Trading around unscheduled announcements

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Abstract

We test the implications of rational information leakage theory using trading patterns around unscheduled corporate announcements in a modern algorithmic market. Employing trade-level data that allows the identification of trades from high-frequency traders (HFT), institutions using algorithmic executions, institutions using manual executions and retail traders, we find that retail traders are the beneficiaries of true information leakage, despite being the least informed traders overall. We attribute the information leakage by insiders to retail traders to social media and bulk messaging service through mobile phones.

1. Introduction

Do insiders voluntarily leak information (perhaps a garbled but still relevant version) to *unrelated* third parties without receiving any direct compensation in return? The theoretical model of Indjejikian et al. (2014) seems to address the question affirmatively. The authors suggest that two opposing effects operate on an insider's expected profit when she/he chooses to voluntarily leak information to unrelated parties. One, the obvious negative effect, leaking information to another trader, reduces the insider's informational advantage regarding the fundamental value of the asset. The other is the positive effect: leaking information increases the insider's informational advantage regarding the execution price path of the asset relative to everyone else, as trades that rely on the leaked information make the asset price sensitive to the nonfundamental part (noise) of the leaked information. If the positive effect outweighs the negative effect, then it would be rational for the insider to leak information to unrelated third parties. The authors find that if other reasonably well-informed traders are present in the market, then the insider finds it logical to leak information and leak it not just to anyone but to the least informed traders as those traders would find it most difficult to eke the signal out of the noise (maximizing the insider's advantage). The insider wins, the least informed traders (beneficiaries of the leakage) win, but the other well-informed traders unfairly lose out in this mechanism.

Does the "rational information leakage" theory work in practice? According to our knowledge, no prior study has attempted to empirically test the primary implications of the theory. Indeed, it is a challenge to test the theory directly as it requires identifying insiders and asking them whether they leaked information! However, the theory could be tested in an indirect way by analyzing the behavior of different trading groups around specific information events. We choose to accomplish the task by investigating trading behavior around unscheduled corporate announcements. Our choice of analyzing information leakage around unscheduled corporate announcements circumvents the identification and analysis of *true* information leakage in financial markets. Past studies analyzing information leakage focus primarily on changes in analysts' recommendations (Irvine et al., 2007; Christophe et al., 2010; Kadan et al., 2018). However, a recent study by Callen et al. (2022) suggests that trading before the revelation of analyst recommendations may not necessarily represent true information leakage as informed traders may be able to gather similar information by performing fundamental analysis themselves. In contrast to informed trading before analysts' recommendations, informed trading before unscheduled announcements such as "equity offering", "share buybacks", M&A announcements, etc., may not be possible using equity research or fundamental analysis alone. For example, for an equity offering or a share buyback, the immediate post-announcement returns primarily depend on the firm's offer price and not on whether the firm is a good long-term investment prospect. It is difficult to fathom that any amount of fundamental research can render some information on the impending possibility of an equity offering or a buyback or uncover information on the offer price. If these types of information are acquired in advance, then it is mostly done with the help of some corporate insiders. Literature also reports evidence of insider information being used to trade before M&A announcements (Ahern, 2017). Augustin et al. (2019) estimate that 25% of M&A announcements are preceded by illegal insider trading.

We first identify the least informed trading group to test the information leakage theory. In contrast to the literature (Callen et al., 2022), which primarily looks at more traditional categorizations of trading groups such as institutions and individuals, we consider a more modern approach. We use a rich and clean trade-level dataset from the National Stock Exchange of India (NSE) that contains identification marks for the nature of traders. NSE is one of the most active stock exchanges, ranked fourth globally in terms of the number of transactions in equity markets. In terms of market capitalization, it is ranked 10th, just marginally behind the LSE and the Toronto Stock Exchange[1]. The data flags every trade on whether it is generated from an algorithmic terminal or not (Algorithmic flag) and whether it is for a proprietary account, a custodial account, or any other type of account (Client flag). These two flags help us understand whether the trade originates from different groups of traders: proprietary algorithmic traders (or HFT)[2], institutional traders executing through trading algorithms, non-algorithmic institutional traders, and retail traders. This rich identification of different trading groups allows us to provide insights that are difficult to obtain using data from stock exchanges in other markets where such distinctions are not provided. For example, in modern markets, trader categorization without considering algorithmic trading may not be appropriate. Several studies have suggested that HFT trades are informed (Baron et al., 2019; Hirschey, 2021; Goldstein et al., 2023). Also, the informativeness of institutional traders executing through algorithms could be different from the informativeness of institutional traders using the traditional routes to execute trades.

We find that the retail traders are the least informed trading group. When considered over all stock-days of our five-year sample, they stack up significant negative profits, whereas the other three groups earn positive profits. We use positional revenue as the measure of trading profits. Interestingly, retail traders lose out on both intraday trading and on their overnight inventories. Additionally, when trade imbalance (trading-group specific) is used to regress the next day's stock return, we find that only retail trading imbalance has a negative coefficient, whereas the imbalances of the other three trading groups have positive coefficients. These findings are consistent with

[1] WFE (World Federation of Exchanges) Statistics

[2] Using data from the same stock exchange, Nawn and Banerjee (2019) show that the proprietary algorithmic traders can be viewed as HFT.

extant literature, which finds that retail traders are uninformed (Odean, 1999; Barber et al., 2009; Nawn and Raizada, 2023). Our findings also suggest that institutions (both algorithmic and non-algorithmic executions) stack up significant positive profits. HFT also make profits, at an absolute level, with lesser magnitude than what institutions make. Overall, there is enough evidence of reasonably informed traders present in the system, providing incentives to the insiders to leak information to the least informed traders.

We then collect our sample of unscheduled announcements using the Bloomberg corporate actions (CACS) function. We use the 500 constituent stocks of NIFTY500. We find there are 1471 unscheduled corporate announcements in these stocks in the five-year sample period. These announcements range from "Acquisition," "Divestiture," "Share Buyback," "Equity Offerings," "Joint Venture," "Merger," and "Spin-offs." We then consider the buying and selling pattern of each trading group leading up to the announcement (Day T-5 to Day T-1) and create group-specific trade imbalance measures (Total shares bought in the five days *minus* Total shares sold in the five days, standardized by their total trading in those five days). We then check how each of these trading group imbalances is related to the post-announcement period returns. Strikingly, we find that stocks purchased by retail traders ahead of the announcements significantly outperform the stocks sold. Further, we find that this is not true for any of the three other informed groups of traders – institutions trading through algorithms, institutions trading traditionally, and HFT. Thus, we find indirect evidence in support of the rational information leakage theory, i.e., the least informed group of traders becomes privy to private information just prior to the announcement, but other informed traders lose out.

Indjejikian et al. (2014) also suggested that rational information leakage is more likely to happen in stocks that have a greater probability of informed trading. Since it is a well-known result that the probability of informed trading is higher for smaller stocks (Aslan et al., 2011; Chen and Zhao, 2012), one cross-sectional implication of the theory is that the leakage would be higher for smaller stocks. Indeed, that is what we observe. When we segregate our unscheduled announcement stock-events by firm size, we see that the retail trader's outperformance is stronger for the events in smaller stocks.

The announcement could turn out to be good or bad news. However, with short-sale constraints on retail traders, one could expect that information leakage would be stronger for good news. Again, that is what we find. We do not find any retail trading outperformance in bad news events, whereas, for good news events, the results seem very strong.

Our results are robust to a battery of alternate specifications. Results remain qualitatively similar even if we use an alternate post-announcement window instead of [T, T + 1], use abnormal (stock index adjusted) returns instead of raw returns, and remove announcements that have no associated coverage in the news or there was some coverage in the media related to the announcements before the actual announcements. Additionally, the results become much stronger if we focus on announcements that have a significant impact on post-announcement returns.

