression analysis has been performed:

$$AR_{[0,0]} = \gamma_0 + \gamma_1.PctChg\_TrdVol + \gamma_2.PctChg\_Del + \gamma_3.ChgLiq + \gamma_{4.}AmihudM8\_37 + \gamma_5.LogMktCap + \gamma_6.Bullish + \\ \gamma_7.Bearish + \gamma_8.SD\_last30dys + \gamma_9.Yield10yr + \gamma_{10}.DPartialBuy + \gamma_{11}.CAR_{[-7,-1]} + \gamma_{12}.BQ\_TQ + \gamma_{12}.DBQ\_TQ\_Par + \varepsilon \quad (8)$$

$$AR_{[0,0]} = \gamma_0 + \gamma_1.PctChg\_TrdVol + \gamma_2.PctChg\_Del + \gamma_3.ChgLiq + \gamma_{4.}AmihudM8\_37 + \gamma_5.LogMktCap + \gamma_6.Bullish + \\ \gamma_7.Bearish + \gamma_8.SD\_last30dys + \gamma_9.Yield10yr + \gamma_{10}.DPartialSell + \gamma_{11}.CAR_{[-7,-1]} + \gamma_{12}.SQ\_TQ + \gamma_{12}.DSQ\_TQ\_Par + \varepsilon \quad (9)$$

Compared to Eqs (5) and (6), Eqs (8) and (9) include one additional explanatory variable and four additional control variables as listed below:

CAR** **[-7,-1]: a new explanatory variable computed as per Eq (8) for the pre-event period [-7, -1]

BQ_TQ: ratio of buy quantity in the bulk deal to total traded quantity on the event day

SQ_TQ: ratio of sell quantity in the bulk deal to total traded quantity on the event day

DBQ_TQ_Par: Interaction term between *BQ_TQ* and *DPartialBuy*

DSQ_TQ_Par: Interaction term between *SQ_TQ* and *DPartialSell*

5. Data

We source bulk deal data of firms listed on NSE from the Prowess database maintained by the Centre for Monitoring Indian Economy (CMIE). The study period ranges from January 2010 to December 2019. We chose data period that covers a long enough period so that results can be generalized and avoided around one year period after the 2008 subprime crisis. We have not considered block trades in our sample because of two reasons: First, block trades constitute only a small portion of all large trades; Second, earlier studies have documented no abnormal returns for block trades due to the time restriction associated and the structure of such deals (Chaturvedula et al., 2015). Therefore, ultimately our sample includes a total of 81,506 bulk deal records. Among them, 39,999 are 'Buy' trades and 41,507 are 'Sell' trades. Table 1 reports the year-wise records of these bulk deals. Panel A of the table lists all 'Buy' and 'Sell' trades together, whereas Panel B and C show the detail of 'Buy' and 'Sell', respectively. All three table panels suggest that the number of bulk trades spikes on two occasions, 2010 and 2017. However, the value (in mn INR) of bulk trades reaches the highest in 2019.

We further classify these bulk deals into five groups: Only Buy, Only Sell, Partial Buy, Partial Sell, and Net Zero. Only Buy and Only Sell are the trades when on a particular security date only 'Buy' or 'Sell' are recorded in bulk deal record respectively. Partial Buys are those where both 'Buy' and 'Sell' trades happened on the event date, but 'Buy' dominates 'Sell' at the end of the day. Similarly, Partial Sell refers to the dominance of 'Sell' over 'Buy' for a security in bulk deal record of a particular day. Only Buy and Only Sell imply the better informed investors' clear preference towards one side of trades. Partial Buy and Partial Sell indicate those investors' disguised preference towards one side. Net Zero, on the other hand, does not explicitly show any preference. Therefore, in our analysis we have not taken Net Zero trade bulk deals. We further divide these trades on the basis of execution. If it is executed by one individual, it is classified as Individual and there are multiple investors involved, we term them as Multiple.

In our analysis to ensure the robustness of the results, we choose the deals for which (a) share price is available for at least 38 days before and 8 days after the event. (b) Share price should be more than Rs. 5. (c) one day returns should be within a range of +-30% (d) There should be some trades in three consecutive days. We also winsorize the data at 1% level at market cap of stocks to filter out very small and very large firms. Table 2 reports descriptive statistics of bulk trades as per the classifications described in the above paragraph. According to this table, the number of Individual trades in Only Buy (N = 1804) and Only Sell (N = 2831) segments are much higher than that of Multiple trades for Only Buy (N = 50) and Only Sell (N =77). However, for Only Sell, the average size of Multiple trades is significantly higher (Rs 58,128 million) than that of Individual trades (Rs 17,444 million). For Partial Buy and Partial Sell segments, both number of trades and average size are comparable between Individual and Multiple traders. Value of the trades and trading quantities are much higher for Multiple trades compared Individual trades within Only Sell, Partial Buy and Partial Sell segments.

6. Empirical Findings

Table 3 computes and lists the AAR at different days within the event window of [-7, +7] for all types of trades performed by Individual and Multiple traders. Interestingly, 'Buy' and 'Sell' trades within block trade records show different market reactions. For most of the 'Buy' trades, the positive and significant market reactions are spotted consistently before the event date. The price reaches the highest level on the event day and it gradually starts falling within one or two days after the event day. For example, at Individual level for Only Buy trades, the stock price increases significantly and consistently from 7 days before the event date. On the event date the price spikes till highest level and keep on rising till next day. From day 2 onwards, the correction of prices starts. Similar stock price movements have been evident in other 'Buy' trades across all groups (Only Buy and Partial Buy) at Individual and Multiple level. Even similar reaction has been observed for Net Zero trades as well. However, for 'Sell' trades, the price reactions are not consistent. For 'Only Sell' at Individual and Multiple levels, the AARs are significantly decreasing from some days before the event date till the event date and start getting reversed from one or two days after the event. But for all 'Partial Sell' the price response is just the opposite. It increases significantly till the event date, and after that, the correction occurs. Therefore, it seems that bulk 'Buy's and 'Only Sell's are anticipated by the market beforehand. In contrast, 'Partial Sell' successfully camouflages the market till the event and brings the surprise on the event date. In all scenarios, the highest impact has been seen on the event date itself. Thus, by and large, this finding supports our hypothesis H1a.

