Are algorithmic traders really distracted: Evidence from Indian financial markets[1]

Kamran Quddus[2]

Indian Institute of Management Calcutta

Ashok Banerjee

Indian Institute of Management Calcutta

[1] We gratefully acknowledge the financial support provided by the NSE-NYU Stern Initiative. We thank the participants at the NSE-NYU Conference on Indian Financial Markets for helpful comments

[2] Corresponding author: Kamran Quddus, Indian Institute of Management Calcutta, kamranq13@iimcal.ac.in

Are algorithmic traders distracted? Evidence from Indian financial markets

Abstract

We present new evidence on the trading behavior of machine traders around systemic distraction events. Using tick-by-tick proprietary data on NSE listed firms, our study provides a client-wise response to positive and negative news sentiment. Our paper offers insights on how value-irrelevant competiting stimuli impact the decision making of machine traders. Using a novel approach, the study evaluates more than 38,000 news headlines to identify value irrelevant distraction events. Non-algorithmic traders are more susceptible to extraneous distractions compared to machine traders. Even within non-algorithmic traders, the inattention phenomenon becomes more pronounced with higher ownership of retail investors. Using Thomson Reuters proprietary news sentiment, we find that traders behave differently during periods of inattention on firm-specific positive and negative news. Time-varying patterns in investor attention interact with news sentiment to influence firm value. The trading pattern of market participants suggests a significant decline in the number of transactions during various distraction periods indicating that investor inattention inhibits the decision making of investors.

Keywords

Investor attention; sentiment; algorithmic traders

Are algorithmic traders distracted? Evidence from Indian financial markets

1. Introduction

Prior studies on underreaction highlight the role of investors' cognitive constraint in explaining the underreaction to new information. Attention is an important factor in agents' learning and decision-making processes (Hou, Xiong, & Peng, 2009). Limited attention may act as an important source of friction in financial markets (Peress, 2008). Psychologists argue that limited cognitive resources hinders human thinking capacity and leads to continuous tension among the multiple information channels competing for limited mental resources (Egeth & Kahneman, 1975; Hirshleifer & Teoh, 2003). Many classical, as well as behavioral researchers, have inquisitively looked into the subject of underreaction. Cognitive sciences literature highlights that investor inattention may be a source of underreaction to firm-specific news (Loh, 2010).

With recent advancements in technology and automation, investors should feel less cognitively challenged in making investment decisions. Chakrabarty & Moulton (2012) postulate that increased reliance on automated decision making alleviates attention constraints. A priori intuition suggests that investors should not display any significant underreaction when they are overwhelmed with plenty of information. We feel it would be quite interesting to examine the impact of limited attention on stock prices in computer-driven financial markets.

We examine the trading behavior of machine traders and test whether the inattention effect is less pronounced among the algorithmic traders (compared to human traders) during times of distraction. The empirical evidence would be particularly useful to market regulators at a time when they are circumspect about the role of high-frequency algorithmic traders[1]. We also aim to present new evidence on how competing stimuli impact investors' decision making. Although researchers argue that irrelevant stimuli can distract investors, relatively fewer studies examine the impact of value irrelevant competing stimuli on decision making (Drake, Gee, & Thornock, 2016). We use distraction events covered on the front page of a newspaper as a proxy for

[1] Reserve Bank of India (RBI) advocates higher monitoring on algorithmic trades to reduce the risk of market manipulation and foul play (FSR Report)

investor inattention. These events act as a shock to individual attention that diverts the minds of investors away from the market. This momentary disturbance hinders their ability to quickly and comprehensively react to firm-specific information. We extend the investor attention literature by investigating the distraction effect using a list of critical non-market distraction events that are, for the most part, value irrelevant. Our study brings two strands of research that examine the behavior of investors, the consumer of news (Dellavigna & Pollet, 2009), and the role of media, the intermediary of news (Bagnoli, Clement, & Watts, 2005; Boulland, Degeorge, & Ginglinger, 2016a). It also addresses the concern as to whether some forms of distraction induces larger underreaction compared to others.

We find that machine traders are less amenable to distraction events. The inattention phenomena remains more pronounced among non-machine traders who rely on limited cognition. The rest of the paper is organized as follows. Section 2 reviews the investor attention literature. Section 3 describes the data and summary statistics. Section 4 presents the hypothesis development and model. Section 5 provides the detailed results of the distraction effect. Section 6 provides additional robustness tests. Section 7 concludes the paper.

2. Literature Review and Motivation

Traditional asset pricing models suggest that stock prices quickly reflect all relevant information without delay. However, one cohort of literature has surprised academia with empirical evidence of a delay in the incorporation of firm-specific information into security prices. They posit underreaction as a natural antecedent to this behavior. Contemporary behavioral finance has extensively studied the phenomenon of underreaction. Cognitive sciences literature highlights that investor inattention may be a source of this underreaction (Loh, 2010). Researchers look at aggregate market outcomes such as extreme returns (Barber & Odean, 2008), trading volume (Hou et al., 2009), and media coverage (Da, Engelberg, & Gao, 2011) to judge whether investors are attentive to the stock. They base their theoretical understanding on the assumption that specific observable and latent market outcomes can influence the level of engagement of investors. For example, higher coverage of a particular stock in media may draw the attention of more investors, and that may lead to unusually high trading volume for a specific stock. Extending this line of thinking, we examine the market dynamics during specific, short periods marked by the systemic noise of a kind. We use "inattention" and "distraction" terms interchangeably to refer to such intermittent periods.