The information leakage results that we obtain around unscheduled announcements should not be true around scheduled earnings announcements. Sophisticated traders (such as institutional investors) spend time and resources before scheduled earnings announcements to conduct fundamental analysis and acquire relevant information that allows them to trade in the correct direction prior to these announcements. Insiders will not obtain much benefit from leaking information here to the least informed traders as the other informed traders are likely to be privy to the information. We replicate our test using the scheduled quarterly earnings announcements for our 500 stocks, and indeed, we find no retail trader outperformance in these scheduled earnings announcements.

Finally, we conduct a placebo test where we randomly choose 1000 stock-days and earmark them as unscheduled announcement event dates and repeat this process 500 times. We see that there is no retail trader outperformance when stock-days are picked randomly, rendering credence to the fact that information leakage to the least informed precisely happens before the unscheduled announcements.

Our results have important implications for information acquisition in capital markets. If insiders enjoy benefits in leaking information to retail traders, then institutional investors would have much fewer incentives to collect and process information. This has been particularly of concern in recent times since the advent of algorithmic trading (AT) and HFT. Research suggested that institutional traders are facing reduced incentives to acquire information because of the advent of AT (Weller, 2018). A part of the reason is that machine traders do not generally spend resources to acquire information themselves but rather "free-ride" on the information of other informed traders, such as institutional traders. For example, Hirschey (2021) finds that HFT "front-run" non-HFT trades, while Van Kervel and Menkveld (2019) and Yang and Zhu (2020) find HFT "back-run" institutional investors eating into their profits. Given these recent developments, if institutional investors are faced with even more concerns about their informational rents reducing through insiders leaking information to retail traders, they might start spending even lesser efforts or altogether disband any effort to acquire information.

Finally, it is also worth discussing how it is possible for the insider to leak information to unrelated third parties who are least informed (retail trading group), bypassing the institutional and other informed traders completely. While there are a few ways this is possible, we shall discuss two avenues. First is the bulk mobile messaging service, which could be sent to individual investors with a little co-operation from brokerage houses. In fact, between 2011 and 2015, the duration of the study, there were no apparent restrictions on sending these bulk messages, with the Indian regulator SEBI publicly coming out against these messages only in 2016. Another way of transmitting the leaked information could be social networks; this includes public networks like Twitter, communities like WallStreetBets, and closed WhatsApp groups. Information can quickly disseminate through these platforms among the class of retail traders, from one WhatsApp group to another or from one social community group to another, through common members. Social media has been linked to transmitting relevant financial information (Chen et al., 2014; Gu and Kurov, 2020), and it has helped retail traders have a significant say in how prices move through their correlated behavior across various social media platforms (Allen et al., 2021).

Our primary contribution to the literature is empirically analyzing "true" information leakage in financial markets, whereas earlier literature (Irvine et al., 2007; Christophe et al., 2010; Kadan et al., 2018) has primarily investigated information leakage prior to analyst recommendations, which could also be consistent with explanations other than information leakage. A recent paper by Callen et al. (2022) analyzes "true" information leakage in a different setting using the 8K filing data. They find that strategic institutional investors are the beneficiaries of information leakage a few days prior to the announcement, and they adopt the "buy the rumor and sell the news strategy." In contrast to Callen et al. (2022), we do not find institutions (neither who trade through algorithms nor who trade manually) to be the beneficiaries of the leakage. There are two ways we contribute to the literature of information leakage. One, Callen et al. (2022) use Abel Noser data to identify institutional trades. The dataset has been widely used in academic literature and has several advantages. However, one of the disadvantages of using this data is it comprises only a subset (about 10%) of all institutional trading in the U.S. stock markets (Puckett and Yan, 2011). It cannot be said with certainty whether the same results will persist if all institutional trading is considered. In contrast, the advantage of using NSE data is that the data is comprehensive and nearly represents the entire market. The Indian equities market has a near unfragmented structure with a two-exchange system (Bombay Stock Exchange or BSE being the other exchange) and the NSE account for 80-90% of the overall volume. Thus, our institutional (retail) trades comprise almost all the institutional (retail) trades done in the country. Two, the threat of litigation is significantly different (lower) in India compared to the U.S. (Choi et al., 2008), and studying information leakage-based trading in such a country provides valuable additional insights.

The paper also contributes to the recent interest in literature on analyzing retail trading informativeness. Past studies on retail trading found the group to be uninformed (Odean, 1999; Barber and Odean, 2000). However, recent evidence has been mixed. On the one hand, Kanel et al. (2012), Kelley and Tetlock (2013, 2017), and Boehmer et al. (2021) find evidence of informativeness in retail trading; on the other, Han and Kumar (2013), Nawn and Raizada (2023) and Barber et al. (2023) continue to find retail traders are uninformed. Farrel et al. (2022) and Malz (2021) suggest that social media have empowered retail traders. We contribute to this debate and find that while retail traders continue to be uninformed traders in an overall sense, they are also the beneficiaries of information leakage before unscheduled announcements, and social media and bulk messaging services (perhaps) help in the transmission of the leakage.

The paper is organized as follows. Section 2 provides information on the data, summary statistics and institutional details. Section 3 develops the hypothesis. Section 4 presents the main results. Section 5 discusses the mechanism and implications of the leakage. Section 6 concludes the paper.

2. Literature review and hypothesis development

Information leakage in financial markets has been a topic of considerable interest for all stakeholders, academicians, and practitioners alike, since it is inherently related to the question of unfairness. Theoretical work on information leakage has focused on how information is leaked (Testa, 2019), why it is leaked (Indjejikian et al., 2014), and what the strategies of traders receiving the leaked information are (Hirshleifer et al., 1994; Brunnermeier, 2005). Testa's (2019) model exploits the leakage in financial markets through word-of-mouth communication among dealers and traders, and it explains the herding and contrarian behavior of traders. The model of Indjejikian et al. (2014) suggests that insiders may have rational reasons to leak information to unrelated third parties over and above the incentives to leak information to family and friends. Both Hirshleifer et al.'s (1994) and Brunnermeier's (2005) models seem to suggest that traders privy to leaked information follow the "buy the rumor, sell the news" strategy, although the traders in the former are risk-averse and in the latter are risk-neutral.

The empirical literature on financial information leakage has a good concentration on analyzing leakage before analyst recommendations. Irvine et al. (2007) find evidence of tipping to institutional traders as those traders start buying on the news five days before the public disclosure of the recommendations. Christophe et al. (2010) also provide evidence of information leakage before analyst downgrades in Nasdaq stocks. They find abnormal levels of short selling prior to the public release of information and find its most likely reason to be the leakage of the analyst report. Kadan et al. (2018) also find evidence of leakage before analyst recommendations but show that only proprietary (and not agency) news-driven institutions follow the "buy the rumor, sell the news" strategy. The agency news-driven institutions while following "buy the rumor", do not square off their positions quickly as they reflect the trades of long-term investors.

There are a few empirical papers analyzing information leakage that look beyond analyst recommendations. Chakrabarty and Shkilko (2014) find evidence that is consistent with institutions becoming privy to private information through monitoring of others' trades as well as those brokerage houses executing insider trades leaking non-public information to the institutions. Sun and Yin (2017) find that information leakage takes place from insiders to short sellers in HK exchange-listed family firms. Using Ancerno (Abel Noser) data, Callen et al. (2022) examine trading patterns before 10-K announcements and find that strategic institutions follow the "buy the rumor, sell the news" strategy. They suggest that trading in the right direction before 10-K announcements provides stronger evidence of information leakage compared to trading in the right direction before analyst recommendations. The reason is that the information released during 10-K announcements is nearly impossible to predict in advance through fundamental analysis, unlike the information released during analyst recommendations. Also, using Ancerno data, Davis et al. (2021) find that institutional traders are able to trade in the correct direction in stocks that eventually become takeover targets. They conclude that institutional traders gather private information to trade rather than being good at analyzing public information.