Panel A of Table 4 lists the abnormal returns generated on the event day by all bulk 'Buy' and bulk 'Sell' deals separately. The 'Buy' trades include 'Only Buy's and 'Partial Buy's made by both individual and multiple investors. Similarly, the 'Sell' trades include 'Only Sell's and 'Partial Sell's. From the table it is evident that abnormal returns earned by both 'Buy' and 'Sell' are significantly greater than zero. Further, it computes the difference between mean abnormal returns earned by these two groups of deals. The *t*-statistic of 31.047 shows that abnormal returns earned by bulk 'Buy' deals are significantly higher than that of bulk 'Sell' deals. Hence, it is in line with the hypothesis H1b of the study. Panel B and of Table 4 reports the abnormal returns earned on the event day by 'Only Buy' and 'Partial Buy' trades. Although both of these trades generate significant positive abnormal returns, the difference in returns between these two groups is surprisingly negative and significant. It's expected that the impact on price would be lower if the traders disguise the market by simultaneous buying and selling of the stock. But our result has shown that the impact on 'Partial Buy' is higher than 'Only Buy'. Thus, it doesn't corroborate to the hypothesis H1c of the study. One possible explanation is that investors are involved in buying and selling simultaneously on the expectation of a higher price impact. Also, investors may initiate the buy trades for more than intended to carry the delivery. Later, during the day, when investors find that the price impact is more due to that bulk trade, they may book some intraday profit and square off a part of their open positions. It is difficult to test the right intention as it requires trading account level tick-by-tick data. The similar thing is evident for 'Partial Sell' and 'Only Sell' as depicted in panel C of Table 4. It seems that through partial sell investors are able to send confusing signals in the market and the impact on price is less.

Table 5 presents the value of average trading volume (ATV) generated by bulk deals around event window of [-7, +7]. In addition, the table computes the average traded volume of 30 days (from -8 to -37 days) before the chosen event window and reports it against day lags [-37,-8]. For all types of trades across all types of investors, the trading volume moves in similar pattern. It starts increasing sometime before the event date, spikes highest on the event date, and then starts declining after the event date. Panel A of Table 6 lists the result of a *t*-test conducted to test the difference in average volume [-37, -8] of 30 days before the event window and volume a day before the event. We use percentage change in volume (*PctChg_TrdVol*) a day before the event from the average 30 days position as one of the predictors of CAR. Around 90.25% volume increase is observed before the event day. *T*-statistic of 16.64 shows that the volume increase is significantly higher than the average volume. This provides a clear evidence of front running and contradicts the view of Sanders and Zdanowicz (1992), which suggests that trading volume picks up only after the event. Thus, this finding clearly supports the hypothesis H2a of the study.

Panel B of Table 6 depicts the result of one sample *t*-test performed on the variable *PctChg_Del,* i.e., percentage change in delivery positions from the average 30 days positions *[-37, -8]* to positions on day *-1.* It has been noticed that delivery positions increase by 1.2% in pre-event period. Significantly higher *t*-statistics supports the hypothesis H2b of the study. Panel C of Table 6 reports the finding from *t*-test that has been performed to measure the change in Amihud illiquidity measure for pre-event window of [-38, -8] and [-7, -1]. The result suggests that there is improvement in liquidity before the event. However, the improvement is not significant at 5% level. Thus, it does not support the hypothesis H2c of the study. Further, we test whether this improvement in liquidity is evident after the event of bulk deals as such deals may attract more investors and thus more trading in the stocks. Results show that the liquidity improves for around a week after the event and then it goes back to its previous levels. However, this change in liquidity is not significant. Results of the same are not reported for the brevity of space but can be requested from the author.

To identify factors that play a crucial role in explaining the front running behaviour of investors, we perform the cross-sectional regression analysis. We report the correlations among the explanatory variables in the correlation matrix reported in Table 7. The table suggests that the variables exhibit very low correlations among them, the highest absolute correlation being 68.6% between change in liquidity (*ChgLiq*) and lagged average liquidity [-37, -8} (*AmihudLiq[-37 , -8]*). Table 8 lists the impact of these factors on the CAR generated for individual investors during two pre-event windows, [-3, -1] and [-7, -1]. Column 1 and 2 of this table explain the CAR for 'Only Buy' and 'Partial Buy' deals, while column 3 and 4 explain the same for 'Only Sell' and 'Partial Sell' deals. From the table it is evident that *PctChg_TrdVol* is positive and significant for individual investors across all deal classifications. This confirms the front running activity and establishes the positive association between the CAR and change in trading volume of a stock. While examining the impact of change in delivery positions, we find that *PctChg_Del* is positive and significant in explaining CAR for all deals. This clearly evinces that there is a front running and leakage of information about the bulk buy or sell; and hence investors prefer to change their delivery positions accordingly rather than squaring off their positions same day. The dummy variable of 'Partial Buy', *DPartialBuy,* is positive but insignificant. However, the dummy of 'Partial Sell', *DPartialSell*, is positive and significant. This essentially suggests that the bulk traders try to minimize the impact of bulk deal on stock price by simultaneously buying and selling of the stock and thus convey a mixed signal to the market. Yet, partial traders on buy side successfully achieve that objective. Among other control variables, *SD_last30dys*, appears to explain CAR positively and significantly. This corroborates the well-known risk-return relationship of a stock. Effect of size (*LogMktCap*) and prior period liquidity (*AmihudLiq[-37 , -8]*) are only significant for sell deals pertaining to [-7, -1] event window and buy deals pertaining to [-3, -1] event window, respectively. Other two dummies, *Bullish* and *Bearish*, exhibit consistently positive and negative association respectively with CAR across all bulk deals. However, the impact of these business cycles is mostly significant in sell trades compared to buy trades. Thus, we find full support of hypotheses H3a and H3b, and partial support of H3c in the context of individual investors.