Few papers look at the derivatives market to provide evidence of information leakage. Qing (2016) uses daily options trading ahead of buyback announcements and concludes that information leakage helps some participants be informed ahead of the announcements. Lin and Lu (2015) show that the power of option-implied volatilities to predict stock returns increases significantly around the analyst recommendation event. The authors conclude that analyst tipping is the most reasonable explanation for options traders becoming informed about upcoming analyst-related news.

Ahern (2017) provides evidence that corporate insiders share material (and illegal) tips with friends and family, and they (and their network) make substantial profits from these tips. While it may be rational (though illegal) for an insider to share insider information with friends, family, and close networks with the hope of completing the trade that she/he cannot make on her/his own, is there some rationale for sharing insider information to unrelated third parties? Indjejikian et al. (2014), in their model, suggest there is. This will be the likely outcome when there are a substantial number of other informed traders present in the market. In situations where insiders have some information that the other informed traders are not privy to (and are unlikely to unearth the same through fundamental analysis), insiders find it profitable to leak the (garbled version) information to the least informed traders. While leaking information, the insiders lose out on the informational advantage regarding the fundamental value of the asset; however, they can more than offset this loss with the relative advantage they have about the execution price path, as trades that rely on the leaked information make the asset price sensitive to the nonfundamental part (noise) of the leaked information. The least informed traders are chosen by insiders (for leakage) as they would find it hardest to decipher the true signal from the noisy information.

Unscheduled corporate announcements provide an excellent setting to empirically test the theory of Indjejikian et al. (2014) as information embedded in announcement of equity offerings (and the offer price), buybacks (and the redemption price), acquisitions (and the potential target), etc., is difficult to unearth by fundamental analysis alone. Our first (and main) hypothesis is thus formulated as follows:

Hypothesis H_A: The least informed traders are privy to the direction of the news prior to unscheduled announcements.

The probability of informed trading is expected to be higher for smaller or less-liquid stocks (Aslan et al., 2011; Chen and Zhao, 2012). The model of Indjejikian et al. (2014) also suggests leakage is expected to be more likely where the probability of informed trading is higher. Thus, a cross-sectional implication of likely information leakage emerges. We should see the implication of the voluntary leakage of information more in smaller stocks than in larger stocks, that is,

Hypothesis H_B: The least informed traders are privy to the direction of the news prior to the unscheduled announcements, more so in small stocks.

3. Data and Summary Statistics

NSE of India is a fully order-driven market with no DMM (designated market maker). Trading in this market takes place using a fully automated order-matching system. The exchange opens on regular weekdays at 9 AM for a 15-minute pre-opening session. After that, from 9:15 AM, it operates as a single continuous session for 6 hours and 15 minutes to close at 3:30 PM. The order matching rules in NSE follow the sequence of price, then visibility, and then time, and priority.

The market structure of the NSE is similar to that of several important European and Asian exchanges around the world, such as the Paris Bourse, HK Stock Exchange, and Tokyo Stock

Exchange. In terms of importance, NSE has the fourth largest trading volume and the 10^{th} largest dollar volume among all global exchanges[3].

Algorithmic trading and direct market access (DMA) have been allowed in the NSE since 2008. However, algorithmic trading started seriously in the exchange after January 2010, when co-location service was also provided[4]. Indeed, since 2010, the message traffic and trading volume due to algorithmic trading have gradually grown in India. For example, Nawn and Banerjee (2019) find that for the largest 50 stocks on the exchange, algorithmic trading contributed 95% of all order messages and 42% of the trading volume in the calendar year 2013.

For academic research, the exchange provides historical trade-level data for stocks trading on the NSE. Apart from the usual information such as transaction price, time, and quantity, the data possesses two flags that enable one to interpret useful information about the trade buyer and seller. The algorithmic flag provides information on whether the buyer/seller was using an algorithmic terminal or not. The client flag provides information on whether the buyer/seller was using a proprietary account, a custodian, or any other type of account. The custodian group consists primarily of foreign institutional investors, mutual funds, and financial institutions, as they are not allowed to conduct their own clearing and settlement and must do that through custodians. Others include all trading accounts, which are non-proprietary and non-custodial.

We use the algorithmic (AT/non-AT) and client flags (Custodian, Proprietary, non-Custodian, and non-Proprietary) to create the different trading groups. Although theoretically it is

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3 https://www.world-exchanges.org/home/index.php/statistics/annual-statistics

4 Co-location amounts to renting rack space on the premise of the exchange itself so that the speed at which orders reach the exchange is minimized.

possible to create (2*3) 6 trading groups, we focus on those groups that beckon academic/practitioner interest and are also not too small.

Group 1: AT Custodian – The institutional group executing through algorithmic trading.

Group 2: AT Proprietary – The group of high-frequency traders (or HFT).

Group 3: Non-AT Custodian - The institutional trading group executing through traditional methods (no trading algorithms).

Group 4: Non-AT, non-custodian and non-proprietary – The retail trading group.

Apart from these four groups, one can also construct two other groups – traders who trade through algorithms but are not part of proprietary or institutional traders, and proprietary traders who trade through traditional (non-AT) means. However, the trading volume contributed by these two trading groups is quite small, and it is also not easy to allocate either of these groups to standard, well-understood trading categories. Therefore, for the rest of our paper, we continue to focus on Groups 1 to 4.

We consider a five-year period for our study, from January 2011 to December 2015. There are about 1500 stocks listed on the NSE; however, to avoid very illiquid stocks, we restrict ourselves to the 500 stocks that are the constituents of the index NIFTY 500 as of the beginning of January 2011. These stocks comprise over 95% of the market capitalization of the exchange. We collect our sample of unscheduled announcement events from Bloomberg through the "CACS" function. However, we are unable to use a few announcements in the same stock that are relatively close to each other as the pre-announcement period of one announcement coincides with the post-announcement period of the other. To be precise, we do not include announcements that are in the same stock and are within eight days of each other. Finally, we are left with 1491 usable, unscheduled announcements.

These announcements are either "Acquisition," "Divestiture," "Spin-off," "Stock buyback," "Joint Venture," or "Equity Offering." For almost all types of announcements, we find that the post-announcement return (day[T, T + 1]) is positive. The only type of announcement that gives a post-announcement average daily negative return is "Equity offering" (commonly known as SEO). This evidence is in line with prior literature- Zheng (2020) finds the CAR on days t and (t + 1) following announcement is significantly negative for SEOs and significantly positive for share repurchases. Baruch et al. (2017) find in the sample of their acquisition announcements that 26 have positive announcement returns, and only 9 have negative announcement returns. Hite and Owers (1983) find positive average excess returns in the two-day interval surrounding the first press announcement for spin-offs.

For each type of announcement, we see a typical pattern. In between days [T-15, T-6], the stock return is very close to 0; between days [T-5, T-1], the stock return is significantly different from 0, mildly indicative that some traders may have started informed trading prior to the actual announcement. However, the return in the period [T, T + 1] is still significantly greater[5] than the return in [T - 5, T - 1], indicating the actual announcements bring out material news. "Acquisition" (480 cases) and "Divestiture" (662 cases) account for the majority of the announcements, and the details can be found in Table 1.

[Insert Table 1 here]

[5] This is not the case for spin-offs and stock buybacks. However, the sample size for these two types of announcements is too small to draw different conclusions.

We split our sample of 500 stocks into market capitalization groups. We call the top 150 and bottom 150 stocks the large and small capitalization group of stocks, respectively. Finally, the remaining 200 stocks are called the mid-capitalization group. There is considerable heterogeneity in the sizes of the stocks across the groups. A large-cap stock has an average size of INR 419 billion compared to a mid-cap stock of INR 38 billion and a small-cap stock of INR 9 billion. Significant differences also exist across the market capitalization categories in INR traded volume and number of shares traded, but the magnitudes of the differences are lower compared to the size difference. The intraday volatility is highest for the small capitalization groups, as expected. Out of our 1491 unscheduled announcements, more than half come from the large-cap stocks. The small-cap group has only 190 announcements, and thus, while testing our second hypothesis (related to the cross-sectional implication), we club the mid and the small capitalization groups. Details are provided in Table 2.