Table 9 reports the explanatory behaviour of different variables in explaining CAR of multiple investors for the same pre-event windows, [-3, -1] and [-7, -1]. The impact of the variables is mostly similar to that of individual investors, although the impact is much weaker. For example, here also *PctChg_TrdVol* is positive and significant at 1% level of significance across all deal specifications. This again supports our initial hypothesis of front-running in bulk deals. However, *PctChg_Del* is positive and significant only for buy deals in the period of [-3, -1]. Most of other control variables (e.g. *LogMktCap, SD_last30dys, AmihudLiq[-37 , -8],* and

ChgLiq) are insignificant. Among the dummies, *Bullish* is consistently positive and significant indicating that the upswing market attracts multiple traders to trade in bulk. For the buy deals, *Yield10Yr* shows a direct and significant association with CAR. Hence, in case of multiple investors our findings corroborate to hypotheses H3a and H3b, but does not support H3c.

Table 8 and 9 provide ample evidences of front running activity exhibited by individual and multiple investors before the event date. Now, we shift our focus towards the event date to measure the impact of such front running on abnormal returns earned by the stocks on the event date. Hence, we run a regression where we use abnormal returns on the event day, AR [0], as a dependent variable and CAR obtained in pre-event period of [-7, -1] as one of the explanatory variables. Table 10 reports the impact of different variables on abnormal returns realized on the event day. First two columns of the table show the impact of buy and sell trades of individual investors whereas last two columns represent the same for multiple investors. All four columns list positive and significant impact of pre-event *CAR* on $AR_{[0]}$. This clearly depicts that there is leakage of information related to block deals in advance and front runners use this information at their advantage. Therefore, we find complete support of our hypothesis H4. We also explore the impact of quantity of a specific type of trade on event date and its interaction with partial trade dummies to explain the $AR_{[0]}$. Surprisingly, the coefficient of *BQ_TQ*, the proportion of buy quantity in the bulk deal to total traded quantity on the event day, is negative and significant. One possible reason may be that the front runners want to liquidate their positions on the event date and book profits as they see the realization of their information. The coefficient of *SQ_TQ*, the ratio sell quantity in the bulk deal to total quantity traded, is not significant. However, the interaction between *SQ_TQ* and *DPartialSell* (*DSQ_TQ_Par*) is negative and significant for the individual investors. This shows that the price impact is less when investor sell more quantity with mix of buying.

7. Conclusion

Stock price manipulation based on large trades is evident in extant literature. Exploring such trade-based manipulation in the context of an emerging market is of much interest as the regulatory mechanism of such markets is still evolving. We employ an event study methodology to find the impact of bulk deal announcements on stocks' market value. We find strong evidence of front running and stock price manipulation in the Indian stock market. Further, we observe strong market reactions on 'Buy' over 'Sell' trades which clearly shows that investors have more information about price increase than decrease. Similar asymmetric market reaction is also evident on 'Only Buy (Sell)' over 'Partial Buy (Sell)' trades. Therefore, it reveals the certainty of information leakage that is related to one-sided trades. We also explore the possible determinants of such abnormal price movement. Trading volume and delivery positions evolve as the most critical factors in explaining the front-running and stock price manipulations in India. However, the evidence of front-running is similar for individual and multiple investors involved in bulk deals.

Our study has important implications for investors and regulators of the Indian stock market. As discussed earlier, SEBI has already implemented several regulatory measures such as creating a separate trading window for Block trades, imposing price restrictions, or limited time boundaries to execute trades. Despite that our study reveals the presence of stock price manipulation and front-running. Hence, further intervention is required to safeguard the interest of common investors. Although our study is limited to the extent of one stock market and exploring the evidence of front running, future studies may further delve deeper to outline the possible measures that SEBI could adopt. We believe specific mechanisms that reduce information asymmetry can be a handy option in this regard.

References

Aggarwal, R. K., & Wu, G. (2003). Stock market manipulation-theory and evidence. *AFA 2004 San Diego Meetings*.

Aggarwal, R. K., & Wu, G. (2006). Stock market manipulations. *The Journal of Business*, *79*(4), 1915–1953.

Aitken, M., & Frino, A. (1996). Asymmetry in stock returns following block trades on the Australian Stock Exchange: A note. *Abacus*, *32*(1), 54–61.

Ajinkya, B. B., & Jain, P. C. (1989). The behavior of daily stock market trading volume. *Journal of Accounting and Economics*, *11*(4), 331–359. https://doi.org/10.1016/0165-4101(89)90018-9

Aktas, O. U., & Kryzanowski, L. (2014). Market impacts of trades for stocks listed on the Borsa Istanbul. *Emerging Markets Review*, *20*, 152–175.

Allen, F., & Gale, D. (1992). Stock-price manipulation. *The Review of Financial Studies*, *5*(3), 503–529.

Alzahrani, A. A., Gregoriou, A., & Hudson, R. (2012). Can market frictions really explain the price impact asymmetry of block trades? Evidence from the Saudi stock market. *Emerging Markets Review*, *13*(2), 202–209.

Amihud, Y. (2002). Illiquidity and stock returns: Cross-section and time-series effects. *Journal of Financial Markets*, *5*(1), 31–56.

Ball, R., & Finn, F. J. (1989). The effect of block transactions on share prices: Australian evidence. *Journal of Banking & Finance*, *13*(3), 397–419.

Banerjee, S., Leleux, B., & Vermaelen, T. (1997). Large shareholdings and corporate control: An analysis of stake purchases by French holding companies. *European Financial Management*, *3*(1), 23–43.

Barclay, M. J., & Holderness, C. G. (1991). Negotiated block trades and corporate control. *The Journal of Finance*, *46*(3), 861–878.

Brockman, P., Chung, D. Y., & Yan, X. (Sterling). (2009). Block ownership, trading activity, and market liquidity. *Journal of Financial and Quantitative Analysis*, 1403–1426.

Cai, F. (2003). Was there front running during the LTCM crisis? *Available at SSRN 385560*.

Chan, L. K., & Lakonishok, J. (1993). Institutional trades and intraday stock price behavior. *Journal of Financial Economics*, *33*(2), 173–199.

Chan, L. K., & Lakonishok, J. (1995). The behavior of stock prices around institutional trades. *The Journal of Finance*, *50*(4), 1147–1174.

Chaturvedula, C., Bang, N. P., Rastogi, N., & Kumar, S. (2015). Price manipulation, front running and bulk trades: Evidence from India. *Emerging Markets Review*, *23*, 26–45.

Chen, S.-S. (2012). Revisiting the empirical linkages between stock returns and trading volume. *Journal of Banking & Finance*, *36*(6), 1781–1788.

Cready, W. M., & Ramanan, R. (1991). The power of tests employing log-transformed volume in detecting abnormal trading. *Journal of Accounting and Economics*, *14*(2), 203–214. https://doi.org/10.1016/0165-4101(91)90005-9

Easley, D., & O'hara, M. (1987). Price, trade size, and information in securities markets. *Journal of Financial Economics*, *19*(1), 69–90.

Frino, A., Jarnecic, E., Johnstone, D., & Lepone, A. (2005). Bid–ask bounce and the measurement of price behavior around block trades on the Australian Stock Exchange. *Pacific-Basin Finance Journal*, *13*(3), 247–262.

Frino, A., Mollica, V., & Romano, M. G. (2012). Asymmetry in the permanent price impact of block purchases and sales: Theory and empirical evidence. *Available at SSRN 2145720*.

Gemmill, G. (1996). Transparency and liquidity: A study of block trades on the London Stock Exchange under different publication rules. *The Journal of Finance*, *51*(5), 1765–1790.

Glosten, L. R., & Milgrom, P. R. (1985). Bid, ask and transaction prices in a specialist market with heterogeneously informed traders. *Journal of Financial Economics*, *14*(1), 71–100.

Grier, P. C., & Albin, P. S. (1973). Nonrandom price changes in association with trading in large blocks. *The Journal of Business*, *46*(3), 425–433.

Holthausen, R. W., Leftwich, R. W., & Mayers, D. (1987). The effect of large block transactions on security prices: A cross-sectional analysis. *Journal of Financial Economics*, *19*(2), 237–267.

Holthausen, R. W., Leftwich, R. W., & Mayers, D. (1990). Large-block transactions, the speed of response, and temporary and permanent stock-price effects. *Journal of Financial Economics*, *26*(1), 71–95.

Huang, Y. C., & Cheng, Y. J. (2015). Stock manipulation and its effects: Pump and dump versus stabilization. *Review of Quantitative Finance and Accounting*, *44*(4), 791–815.

Keim, D. B., & Madhavan, A. (1995). Anatomy of the trading process empirical evidence on the behavior of institutional traders. *Journal of Financial Economics*, *37*(3), 371–398.

Keim, D. B., & Madhavan, A. (1996). The upstairs market for large-block transactions: Analysis and measurement of price effects. *The Review of Financial Studies*, *9*(1), 1–36.

Keim, D. B., & Madhavan, A. (1997). Transactions costs and investment style: An inter-exchange analysis of institutional equity trades. *Journal of Financial Economics*, *46*(3), 265–292.

Kyle, A. S. (1985). Continuous auctions and insider trading. *Econometrica: Journal of the Econometric Society*, 1315–1335.

Kyle, A. S. (1989). Informed speculation with imperfect competition. *The Review of Economic Studies*, *56*(3), 317–355.

Madhavan, A., & Cheng, M. (1997). In search of liquidity: Block trades in the upstairs and downstairs markets. *The Review of Financial Studies*, *10*(1), 175–203.

Manahov*, V. (2016). Front-running scalping strategies and market manipulation: Why does high-frequency trading need stricter regulation? *Financial Review*, *51*(3), 363–402.

Markham, J. W. (1988). Front-running-insider trading under the commodity exchange act. *Cath. UL Rev.*, *38*, 69.

Mikkelson, W. H., & Partch, M. M. (1985). Stock price effects and costs of secondary distributions. *Journal of Financial Economics*, *14*(2), 165–194.

Pagan, A. R., & Sossounov, K. A. (2003). A simple framework for analysing bull and bear markets. *Journal of Applied Econometrics*, *18*(1), 23–46.

Sanders, R. W., & Zdanowicz, J. S. (1992). Target Firm Abnormal Returns and Trading Volume Around the Initiation of Change in Control Transactions. *The Journal of Financial and Quantitative Analysis*, *27*(1), 109–129. JSTOR. https://doi.org/10.2307/2331301

Scholes, M. S. (1972). The market for securities: Substitution versus price pressure and the effects of information on share prices. *The Journal of Business*, *45*(2), 179–211.

Shleifer, A. (1986). Do demand curves for stocks slope down? *The Journal of Finance*, *41*(3), 579–590.

Sudarsanam, S. (1996). Large shareholders, takeovers and target valuation. *Journal of Business Finance & Accounting*, *23*(2), 295–314.

Van Bommel, J. (2003). Rumors. *The Journal of Finance*, *58*(4), 1499–1520.

Table 1: Sample of Bulk Trades

Year	Number of Records	Average Trade Qty	Average Trade Volume (in Mn)	Total Trade Value (in Mn)
Panel A: All Trades				
2010	16,174	495.55	1.25	20,211.22
2011	12,787	574.03	1.12	14,300.71
2012	4,908	1,377.14	2.85	14,001.22
2013	2,873	1,325.18	2.30	6,604.97
2014	3,859	1,807.11	1.95	7,523.30
2015	4,349	2,071.08	3.25	14,141.54
2016	6,225	1,332.94	1.65	10,279.18
2017	10,068	1,590.48	2.33	23,472.38
2018	7,806	2,015.80	2.60	20,260.56
2019	7,540	3,602.44	4.35	32,835.91
2020	4,917	4,165.32	4.00	19,671.32
Total	81,506			1,83,302.30
Panel B: Buy Trades				
2010	7,942	484.09	1.22	9,652.00
2011	6,330	556.26	1.10	6,989.68
2012	2,373	1,299.68	2.22	5,269.05
2013	1,394	1,236.87	2.32	3,238.04
2014	1,794	1,744.05	1.77	3,166.56
2015	2,108	2,007.66	2.90	6,112.30
2016	3,009	1,273.80	1.52	4,568.03
2017	4,936	1,560.12	2.26	11,163.63
2018	3,975	1,784.09	2.28	9,064.95
2019	3,693	3,439.05	3.87	14,296.43
2020	2,445	4,024.05	3.43	8,392.46
Total	39,999			81,913.13
Panel C: Sell Trades				
2010	8,232	506.06	1.28	10,559.22
2011	6,457	591.44	1.13	7,311.03
2012	2,535	1,449.66	3.44	8,732.17
2013	1,479	1,408.41	2.28	3,366.93
2014	2,065	1,861.89	2.11	4,356.75
2015	2,241	2,130.73	3.58	8,029.24
2016	3,216	1,388.27	1.78	5,711.15
2017	5,132	1,619.68	2.40	12,308.75
2018	3,831	2,256.23	2.92	11,195.61
2019	3,847	3,759.29	4.82	18,539.48
2020	2,472	4,305.04	4.56	11,278.86
Total	41,507			101,389.19