[Insert Table 2 here]

Table 3 provides certain details about our four groups of traders. We find retail traders contribute about 50% of the trading volume. While this is significantly more than the generally observed 20% in the U.S. (McCabe, 2021), it is much lower than the 80-90% observed in Taiwan (Barber et al., 2009) and China (Jones et al., 2023). Institutional traders account for 25% of the volume, with an almost equal split between traders executing through algorithms and traders using traditional means of trading. HFT's share of trading is 7%. If we note the difference in pattern across the stock size groups, we find that both the institutional trading groups and HFT together account for almost 46% of the volume of the large-cap stocks, while retail participation increases significantly (69%) in the smallest size category. These facts are in line with Aggarwal et al., (2005); and Biais and Foucault (2014).

Interesting anecdotal evidence can also be drawn from the other variable-closing inventory-provided in the table. This variable indicates directional trading performed by each group of traders. We note the intraday unsigned closing inventory (as a percentage) for each trading group for each stock day as below

Unsigned inventory (%) = abs (buy volume – sell volume)/(buy volume + sell volume)

Institutional traders have a tendency to be on only one side of the market. This is true for both the institutional trading groups. Their tendency to perform directional trading in a day is close to 65%. Again, this is consistent with the prior findings (e.g., Van Kervel and Menkveld, 2019). In contrast, the directional trading for HFT is only 5%. This suggests that HFT trades on both sides of the market and thus ends the day with a near-zero inventory position. Studies find that HFT has taken over the mantle of market-makers in modern markets (Hagströmer and Nordén, 2013). Even for retail traders, this number is close to only 10%, suggesting that retail traders also do not perform directional trading.

[Insert Table 3 here]

4. Empirical Results

Our first task is to identify the group of least informed traders. For this purpose, we compute trading profits of all the trading groups through position revenue. Trading profits are computed through two components – overnight profits and intraday profits. We assume that all trading groups begin with no inventory at the start of the sample period (January 1, 2011) and for the first trading day, the intraday profit for each group in each stock is as follows:

Cash received by selling shares – cash spent by buying shares + closing inventory*closing price

Overnight profit for the first day is zero but for every subsequent day it is computed for each group in each stock as

Cumulative inventory carried overnight*(closing price – previous day's closing price)

Similarly, intraday profit for each group in each stock for every subsequent day is

Cash received on the day by selling shares – cash spent on the day by buying shares + intraday position at the close of day*closing price

Finally, the overall trading day profit is the sum of overnight and intraday profits. While computing these profits, we carefully adjust for any dividend announcements and stock splits (or reverse splits).

In Table 4, we provide the stock-day average profits for each of the four trading groups. We see that retail traders perform the worst – both in the overnight and intraday profits. They respectively lose INR 0.1 and 0.2 million per stock per day in intraday and overnight profits. Note that our sample consists of the top 500 stocks of the NSE of India, accounting for approximately 95% of the market capitalization of the exchange, and the Indian trading microstructure is characterized by a near unfragmented structure. This points to the fact that retail traders in the entire market are the least informed group of traders. Several landmark papers have shown retail traders earn poor returns (Odean, 1999; Barber and Odean, 2000; Barber et al., 2009). Kuo and Lin (2013) document that retail traders lose a significant amount in day-trading. Recently, Nawn and Raizada (2023), using TBCT methodology in the same market (NSE), establish that retail trades are the least informed. Barber et al. (2023) reestablish that retail trades are non-profitable after some intermediate literature suggests otherwise (Kelly and Tetlock, 2013; Boehmer et al., 2021). The performance of retail traders does not show any qualitative differences across the three size categories of stocks. Results show consistent negative numbers for both overnight and intraday profits for all three size categories.

Apart from retail traders, all three other categories of traders show consistent profits. Institutional traders trading through algorithms earn a substantial profit of INR 0.2 million per stock per day. The majority of this profit comes from overnight profits rather than intraday profits. Similarly, institutional traders trading through traditional means also earn a substantial profit of INR 0.1 million per stock per day, and even for them, a major part of the profit is from overnight profits. Again, these facts are also consistent with the literature. Several papers have shown institutional trading predicts stock returns (Boehmer and Wu, 2008; Boulatov et al., 2013), stocks with high institutional ownership beat stocks with low institutional ownership (Badrinath, et al., 1995), and efficient prices are linked to higher institutional holdings (Sias and Starks, 1997; Boehmer and Kelley, 2009). Hendershott et al. (2015) provide evidence that institutions are informed in advance about various types of news, including important company-specific news and earnings surprises.

Finally, we see HFT are also earning positive profits. However, HFT profits are much less compared to institutional profits on an average stock-day basis. At the same time, HFT's share of trades is also much less compared to institutions, and hence, the INR profits may be less. Interestingly, almost all of HFT's profits come from intraday profits and very few from overnight profits. This is in line with the fact that one of the primary HFT strategies is market-making (Menkveld, 2013; Hagströmer and Nordén, 2013), and HFT are expected to carry very little inventory overnight. Positive profits for HFT are consistent with them being aware of future price movements (Hirschey, 2021), their limit (Brogaard et al., 2019), and the market (Brogaard et al., 2014) orders.

In panel B of Table 4, we use the lagged buy-sell imbalance for each trading group to regress the next day's stock return. The imbalance for each group for each stock-day is computed as

(Number of shares bought – Number of shares sold)/ (Number of shares bought + Number of shares sold)

In the regression, we add stock-day volatility and total traded volume as control variables. Our aim is to observe whether a trading group's buy-sell imbalance is able to predict the next day's stock return correctly. The model is as follows:

$$\mathrm{Ret}_{i,t} = \beta_1 * \mathrm{IMB}_{i,t-1,j} + \beta_2 * \mathrm{Volat}_{i,t} + \beta_3 * \mathrm{Volume}_{i,t} + \epsilon_{i,t} \quad (1)$$

where

$\mathrm{Ret}_{i,t}$ is stock return of the i^{th} stock for the t^{th} day

$\mathrm{Volat}_{i,t}$ is daily volatility (max price/min price - 1) of the i^{th} stock for the t^{th} day

$\mathrm{Volume}_{i,t}$ is total traded volume of the i^{th} stock for the t^{th} day

$\mathrm{IMB}_{i,t-1,j}$ is buy sell imbalance of the i^{th} stock for the $t - 1^{th}$ day for the j^{th} trading group

The trading group specific regressions are estimated by GLM with stock fixed effects. The results of panel B are consistent with that of panel A. Out of the four trading groups, only the retail traders coefficient (β_1) is negative and significant, while that of the other three groups is positive and significant.

The upshoot of the above discussion is that retail is consistently the least informed trading group and there are well-informed groups of traders such as institutions (both trading through algorithms and without algorithms) and HFT in the market.

[Insert Table 4 here]

Having identified the least informed group of traders, we next check whether this group of traders is privy to the news before the unscheduled announcements. Our method to test the same is motivated by Kaniel et al. (2012). For each of our 1491 unscheduled announcements, we compute the buy-sell imbalance for each of the trading groups accumulated over the five days prior to the announcements, i.e., over days [T – 5, T – 1]. Day T is denoted as the day of the announcement. While we note the day of the announcement from Bloomberg, it does not directly provide the time of the announcement. We, therefore, note the first news pertaining to the announcement that appeared in Bloomberg News (the news feed in Bloomberg provides consolidated newsfeeds from several top providers). If the time of the first news is after 3:30 PM (end of the trading hours), then we note Day T as the next working day.

For each of the trading groups, we then sort the five-day imbalance measure for the 1491 announcements and create a quartile portfolio of events. For each trading group, Q1 (Q4) means the assortment of events in which that trading group in the week prior to the announcement sold (bought) the corresponding stock the most. Next, we note the stock return in the post-announcement period days [T, T + 1] for each of the quartile portfolios of events. As a measure of the trading informativeness of each group, we take the difference in stock returns between Q4 and

Q1. Table 5 provides the details. If the average post-announcement return for Q4 is more than that for Q1 for some trading groups, then it signifies that the stocks the trading group has purchased prior to the announcements have outperformed the stocks they have sold.

The exercise is conducted for each trading group and the results are presented in Table 5. In support of our hypothesis, we find retail traders' Q4 – Q1 returns are 1.1% on average, and that is statistically significantly different from zero at the 1% level. Having so far shown that retail traders incur significant losses and are the least informed group; these results, pertaining to unscheduled announcements, suggest retail traders are privy to the impending information, and are consistent with information leakage (H_A).

For all the other three trading groups, we find that Q4 stock events do not outperform Q1 stock-events. Even though all these traders are "informed" and make profits overall, they lose out around unscheduled announcements. The stocks that institutions (traditional) purchase the most (Q4) underperform the stocks they sell the most (Q1) by 0.9%. Similar underperformance is also seen for institutions (algorithmic) and HFT; however, the numbers are statistically insignificant. Overall, we find that while the "uninformed" traders make money around unscheduled announcements, the "informed" traders are unable to do so, matching the implications of the rational information leakage theory of Indjejikian et al. (2014).

[Insert Table 5 here]

Next, we turn to our cross-sectional prediction about information leakage (H_B). To investigate whether our results show a difference between bigger and smaller stocks in our sample, we run our test for the announcements in bigger and smaller stocks separately. As discussed before, the large capitalization group of stocks has 785 announcements, while the mid and small capitalization groups of stocks together have 706 announcements.

Table 6 provides the details. Retail traders' outperformance is visible in both groups of stocks, with Q4 – Q1 showing positive and significant numbers. However, the outperformance is greater in smaller stocks (1.3%) compared to larger stocks (1.1%). Most importantly, while in the smaller stocks, the average returns increase (near) monotonically from Q1 to Q4, there is a clear break in monotonicity in the case of large stocks. The highest returns are achieved in Q3 for the large -cap stockgroup. Similarly, the underperformance of the other informed traders is much stronger in the case of smaller stocks compared to larger stocks. HFT and institutions (traditional) have Q4 – Q1 returns of -1.7% and -1.3%, respectively, for smaller stocks, compared to 0.2% and -0.5%, respectively, for larger stocks. In sum, we see that the impact of information leakage on the least informed traders is stronger in smaller stocks compared to larger stocks supporting H_B.

[Insert Table 6 here]

If insiders leak material information to retail traders ahead of unscheduled corporate announcements, then will the retail traders be able to take advantage of all types of announcements? Literature suggests that because of the presence of short-sale constraints, many investors are not able to trade against the overpriced stocks they do not own (Nagel, 2005). Thus, we expect that while our results will be stronger for good news announcements, they will be much weaker in the case of bad news announcements. To test the same, we split the sample of unscheduled announcements into two parts – ones where the post-announcement returns [T, T + 1] is positive and the others where it is negative. We then run our test on both samples. The results are represented in Table 7.

Clearly, the outperformance of the retail traders, measured by Q4 – Q1 returns, is much stronger at 1.5% for good news announcements compared to the overall sample results. There is also a consistent monotonic pattern from Q1 to Q4 for the good news announcements. In contrast, we find that for bad news announcements, there is no outperformance for retail traders. Q4 – Q1 returns are -0.3% for retail traders. There is hardly any variation across the four quartiles in average returns for retail traders. Thus, in line with our expectations, the information leakage to retail traders seems to only happen for good news announcements.

[Insert Table 7 here]

We then look at some alternate definitions to examine whether our results are reasonably robust. So far, we have only considered a post-announcement period of two days. This is consistent with literature (Chambers and Penman, 1984; Kaniel et al., 2012). However, there are examples of studies using periods of other lengths, and there is nothing sacrosanct in a two-day period. Thus, we consider an alternate definition of the post-announcement period, a period length of four days, i.e., we consider returns over [T, T + 3] and repeat our analysis. In panel A of Table 8, we provide the associated results. There are no material changes in the results, and they are qualitatively similar to our main results in Table 5.

We have so far used raw stock returns as a measure of performance since we have been dealing with idiosyncratic stock-specific events such as unscheduled corporate announcements. However, few studies have preferred to use abnormal returns instead of raw returns (Kaniel et al., 2012). We also use abnormal returns, measured as raw stock returns minus NIFTY500 index returns, and repeat our main test. Again, we find our main results to be qualitatively similar. There is a strict monotonic pattern in the average returns from Q1 to Q4 for retail traders, and the Q4 – Q1 outperformance is significant at 1.0%. The institutions (traditional) continue to underperform significantly at -0.8%. HFT and institution (algorithmic) have insignificant outperformance. Panel B of Table 8 represents the results.

If the insiders leak information to uninformed traders, then they are less likely to do so in the case of less impactful news (as the information advantage compared to other informed traders would be small) and more likely to do so in the case of more impactful news. We check whether our results are indeed stronger for more impactful news. We call an announcement more impactful if the absolute value of the post-announcement returns days [T, T + 1] is greater than 3%. We then rerun our test only for the more impactful news and find that retail outperformance is indeed stronger. Q4 – Q1 average return difference is 2.9%, much higher than the overall 1.1%. Panel C of Table 8 shows the results.

We use a sample of unscheduled announcements gathered from Bloomberg through the CACS function. However, for robustness purposes, we also check whether the same is reflected in the "Company News" section in Bloomberg. For example, in the case of some announcements, we do not find any related news pertaining to the particular announcement, and in the case of others, we find some related news was already published prior to the announcements. Although the number of such announcements is small, we want to make sure our results are unaffected by them. Thus, in panel D of Table 8, we rerun the test, removing the types of announcements just discussed. We find our main results to remain qualitatively similar.

[Insert Table 8 here]

Thus far, we have shown that our results are robust to alternate specifications. However, since our primary methodology is motivated by Kaniel et al. (2012), all our tests are conducted in a univariate setup. We conduct one robustness test to show that the results hold good in a multivariate setup that controls for both volume and volatility. Specifically, we estimate the following:

$$\text{PostRet}_{i,[T,T+1]} = \beta_1 * \text{IMB}_{i,[T-5,T-1],j} + \beta_2 * \text{Volat}_{i,[T,T+1]} + \beta_3 * \text{Volume}_{i,\{T,T+1]} + \epsilon_{i,T} \tag{2}$$

where

$\text{PostRet}_{i,[T,T+1]}$ is stock return of the i^{th} stock for the post-announcement period

$\text{Volat}_{i,[T,T+1]}$ is average daily volatility (max price/min price - 1) of the i^{th} stock over the t^{th} and $(t + 1)^{th}$ day

$\text{Volume}_{i,[T,T+1]}$ is total traded volume of the i^{th} stock over the t^{th} and $(t + 1)^{th}$ day

$\text{IMB}_{i,[T-5,T-1],j}$ is composite buy-sell imbalance of the i^{th} stock for the $t - 1^{th}$ to $t - 5^{th}$ day for the j^{th} trading group

We run trading group specific OLS regressions over 1491 unscheduled announcements and note the coefficient β_1 for each group. The estimates are provided in Table 9 and significance is measured using hcc-corrected T-stats. The coefficient for retail traders is positive and significant, while that of the other three groups is not – a result that is consistent with our main tests.