Table 2: Descriptive Statistics

Particulars	No of deals	Minimum	Maximum	Mean	Standard Deviation
Panel A: Only Buy					
Individual Investor					
Market Cap	1804	20.88	9,81,154.44	18,363.0	59,867.3
Shares Outstanding	1804	0.81	28,735.39	144.9	735.1
Trade Value	1804	0.21	23,547.88	482.2	1,425.2
Trade Quantity	1804	12410	1,24,49,08,416.00	42,18,585.5	3,07,76,992.0
Multiple Investors					
Market Cap	50	99.45	1,57,276.86	14,397.6	31,948.1
Shares Outstanding	50	2.89	1,058.80	102.2	188.0
Trade Value	50	1.61	4,207.10	503.6	963.5
Trade Quantity	50	50000	5,40,55,748.00	46,11,698.5	1,06,17,344.0
Panel B: Only Sell					
Individual Investor					
Market Cap	2831	6.6	11,20,201.88	16,714.2	62,739.0
Shares Outstanding	2831	1.32	5,290.80	167.0	381.4
Trade Value	2831	0.08	56,918.06	447.5	2,179.0
Trade Quantity	2831	7241	14,97,31,808.00	38,48,905.8	1,00,75,711.0
Multiple Investors					
Market Cap	77	47.97	23,61,955.25	58,812.2	2,90,743.4
Shares Outstanding	77	3.38	2,432.46	239.8	423.6
Trade Value	77	0.9	1,03,201.90	2,488.5	12,628.9
Trade Quantity	77	63000	8,38,59,904.00	1,02,08,590	1,78,87,428.0
Panel C: Partial Buy					
Individual Investor					
Market Cap	2040	12.31	8,24,659.81	10,827.9	34,991.3
Shares Outstanding	2040	0.7	28,735.39	278.2	911.0
Trade Value	2040	0.19	43,676.79	444.6	1,633.4
Trade Quantity	2040	4513	1,82,29,88,800.00	99,10,637.0	4,66,04,240.0
Multiple Investors					
Market Cap	1521	51.8	2,86,697.84	9,727.8	19,759.6
Shares Outstanding	1521	0.81	28,735.39	232.3	908.0
Trade Value	1521	0.54	43,857.16	1,152.0	2,967.7
Trade Quantity	1521	13601	1,46,85,50,528.00	1,88,22,392	5,76,74,328.0
Panel D: Partial Sell					
Individual Investor					
Market Cap	1837	16.1	14,19,488.88	12,246.1	47,619.0
Shares Outstanding	1837	0.81	28,735.39	274.3	929.6
Trade Value	1837	0.09	43,087.90	495.0	1,762.2
Trade Quantity	1837	12300	79,42,72,000.00	91,35,408.0	2,90,13,088.0
Multiple Investors					
Market Cap	2069	8.24	7,34,202.00	11,173.6	38,437.9
Shares Outstanding	2069	0.81	5,319.77	207.6	514.8
Trade Value	2069	0.25	54,587.09	1,101.3	3,379.0
Trade Quantity	2069	40804	82,77,13,984.00	1,67,49,073	4,85,11,676.0
Panel E: Net Zero					
Individual Investor					
Market Cap	3158	40.13	6,73,976.81	13,108.0	29,373.2

Shares Outstanding	3158	0.81	5,319.77	206.5	520.4
Trade Value	3158	0.3	31,534.55	844.8	1,948.3
Trade Quantity	3158	6963	29,34,35,840.00	1,01,51,085	2,59,86,806.0
Multiple Investors					
Market Cap	720	23.41	1,35,176.03	11,873.3	17,360.1
Shares Outstanding	720	0.81	2,765.53	124.5	348.2
Trade Value	720	0.51	17,219.10	1,476.4	2,441.5
Trade Quantity	720	37200	35,36,49,216.00	1,21,34,443	3,11,48,960.0

Table 3: Average Abnormal Returns (AAR)

Lags	Individual Investor				Multiple Investors			
	No of deals	AAR	t-Statistics	CAR	No of deals	AAR	t-Statistics	CAR
Panel A: Only Buy								
-7	1804	0.119	1.365	0.119	50	1.424	2.527	1.424
-6	1804	0.267	2.929	0.385	50	-0.513	-1.067	0.911
-5	1804	0.302	3.176	0.687	50	1.495	2.204	2.406
-4	1804	0.303	3.213	0.99	50	0.737	1.246	3.143
-3	1804	0.304	3.203	1.295	50	1.136	1.698	4.279
-2	1804	0.555	5.304	1.85	50	0.63	1.242	4.91
-1	1804	0.992	8.148	2.842	50	0.751	1.097	5.661
0	1804	3.461	22.942	6.303	50	4.834	4.008	10.495
1	1804	0.714	6.454	7.017	50	1.459	2.234	11.954
2	1804	-0.151	-1.572	6.866	50	0.335	0.715	12.289
3	1804	-0.223	-2.527	6.643	50	0.921	1.659	13.21
4	1804	-0.31	-3.676	6.333	50	-1.046	-2.279	12.164
5	1804	-0.158	-1.86	6.175	50	0.715	1.532	12.878
6	1804	-0.163	-2.017	6.012	50	-0.582	-1.135	12.297
7	1804	-0.096	-1.166	5.916	50	0.207	0.496	12.504
Panel B: Only Sell								
-7	2831	-0.275	-3.648	-0.275	77	0.076	0.149	0.076
-6	2831	-0.22	-2.862	-0.495	77	-0.749	-1.533	-0.673
-5	2831	-0.207	-2.673	-0.702	77	0.068	0.144	-0.605
-4	2831	-0.171	-2.077	-0.873	77	0.204	0.351	-0.401
-3	2831	-0.137	-1.63	-1.01	77	-0.324	-0.562	-0.726
-2	2831	-0.025	-0.274	-1.035	77	-0.595	-1.012	-1.32
-1	2831	-0.3	-2.962	-1.335	77	-2.212	-2.535	-3.532
0	2831	-0.871	-7.121	-2.206	77	-1.94	-2.245	-5.472
1	2831	0.376	3.886	-1.829	77	1.628	2.249	-3.844
2	2831	0.262	3.105	-1.568	77	1.511	2.58	-2.333
3	2831	0.162	1.923	-1.406	77	0.47	0.885	-1.863
4	2831	0.082	1.045	-1.323	77	0.415	0.626	-1.448
5	2831	0.053	0.69	-1.27	77	-0.124	-0.272	-1.572
6	2831	0.061	0.805	-1.209	77	0.285	0.637	-1.287
7	2831	0.039	0.542	-1.169	77	0.336	0.721	-0.951