[Insert Table 9 here]

Having established our main result in the case of unscheduled announcements, we now conduct two important placebo tests to show that indeed, the results are only true for unscheduled announcements. In the first test, we look at the sample of scheduled quarterly earnings announcements for the 500 stocks. All publicly listed stocks in India are mandated to announce financial statements once every quarter. Thus, in theory, we have close to 500*4*5 = 10000 scheduled earnings announcement events in our sample. We collect data on the dates of these events from the Bloomberg and Prowess databases. We end up with 9733 events as some of the stocks in the sample stopped trading during the sample period, while others merged or acquired, and information on some of the events was unavailable in either Bloomberg or Prowess.

Institutional investors are known to conduct fundamental analysis themselves (Chan et al., 2013) and earn profits following analyst recommendations in their trades (Kong et al., 2021). It is thus not surprising that several studies report institutions can predict earnings announcement surprises – not just in the U.S. markets (Hendershott et al., 2015), but also in the Korean markets (Park et al., 2014). Also, since HFT is known to piggyback on the trades of institutional traders (Yang and Zhu, 2020), HFT trades may also be informed about impending earnings surprises. Since the earnings news announcement time is known in advance and sophisticated traders spend considerable time and energy predicting the content of the news, insiders may not have sufficient incentives to leak the news content to the least informed traders, as other informed traders are already privy to the information. Even if they leak information, the benefits that accrue to the least informed traders would be much less compared to what we see in the case of unscheduled announcements. We repeat our main test, but this time for a sample of scheduled earnings announcements. Table 10 provides the details. We see that Q4 – Q1 outperformance is zero for retail traders, suggesting that the least informed traders are not privy to the information ahead of the scheduled earnings announcements. In the same table, we also find institutions (traditional) and HFT have positive and significant outperformance (at the 10% level) in Q4 – Q1. Thus, retail traders are not privy to the information ahead of scheduled earnings announcements, but other informed traders are.

[Insert Table 10 here]

In the second placebo test, we randomly earmark 1000 stock-days as unscheduled announcement days and compute the buy-sell imbalance for all groups over five trading days prior to the announcement days and the post-announcement returns days [T, T + 1]. We repeat this exercise 500 times and then create quartile portfolios as before. Table 11 provides the results. We do not find any outperformance by retail traders. The Q4 – Q1 average returns are, in fact, negative (though insignificant). The institutions (algorithmic) and HFT have positive and significant outperformance. This is not surprising as the events are chosen randomly, and hence, only the so-called informed traders show some outperformance, and uninformed traders show underperformance.

[Insert Table 11 here]

5. Discussion

5.1. Mechanism of the leakage

How is it possible that insiders are able to leak information to the least informed traders, completely bypassing the other informed traders? One possible avenue is the bulk short messaging service to mobile phones (SMS). Before 2016, it was not uncommon to see individuals with trading accounts receive unsolicited trading tips. In fact, at times, it used to come from the official brokerage house. Only in 2016 did the capital market regulator SEBI come out publicly against these unsolicited trading tips on phones and propose a ban. Thus, before 2016, it was clearly possible for an insider who wanted to leak information to individual traders to do so easily with some help from the stock broking house. The broking houses did not worry as it was not illegal to do so.

The other mechanism that can help spread the leaked information among retail investors is social media. Farrell et al. (2022) suggest that information shared through social media has helped retail traders improve their trading performance. Modern finance social media websites have provided platforms for debating investment strategies and sharing investment research (Grennan and Michaely, 2021). Retail investors have also used social media to "gang up" by spurring each other on various platforms (Reddit, Twitter, YouTube, etc.), at times irrationally, to trade in one direction of the market (Pedersen, 2022).

Thus, it is also possible that the insider leaks the news (pertaining to unscheduled announcements) to some retail traders through a social media closed club (say a WhatsApp group), and then a few members share that information with other groups or chatrooms they are part of, and with a cascading effect, the news spreads in quickly to a significant proportion of the retail trading group.

5.2. Implications of the leakage

Institutional investors are known to spend efforts acquiring information through direct interactions with managers (Zhang, 2023) or through performing or following fundamental analysis (Chuang and Lee, 2011; Kong et al., 2021). They are characterized by an information-production role in financial markets (Chemmanur et al., 2009). Theoretical research has shown that expected profit is a must for investors to spend effort on information acquisition (Grossman and Stiglitz, 1980). However, the advent of algorithm trading (AT)/ HFT has put some brakes on the incentives of institutions to acquire information. Stiglitz (2014) suggests that by reducing informational rents, HFT is responsible for dissuading information acquisition by other traders. Weller (2018) provides an interesting tension, suggesting that while AT is responsible for incorporating existing information into market prices, they do not spend resources on acquiring new fundamental information, and their presence also deters other traders from doing so. An important mechanism for such a phenomenon is the "back running" of institutional traders' orders by AT/HFT, modeled theoretically by Yang and Zhu (2020) and demonstrated empirically by Van Kervel and Menkveld (2019).

Under a market structure where the share of AT/HFT is increasing gradually across the globe, and consequently, the incentives for information acquisition by institutional traders are on the wane, our finding that insiders leak information to the least informed traders is particularly disturbing. If sophisticated institutions realize that not only HFT but also the least informed traders eat into their informational rent, their incentives to acquire new information will reduce further.

The regulators, though, may find it difficult to control the leakage of information by insiders to unrelated third parties. While, in most countries including India, there are systems in place to curb sharing of information by insiders with related parties by monitoring the trading accounts of family members and close associates, it may be almost impossible to stop leaking information to unrelated parties. One way to change the entire mechanism and incentives for leaking information could be to mandate the companies to make a public intimation of an impending announcement, perhaps five to ten days ahead of the actual announcement. Once notified, the institutions can spend the effort to acquire more information on the particular company in these five to ten days and reduce some of the information asymmetries.

6. Conclusion

In this study, we empirically test the rational information leakage theory of Indjejikian et al. (2014). Studies on information leakage thus far have primarily focused on analyst tipping and trading before analyst recommendation as evidence of leakage. However, institutions are known to conduct fundamental analyses themselves and can obtain the same information without analysts tipping them. Thus, informed trading before analyst recommendation cannot be considered as evidence of information leakage without ambiguity.

In contrast, we analyze information leakage by observing trading before unscheduled announcements such as acquisitions, buybacks, equity offerings, divestitures, etc. The information contained in these unscheduled announcements is quite difficult to predict through fundamental analysis, and thus, these provide a satisfactory setting to test leakage.

We first establish that retail traders are the least informed trading group, and there are other informed trading groups present in the market, such as institutions (trading through algorithms), institutions (trading manually), and HFT. Our main finding shows that retail traders are privy to the information ahead of the unscheduled announcements. This is in line with rational information leakage theory, which suggests that insiders find incentives to leak information to the least informed traders. The finding is consistent with several alternate definitions and robustness tests. We attribute this information leakage by the insiders to the least informed traders to the use of bulk messaging services through mobile phones and social media.

In a world where AT/HFT has started taking a bite of the informational rents from institutional traders, the evidence of insiders leaking information to uninformed traders is disturbing. Institutional traders spend effort to acquire new information and bring that information to financial markets; their expected profits need to be high for them to continue doing so. If the information leakage ensures that institutional traders do not earn sufficiently from the trading process, then the institutions may reduce their effort at information acquisition or completely disband the effort!

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Table 1: Number of different types of unscheduled announcements, and the corresponding average stock returns prior to the announcements and following the announcements. Our sample is 500 stocks of the constituents of NIFTY500 Index and period of study is 5 calendar years [2011, 2015].