Panel C: Partial Buy								
-7	2040	0.18	1.905	0.18	1521	0.063	0.538	0.063
-6	2040	0.362	3.589	0.542	1521	0.293	2.3	0.355
-5	2040	0.082	0.85	0.624	1521	0.037	0.303	0.392
-4	2040	0.426	4.26	1.049	1521	0.523	4.063	0.915
-3	2040	0.571	5.381	1.62	1521	0.362	2.575	1.277
-2	2040	0.748	6.561	2.368	1521	0.554	3.692	1.831
-1	2040	1.316	9.994	3.684	1521	1.593	8.354	3.425
0	2040	4.187	25.861	7.871	1521	5.475	23.987	8.899
1	2040	-0.073	-0.626	7.798	1521	-0.354	-2.37	8.545
2	2040	-0.48	-4.957	7.318	1521	-0.561	-4.515	7.984
3	2040	-0.282	-3.018	7.036	1521	-0.439	-3.666	7.545
4	2040	-0.399	-4.362	6.636	1521	-0.418	-3.887	7.127
5	2040	-0.335	-3.754	6.301	1521	-0.551	-4.971	6.576
6	2040	-0.369	-4.205	5.932	1521	-0.39	-3.718	6.186
7	2040	-0.136	-1.617	5.796	1521	-0.554	-5.297	5.631
Panel D: Partial Sell								
-7	1837	0.185	1.804	0.185	2069	-0.154	-1.465	-0.154
-6	1837	0.307	3.205	0.492	2069	-0.175	-1.571	-0.33
-5	1837	0.205	1.942	0.698	2069	0.043	0.38	-0.286
-4	1837	0.318	2.974	1.016	2069	-0.02	-0.166	-0.306
-3	1837	0.674	5.787	1.689	2069	0.012	0.095	-0.294
-2	1837	1.217	9.488	2.907	2069	0.181	1.293	-0.113
-1	1837	2.173	13.969	5.08	2069	1.39	7.915	1.277
0	1837	1.765	10.956	6.845	2069	0.071	0.386	1.348
1	1837	0.503	4.242	7.348	2069	-0.019	-0.151	1.329
2	1837	-0.046	-0.437	7.302	2069	-0.412	-3.737	0.917
3	1837	-0.317	-3.168	6.985	2069	-0.267	-2.538	0.65
4	1837	-0.233	-2.508	6.752	2069	-0.217	-2.233	0.433
5	1837	-0.267	-3.015	6.485	2069	-0.41	-4.166	0.023
6	1837	-0.268	-3.092	6.217	2069	-0.343	-3.506	-0.32
7	1837	-0.228	-2.546	5.989	2069	-0.307	-3.254	-0.627
Panel E: Net Zero								
-7	3158	0.194	2.553	0.194	720	0.005	0.025	0.005
-6	3158	0.252	3.377	0.446	720	0.106	0.559	0.11
-5	3158	0.195	2.491	0.642	720	-0.042	-0.217	0.068
-4	3158	0.223	2.758	0.865	720	0.345	1.698	0.413
-3	3158	0.429	5.115	1.294	720	0.218	1.029	0.631
-2	3158	0.508	5.568	1.802	720	1.12	4.946	1.751
-1	3158	1.483	13.103	3.285	720	1.774	6.402	3.525
0	3158	2.572	21.189	5.857	720	1.446	5.241	4.971
1	3158	-0.256	-3.052	5.601	720	-0.705	-3.731	4.266
2	3158	-0.394	-5.337	5.207	720	-0.649	-3.784	3.617
3	3158	-0.324	-4.387	4.883	720	-0.487	-2.707	3.131
4	3158	-0.396	-5.668	4.487	720	-0.504	-3.179	2.627
5	3158	-0.32	-4.61	4.168	720	-0.421	-2.714	2.206

6	3158	-0.246	-3.566	3.921	720	-0.035	-0.213	2.17
7	3158	-0.276	-4.057	3.646	720	-0.036	-0.218	2.134

Table 4: Test of Asymmetry

Particulars	Number of Deals	Mean	Difference	*t*-Statistics
Panel A: Bulk Buy v/s Bulk Sell				
Bulk Buy	5,415	0.043	0.042	31.047
Bulk Sell	6,814	0.001		
Panel B: Only Buy V/s Partial Buy				
Only Buy	1,854	0.035	-0.012	-5.729
Partial Buy	3,561	0.047		
Panel C: Only Sell V/s Partial Sell				
Only Sell	2,908	-0.009	-0.018	-9.935
Partial Sell	3,906	0.009		

Table 5: Average Trading Volume (ATV)

Lags	Individual Investor			Multiple Investors		
	No of deals	ATV	Change (%)	No of deals	ATV	Change (%)
Panel A: Only Buy						
[-37,-8]	1804	134.92		50	84.48	
-7	1804	145.77	8.05	50	83.78	-0.83
-6	1804	149.97	11.16	50	60.57	-28.3
-5	1804	157.03	16.39	50	92.71	9.74
-4	1804	165.82	22.91	50	96.41	14.11
-3	1804	188.16	39.47	50	85.4	1.08
-2	1804	189.12	40.17	50	76.07	-9.95
-1	1804	220.96	63.77	50	158.98	88.18
0	1804	482.16	257.38	50	503.55	496.04
1	1804	269.43	99.7	50	206.72	144.69
2	1804	206.89	53.35	50	110.47	30.76
3	1804	190.1	40.9	50	123.19	45.82
4	1804	191.9	42.24	50	92.81	9.86
5	1804	200.72	48.78	50	113.21	34.01
6	1804	184.57	36.81	50	104.6	23.82
7	1804	168.94	25.22	50	90.85	7.54
Panel B: Only Sell						
[-37,-8]	2831	96.1		77	172.9	
-7	2831	110.3	14.78	77	132.99	-23.08
-6	2831	110.33	14.81	77	161.06	-6.85
-5	2831	111.21	15.72	77	871.02	403.78
-4	2831	117.08	21.83	77	177.53	2.68
-3	2831	124.8	29.86	77	211.68	22.43
-2	2831	130.68	35.98	77	200.13	15.75
-1	2831	145.89	51.82	77	276.58	59.97

0	2831	447.53	365.7	77	2488.48	1339.29
1	2831	185.88	93.42	77	294.72	70.46
2	2831	149.17	55.22	77	401.2	132.05
3	2831	145.78	51.7	77	256.26	48.22
4	2831	133.57	38.99	77	303.09	75.3
5	2831	145.58	51.49	77	194.84	12.69
6	2831	126.92	32.08	77	179.83	4.01
7	2831	129.51	34.77	77	179.69	3.93
Panel C: Partial Buy						
[-37,-8]	2040	132.7		1521	303.57	
-7	2040	153.89	15.97	1521	385.2	26.89
-6	2040	170.35	28.37	1521	378.49	24.68
-5	2040	169.52	27.75	1521	415.37	36.83
-4	2040	179.19	35.03	1521	434.93	43.27
-3	2040	177.88	34.05	1521	460.97	51.85
-2	2040	198.14	49.31	1521	483.88	59.4
-1	2040	216.58	63.2	1521	643.04	111.83
0	2040	444.61	235.05	1521	1152	279.49
1	2040	260.81	96.54	1521	726.6	139.36
2	2040	209.03	57.52	1521	599.04	97.33
3	2040	199.55	50.37	1521	526.06	73.29
4	2040	183.59	38.34	1521	493.31	62.5
5	2040	171.37	29.14	1521	444.74	46.51
6	2040	165.16	24.46	1521	451.59	48.76
7	2040	168.03	26.62	1521	424.19	39.74
Panel D: Partial Sell						
[-37,-8]	1837	132.12		2069	247.14	
-7	1837	152.93	15.75	2069	276	11.68
-6	1837	156.51	18.46	2069	304.65	23.27
-5	1837	162.54	23.03	2069	304.14	23.06
-4	1837	176.86	33.87	2069	329.05	33.14
-3	1837	179.62	35.95	2069	398.76	61.35
-2	1837	198.26	50.06	2069	439.31	77.76
-1	1837	259.95	96.75	2069	533.59	115.91
0	1837	495.02	274.68	2069	1101.28	345.61
1	1837	259.42	96.35	2069	594.75	140.66
2	1837	213.05	61.26	2069	479.73	94.11
3	1837	190.13	43.91	2069	431.57	74.63
4	1837	183.57	38.95	2069	381.36	54.31
5	1837	176.95	33.93	2069	362.26	46.58
6	1837	173.71	31.48	2069	330.45	33.71
7	1837	156.96	18.8	2069	318.78	28.99
Panel E: Net Zero						
[-37,-8]	3158	398.64		720	501.46	
-7	3158	466.45	17.01	720	670.3	33.67
-6	3158	488.82	22.62	720	756.27	50.82
-5	3158	479.88	20.38	720	807.51	61.03

-4	3158	505.52	26.81	720	841.73	67.86
-3	3158	506.76	27.12	720	907.06	80.89
-2	3158	517.53	29.82	720	1036.88	106.77
-1	3158	614.79	54.22	720	1184.51	136.21
0	3158	844.83	111.93	720	1476.35	194.41
1	3158	604.37	51.61	720	1058.75	111.14
2	3158	515.85	29.4	720	902.53	79.98
3	3158	475.56	19.29	720	791.4	57.82
4	3158	448.83	12.59	720	764.38	52.43
5	3158	441.16	10.67	720	669.03	33.42
6	3158	431.92	8.35	720	660.56	31.73
7	3158	437.08	9.64	720	689.09	37.42

Table 6: Test on Variables

Particulars	Number of Deals	Mean	Difference	*t*-Statistics
Panel A: *PctChg_TrdVol*				
Average Volume[-37, -8]	12,229	165.14	149.05 (90.25%)	16.64
Volume [-1]	12,229	314.19		
Panel B: *PctChg_Del*				
Average Delivery[-37, -8]	12,229	0.003	.012	100.65
Delivery [-1]	12,229	.015		
Panel C: *AmihudLiq[-7 , -1]v/s AmihudLiq[-37 , -8]*				
AmihudLiq[-37 , -8]	12,229	2.249	0.586	1.582
AmihudLiq[-7 , -1]	12,229	1.663		

Table 7: Correlation Matrix

	PctChg_TrdVol	*PctChg_Del*	*ChgLiq*	*AmihudLiq[-37 , -8]*	*LogMktCap*	*SD_last30Dys*	*Yield10yr*	*CAR* $_{[-7,-1]}$
PctChg_TrdVol	1.000							
PctChg_Del	0.072	1.000						
ChgLiq	0.038	0.005	1.000					
AmihudLiq[-37 , -8]	0.072	-0.006	0.686	1.000				
LogMktCap	-0.064	0.004	-0.026	-0.102	1.000			
SD_last30Dys	-0.057	-0.145	0.016	0.032	-0.242	1.000		
Yield10yr	0.018	-0.004	0.002	0.025	-0.065	-0.047	1.000	
CAR $_{[-7,-1]}$	0.172	0.064	-0.006	-0.011	0.015	-0.032	0.002	1.000

Table 8: Regression on Pre-event CAR (Individual Investor)