Type	Number of Announcements	Avg returns in Days [T - 15, T – 6]	Avg returns in Days [T - 5, T – 1]	Avg returns in Days [T, T + 1]
Acquisition	480	0.01%	0.78%	1.16%
Divestiture	662	0.00%	0.70%	0.94%
Equity Offering	183	-0.12%	0.59%	-1.25%
Joint Venture	100	0.06%	0.95%	0.14%
Spin-off	24	-0.15%	3.29%	1.67%
Stock Buyback	42	-0.01%	3.60%	1.06%

Table 2: Characteristics of the sample stocks divided across three market capitalization groups. Our sample is 500 stocks of the constituents of NIFTY500 Index and period of study is 5 calendar years [2011, 2015]. The largest(smallest) 150 stocks form the large(small) cap group. The other 200 stocks form the mid cap group. Market capitalization and traded volume are presented in INR million. Volatility is the average daily volatility. Daily volatility is computed as maximum price/minimum price – 1. The last column records the number of unscheduled announcements in the market capitalization category.

	Market Capitalization	Traded Volume	Shares traded	Volatility	Number of announcements
Large Cap	419078	1361	4331868	3.4%	785
Mid Cap	37541	218	2443655	4.1%	516
Small Cap	8769	87	1079522	4.8%	190

Table 3: Characteristics of the sample stocks divided across three market capitalization groups. Our sample is 500 stocks of the constituents of NIFTY500 Index and period of study is 5 calendar years [2011, 2015]. The largest(smallest) 150 stocks form the large(small) cap group. The other 200 stocks form the mid cap group. Data provides the share of trading volume and intraday closing inventory (computed as absolute buy volume minus sell volume over total volume) for each trading group, for overall sample as well as for each market cap group.

		Institutions (algorithm)	HFT	Institutions (manual)	Retail
Full Sample					
	Share of trading vol	13.0%	6.9%	12.6%	54.1%
	Closing Inventory	64.2%	5.3%	63.9%	11.6%
Large Cap					
	Share of trading vol	18.6%	10.9%	16.1%	38.6%
	Closing Inventory	47.0%	7.3%	47.0%	12.4%
Mid Cap					
	Share of trading vol	10.5%	5.9%	13.0%	57.1%
	Closing Inventory	74.7%	4.7%	70.0%	13.4%
Small Cap					
	Share of trading vol	7.4%	4.1%	7.8%	68.9%
	Closing Inventory	88.1%	3.6%	84.5%	8.4%

Table 4: General profitability of the sample stocks divided across three market capitalization groups over the entire sample period. Our sample is 500 stocks of the constituents of NIFTY500 Index and period of study is 5 calendar years [2011, 2015]. The largest(smallest) 150 stocks form the large(small) cap group. The other 200 stocks form the mid cap group. Panel A provides the trading profits. Intraday profit (in INR) is computed as cash received from selling shares – cash paid to purchase shares plus intraday ending inventory*closing price. Overnight profit (in INR) is overnight inventory*change in stock price. Each number represents the average across over stock-days. Panel B provides the estimates of the regression of stock return on previous day trading imbalances of each group. Imbalance is computed as shares bought minus shares sold over traded volume. Trading volume and volatility are included as control variables. Grp 1 is institutions (algo), Grp 2 is HFT, Grp 3 is institutions (manual) and Grp 4 is retail. Model is estimated by GLM with stock fixed effects. The significance of the coefficients are included below the coefficients, ***, ** and * mean the coefficients are significant at the 1%, 5%, and 10% levels, respectively.

Panel A:			Institutions (algorithm)	HFT	Institutions (manual)	Retail
Overall						
	Day profit		204417	8281	94253	-289438
		Overnight Profit	142928	1225	70671	-192475
		Intraday Profit	61488	7056	23582	-96963
Large Cap						
	Day profit		557578	28750	115564	-639204
		Overnight Profit	406023	12529	63911	-414198
		Intraday Profit	151555	16221	51653	-225006
Mid Cap						
	Day profit		72906	-2076	72260	-147682
		Overnight Profit	40393	-6419	56637	-89646
		Intraday Profit	32514	4344	15623	-58036
Small Cap						
	Day profit		19007	1347	102576	-121751
		Overnight Profit	11414	66	97166	-104409
		Intraday Profit	7593	1281	5410	-17342

Panel B:

Dep Var: Stock Return (t)

	Institutions (algorithm)	HFT	Institutions (manual)	Retail
Volatility(t)	-0.0071 ***	0.049291 ***	0.02406 ***	0.060177 ***
Volume(t)	0.02 ***	0.03 ***	0.02 ***	0.02 ***
Imb_Grp1(t-1)	0.00082 ***			
Imb_Grp2(t-1)		0.00081 ***		
Imb_Grp3(t-1)			0.00072 ***	
Imb_Grp4(t-1)				-0.00166 ***

Table 5: Average post-announcement returns (days[T, T + 1]) of the quartile portfolio of unscheduled announcement events. For each group, the portfolios are formed by sorting the five-day trading imbalance measure computed over days [T – 5, T – 1] with Q1 being the portfolio with most negative values (or with the stock-events that the group has been a heavy seller on days [T – 5, T – 1]). Trading imbalance is buy volume minus sell volume over total volume. Our sample is 500 stocks of the constituents of NIFTY500 Index and period of study is 5 calendar years [2011, 2015]. ***, ** and *, respectively denote whether the returns are significantly different from 0 at the 1%, 5%, and 10% levels.

	Institutions (algorithm)		HFT		Institutions (manual)		Retail	
Q1	0.77%	*	0.46%		1.27%	***	0.07%	
Q2	1.13%	***	1.32%	***	0.01%		0.59%	*
Q3	0.37%		0.11%		1.18%	***	0.98%	**
Q4	0.54%	*	0.39%		0.38%		1.20%	***
Q4 - Q1	-0.23%		-0.07%		-0.89%	**	1.12%	***

Table 6: Average post-announcement returns (days[T, T + 1]) of the quartile portfolio of unscheduled announcement events. For each group, the portfolios are formed by sorting the five-day trading imbalance measure computed over days [T – 5, T – 1] with Q1 being the portfolio with most negative values (or with the stock-events that the group has been a heavy seller on days [T – 5, T – 1]). Trading imbalance is buy volume minus sell volume over total volume. Our sample is 500 stocks of the constituents of NIFTY500 Index and period of study is 5 calendar years [2011, 2015]. The largest(smallest) 150 stocks form the large(small) cap group. The other 200 stocks form the mid cap group. Panel A presents the results for the large capitalization group. Panel B presents the results of the combined group of small and mid capitalization stocks. ***, ** and *, respectively denote whether the returns are significantly different from 0 at the 1%, 5%, and 10% levels.

Panel A: Large Capitalization Stocks

	Institutions (algorithm)		HFT		Institutions (manual)		Retail	
Q1	0.70%	**	0.51%		0.71%		-0.38%	*
Q2	0.16%		0.40%		0.29%		0.50%	
Q3	0.45%		0.06%		0.48%		0.95%	**
Q4	0.36%		0.68%		0.19%		0.59%	
Q4 - Q1	-0.34%		0.17%		-0.52%		0.97%	**

Panel B: Small and Mid Capitalization Stocks

	Institutions (algorithm)		HFT		Institutions (manual)		Retail	
Q1	0.94%		1.62%	***	1.87%	***	0.57%	
Q2	1.83%	***	1.08%		-0.28%		0.56%	
Q3	0.47%		1.33%	***	2.04%	***	1.11%	
Q4	0.56%		-0.06%		0.53%		1.91%	***
Q4 - Q1	-0.38%		-1.68%	**	-1.33%	**	1.34%	**

Table 7: Average post-announcement returns (days[T, T + 1]) of the quartile portfolio of unscheduled announcement events. For each group, the portfolios are formed by sorting the five-day trading imbalance measure computed over days [T – 5, T – 1] with Q1 being the portfolio with most negative values (or with the stock-events that the group has been a heavy seller on days [T – 5, T – 1]). Trading imbalance is buy volume minus sell volume over total volume. Our sample is 500 stocks of the constituents of NIFTY500 Index and period of study is 5 calendar years [2011, 2015]. Panel A presents the results for the stock-events with positive news (post-announcement returns positive). Panel B presents the results of the stock-events with negative news (post-announcement returns negative). ***, **, and *, respectively denote whether the returns are significantly different from 0 at the 1%, 5%, and 10% levels and are included only for the Q4 – Q1 groups in this table.