	(1)	(2)	(3)	(4)
	Only Buy	Partial Buy	Only Sell	Partial Sell
	CAR $_{[-3,-1]}$	*CAR* $_{[-7,-1]}$	*CAR* $_{[-3,-1]}$	CAR $_{[-7,-1]}$
PctChg_TrdVol	0.057*** (11.471)	0.075*** (10.320)	0.101*** (14.722)	0.136*** (13.628)
PctChg_Del	1.397*** (7.289)	1.865*** (6.601)	0.636*** (3.624)	1.070*** (4.188)
ChgLiq	0.376 (0.787)	0.841 (1.199)	-0.084 (-0.220)	-0.498 (-0.901)
AmihudLiq[-37 , -8]	-1.500** (-2.143)	-1.499 (-1.453)	-0.594 (-1.477)	-0.730 (-1.254)
LogMktCap	-0.157 (-1.610)	-0.098 (-0.681)	0.154* (1.681)	0.547*** (4.078)
Bullish	0.271 (0.472)	1.082 (1.268)	1.430** (2.406)	1.979** (2.287)
Bearish	-1.555** (-2.486)	-1.796* (-1.952)	-0.655 (-1.030)	-2.197** (-2.362)
SD_last30Dys	0.241** (2.190)	0.439*** (2.698)	0.022 (0.209)	0.306** (2.041)
Yield10yr	0.003 (1.201)	0.004 (1.280)	0.001 (0.448)	0.004 (1.330)
DPartialBuy	0.004 (1.373)	0.004 (0.789)	--	--
DPartialSell	--	--	0.042*** (13.169)	0.059*** (12.699)
Intercept	0.009 (0.312)	-0.021 (-0.503)	-0.060** (-2.251)	-0.185*** (-4.772)
Adj R-Square	0.057	0.048	0.094	0.094
No. of Obs	3,844	3.844	4,668	4,668

*Note: t-statistics are reported in parentheses. '***', '**', and '*' denote significance at 1%, 5% and 10% level, respectively*

Table 9: Regression on Pre-event CAR (Multiple Investors)

	(1)	(2)	(3)	(4)
	Only Buy	Partial Buy	Only Sell	Partial Sell
	CAR $_{[-3,-1]}$	*CAR* $_{[-7,-1]}$	*CAR* $_{[-3,-1]}$	CAR $_{[-7,-1]}$
PctChg_TrdVol	0.055*** (7.23)	0.063*** (5.78)	0.082*** (10.37)	0.118*** (10.50)
PctChg_Del	0.502** (2.39)	0.568 (1.88)	-0.116 (-0.79)	-0.385 (-1.82)
ChgLiq	2.213 (1.07)	4.361 (1.47)	-2.309 (-0.87)	-3.538 (-0.93)
AmihudLiq[-37 , -8]	-3.977 (-1.53)	-5.927 (-1.58)	-3.332 (-1.19)	-4.560 (-1.13)
LogMktCap	-0.232 (-1.15)	-0.283 (-0.98)	0.258 (1.42)	0.523* (2.01)
Bullish	2.880** (2.45)	4.144** (2.46)	3.072*** (2.87)	4.915*** (3.20)
Bearish	0.565 (0.45)	-0.903 (-0.50)	-1.740 (-1.52)	-3.287** (-2.00)
SD_last30Dys	-0.150 (-0.75)	-0.347 (-1.21)	0.227 (1.24)	-0.073 (-0.28)
Yield10yr	0.010** (2.02)	0.014 (1.92)	-0.006 (-1.42)	-0.006 (-0.89)
DPartialBuy	-0.001 (-0.08)	-0.022 (-0.86)	--	--
DPartialSell	--	--	0.043*** (2.77)	0.043 (1.930)
Intercept	-0.031 (-0.48)	-0.017 (-0.18)	-0.058 (-1.01)	-0.110 (-1.35)
Adj R-Square	0.0495	0.0444	0.0729	0.0827
No. of Obs	1,571	1,571	2,146	2,146

*Note: t-statistics are reported in parentheses. '***', '**', and '*' denote significance at 1%, 5% and 10% level, respectively.*

Table 10: Regression on AR at event day

	Individual Investor		Individual Investor	
	Buy	Sell	Buy	Sell
	$AR_{[0]}$	$AR_{[0]}$	$AR_{[0]}$	$AR_{[0]}$
	(1)	(2)	(3)	(4)
PctChg_TrdVol	-0.007** (-2.071)	-0.009** (-2.182)	-0.002 (-0.388)	-0.003 (-0.648)
PctChg_Del	1.448*** (11.245)	0.791*** (7.130)	0.803*** (5.762)	-0.011 (-0.121)
ChgLiq	0.195 (0.626)	-0.097 (-0.408)	0.686 (0.500)	0.031 (0.020)
AmihudLiq[-37 , -8]	-0.247 (-0.542)	0.446 (1.795)	-2.019 (-1.161)	0.687 (0.401)
LogMktCap	-0.693*** (-10.500)	-0.092 (-1.579)	-0.878*** (-6.062)	-0.361*** (-3.062)
Bullish	0.373 (0.981)	0.780** (2.122)	1.533** (1.974)	0.455 (0.691)
Bearish	-0.046 (-0.110)	0.325 (0.820)	-0.522 (-0.631)	-0.300 (-0.434)
SD_last30Dys	-0.088 (-1.212)	-0.300*** (-4.641)	-0.273** (-2.080)	-0.428*** (-3.802)
Yield10yr	0.003 (1.620)	-0.001 (-0.469)	-0.004 (-1.308)	-0.010*** (-3.502)
CAR $_{[-7,-1]}$	0.026*** (3.643)	0.056*** (8.803)	0.048*** (4.110)	0.036*** (3.858)
DPartialBuy	0.001 (0.388)	--	-0.007 (-0.270)	--
BQ_TQ	-0.072*** (-13.202)	--	-0.098** (-2.221)	--
*DBQ_TQ_Par (SQ_TQ * DPartialBuy)*	-0.011 (-1.493)	--	-0.001 (-0.010)	--
DPartialSell	--	0.037*** (10.031)	--	0.029 (1.190)
SQ_TQ	--	-0.005 (-1.060)	--	-0.016 (-0.382)
*DSQ_TQ_Par (SQ_TQ * DPartialSell)*	--	-0.036*** (-5.222)	--	-0.028 (-0.649)
Intercept	0.172*** (8.950)	0.015 (0.880)	0.291*** (5.722)	0.148*** (3.441)
No. of Obs	3,844	4,668	1,571	2,146

*Note: t-statistics are reported in parentheses. '***', '**', and '*' denote significance at 1%, 5% and 10% level, respectively*