Panel A: Positive News

	Institutions (algorithm)		HFT		Institutions (manual)		Retail	
Q1	3.92%		3.17%		4.31%		3.14%	
Q2	4.94%		5.16%		3.50%		3.74%	
Q3	3.45%		4.38%		4.79%		4.30%	
Q4	3.34%		3.45%		3.18%		4.60%	
Q4 - Q1	-0.58%	*	0.28%		-1.13%	**	1.46%	***

Panel B: Negative News

	Institutions (algorithm)		HFT		Institutions (manual)		Retail	
Q1	-2.97%		-2.44%		-2.49%		-2.76%	
Q2	-3.38%		-2.94%		-3.55%		-2.80%	
Q3	-3.11%		-3.69%		-3.12%		-3.22%	
Q4	-2.36%		-3.06%		-2.66%		-3.04%	
Q4 - Q1	0.62%	*	-0.62%	**	-0.17%		-0.28%	

Table 8: Average post-announcement returns (days[T, T + 1]) of the quartile portfolio of unscheduled announcement events. For each group, the portfolios are formed by sorting the five-day trading imbalance measure computed over days [T – 5, T – 1] with Q1 being the portfolio with most negative values (or with the stock-events that the group has been a heavy seller on days [T – 5, T – 1]). Trading imbalance is buy volume minus sell volume over total volume. Our sample is 500 stocks of the constituents of NIFTY500 Index and period of study is 5 calendar years [2011, 2015]. Panel A presents the results changing the definition of post announcement returns to days [T, T + 3]. Panel B presents the results changing the definition of returns to abnormal stock returns (i.e., raw stock return minus NIFTY500 index returns). Panel C presents the results for only the significant events (with absolute post-announcement returns more than 3%). Panel D presents the results ignoring events with some public news leakage or events that has no corresponding news coverage. ***, **, and *, respectively denote whether the returns are significantly different from 0 at the 1%, 5%, and 10% levels.

Panel A: Four-day Post-announcement Period

	Institutions (algorithm)		HFT		Institutions (manual)		Retail	
Q1	0.65%		0.50%		1.05%	**	-0.11%	
Q2	0.72%	*	1.10%	**	-0.18%		0.39%	
Q3	0.09%		-0.21%		0.76%		0.68%	
Q4	0.48%		-0.02%		0.34%		1.01%	**
Q4 - Q1	-0.17%		-0.52%		-0.71%		1.11%	**

Panel B: Abnormal Returns

	Institutions (algorithm)		HFT		Institutions (manual)		Retail	
Q1	0.54%		0.18%		1.11%	***	-0.01%	
Q2	0.96%	**	1.17%	**	-0.03%		0.64%	
Q3	0.37%		0.23%		1.11%	***	0.89%	*
Q4	0.61%		0.48%		0.31%		0.98%	**
Q4 - Q1	0.07%		0.29%		-0.80%	**	0.98%	**

Panel C: Significant Events

	Institutions (algorithm)		HFT		Institutions (manual)		Retail	
Q1	1.99%	**	1.39%	**	2.96%	***	0.04%	
Q2	1.50%	**	3.36%	***	0.32%		1.70%	***
Q3	2.12%	***	0.39%		2.61%	***	2.35%	***
Q4	1.36%	*	0.63%		1.18%	**	2.97%	***
Q4 - Q1	-0.63%		-0.77%		-1.78%	*	2.92%	***

Panel D: Ignoring No News and Public Leakage Events

	Institutions (algorithm)		HFT		Institutions (manual)		Retail	
Q1	0.88%	*	0.22%		1.64%	***	0.10%	
Q2	1.88%	***	1.84%	***	0.13%		0.68%	*
Q3	0.14%		0.33%		1.35%	**	1.15%	**
Q4	0.64%		0.48%		0.42%		1.61%	***
Q4 - Q1	-0.24%		0.25%		-1.22%	**	1.52%	***

Table 9: Results of OLS regressions of post-announcement stock returns on pre-announcement trading imbalance of each trading group. Each regression is estimated over 1491 events. Our sample is 500 stocks of the constituents of NIFTY500 Index and period of study is 5 calendar years [2011, 2015]. Imbalance is computed as shares bought minus shares sold over traded volume in five days prior to the unscheduled announcement. Trading volume and volatility are included as control variables. Grp 1 is institutions (algo), Grp 2 is HFT, Grp 3 is institutions (manual) and Grp 4 is retail. The significance of the coefficients is included below the coefficients, ***, ** and * mean the coefficients are significant at the 1%, 5% and 10% levels, respectively. T-stats are computed from heteroskedasticity corrected s.e.

Dep Var: Post-announcement stock return of day[T, T + 1]

	Institutions (algorithm)	HFT	Institutions (manual)	Retail
Volatility	2.320 ***	2.324 ***	2.325 ***	2.309 ***
Volume	-0.155 *	-0.154 *	-0.155 *	-0.157 *
Imb_Grp1	-0.022			
Imb_Grp2		0.074		
Imb_Grp3			-0.077 ***	
Imb_Grp4				0.073 ***
Intercept	-0.015 *	-0.015 *	-0.015 *	-0.015 *

Table 10: Average post-announcement returns (days[T, T + 1]) of the quartile portfolio of scheduled earnings announcement events. For each group, the portfolios are formed by sorting the five-day trading imbalance measure computed over days [T – 5, T – 1] with Q1 being the portfolio with most negative values (or with the stock-events that the group has been a heavy seller on days [T – 5, T – 1]). Trading imbalance is buy volume minus sell volume over total volume. Our sample is 500 stocks of the constituents of NIFTY500 Index and period of study is 5 calendar years [2011, 2015]. ***, ** and *, respectively denote whether the returns are significantly different from 0 at the 1%, 5% and 10% levels.

	Institutions (algorithm)		HFT		Institutions (manual)		Retail	
Q1	-0.13%	***	-0.37%	***	-0.34%	***	-0.30%	***
Q2	-0.49%	***	-0.34%	***	-0.42%	***	-0.42%	***
Q3	-0.41%	***	-0.90%	***	-0.50%	***	-0.36%	***
Q4	-0.37%	***	-0.22%	***	-0.17%	***	-0.33%	***
Q4 - Q1	-0.25%	*	0.15%	*	0.17%	*	-0.03%	

Table 11: Average post-announcement returns (days[T, T + 1]) of the quartile portfolio of unscheduled announcement events, where the announcements are randomly chosen 1000 sample stock days and the process is repeated 500 times. For each group, the portfolios are formed by sorting the five-day trading imbalance measure computed over days [T – 5, T – 1] with Q1 being the portfolio with most negative values (or with the stock-events that the group has been a heavy seller on days [T – 5, T – 1]). Trading imbalance is buy volume minus sell volume over total volume. Our sample is 500 stocks of the constituents of NIFTY500 Index and period of study is 5 calendar years [2011, 2015]. ***, ** and *, respectively denote whether the returns are significantly different from 0 at the 1%, 5%, and 10% levels.

	Institutions (algorithm)		HFT		Institutions (manual)		Retail	
Q1	-0.07%		-0.08%		0.02%	***	0.09%	***
Q2	0.07%	***	0.11%	***	0.04%	***	0.03%	***
Q3	0.11%	***	0.08%	***	0.09%	***	0.03%	***
Q4	0.11%	**	0.10%		0.04%	***	0.05%	***
Q4 - Q1	0.18%	*	0.19%	*	0.02%		-0.04%	