Psychologists argue that the information-processing capacity of the human mind is limited due to continuous tension among the multiple information channels competing for limited mental resources (Egeth & Kahneman, 1975; Hirshleifer & Teoh, 2003). The cognitive models have aided the understanding of complex human interactions and have proved to be the quintessential missing link so far. Behavioral finance researchers have recently started exploring this line of thinking. This strand of research leans back on the theoretical underpinnings of cognitive limitation to justify the time delay in the market reaction to firm-related information.

To illustrate investor inattention, we highlight one major political event in India that attracted nationwide attention, as evident from national and local media coverage. In April 2011, Anna Hazare, a social activist, launched India against Corruption (IAC) campaign demanding stronger Lokpal (Ombudsman) Bill in India. The general public in India was keenly following the details of the incident and every major sequence of developments as it unfolded. Even though Anna and his team protested in Delhi, almost the entire nation eagerly followed the events through media. News channels witnessed a drastic jump in viewership, with approximately 2.5 million new viewers joining every week during Hazare agitation compared to the previous week (Stancati & Pokharel, 2011). The IAC campaign was a media hit with a viewership of news channels jumping up by almost six percent[2] in the week through 27th August 2011. The incidence of coverage of related news in various media shot up nearly 1,000 percent in the same week[3].

What is more intriguing is the response of investors to corporate announcements during this period. As anecdotal evidence, we handpick a few corporate announcements during distraction times to convey our message. For example, when Hazare was on his fast, a positive news item on Coal India gaining Maharatna status generated negative sentiment. Its price fell by almost two percent over the next two days. Around the same period, there was neutral-to-positive news that

---

[2] As per News Content Track, a tool of media research firm TAM. Refer The Wall Street Journal blog at http://blogs.wsj.com/indiarealtime/2011/09/05/why-was-hazare-such-a-media-hit/

[3] Factiva is a global news database featuring nearly 33,000 news sources across geographies, including The Wall Street Journal, Dow Jones Newswires and Barron's

Infosys officials are reportedly in talks to have the IT company set up a local presence in other emerging countries including Brazil. Strangely, the stock reported a negative cumulative abnormal return of one percent in the two days around the Hazare event.

The majority of the existing studies consider the impact of distraction events on the pricing of earnings (Drake et al., 2016). We argue that earnings information is a backward-looking number that appears with a lag. Investors react to all firm-related information promptly and do not wait for the reporting of the accounting number. Therefore, we take a slightly different approach and consider the impact of a distraction event on the market response to all firm-relevant information. This idea may not have been explored earlier for lack of authentic information on all firm-relevant news in a structured format. We rely on Thomson Reuters News Analytics (TRNA) for their database on corporate news and sentiment scores.

We make four significant contributions to the investor attention literature. First, most importantly, we provide evidence whether distraction events affect algorithmic traders differently. Second, we find empirical support for the notion that non-market distraction events impair the ability of investors to incorporate relevant company-specific information into prices. We classify the distraction events into subcategories using the machine learning algorithm. Third, we highlight that investors do not react homogeneously to the different non-market distraction events. For instance, a distraction caused by any political situation may produce smaller underreaction, whereas a distraction triggered by sports and entertainment event may have larger underreaction. Fourth, we provide new evidence that time-varying investor attention may moderate or accentuate sentiment to influence short-term firm value. The empirical evidence is robust across models even after controlling for relevance, novelty, and sentiment of the news.

Contemporary studies, which have examined the impact of investor attention, look at scheduled events such as the NCAA basketball tournament (Drake et al., 2016). Our work differs from previous studies in that we examine major systemic distractions, which were mostly unexpected such as a major earthquake, political crisis, among others. Moreover, we filter out these systemic events through a rigorous and scientific approach. These non-market distraction events concern a vast majority of the nation, as demonstrated through their coverage in the popular media. Earlier studies hint at the possible interaction of distraction with investor biases, such as “mood swings” triggered by World Cup soccer games impacting the stock market outcomes (Edmans, Garcia, & Norli, 2007). We allow this potential interaction of investor biases with a variety of distraction events.

Several studies demonstrate market underreaction by using proxies for investor inattention such as trading volume (Hou et al., 2009), event occurrence on Fridays (Dellavigna & Pollet, 2009), down-market periods (Hou et al., 2009), and non-trading hours (Francis, Pagach, & Stephan, 1992). Barber & Odean (2008) focus on the buying behavior of investors in attention-grabbing stocks. They hypothesize that investors face a search cost while choosing from a large subset of stocks and that stocks in the news, stocks experiencing high abnormal trading volume, and stocks with extreme one-day returns draw their attention and form the subset to choose from. Odean (1999) suggests that investors choose from attention-grabbing stocks based on their preferences. We study the opposite — investors' lack of attention to stocks in the news during periods of distraction.

3. Data

Our study involves three unique datasets. First, we use tick-level proprietary data from the National Stock Exchange (NSE) of India to investigate the trading pattern of different categories of traders. The data contains a detailed representation of each trade executed in the cash market on the exchange. The data provides details of all trades executed on NSE along with a timestamp and other particulars of trade, such as the number of shares bought or sold, average transaction price, order type, and other metadata. The algorithmic indicator flags a trade based on whether the trade originates from a terminal using the algorithmic trading facility or an ordinary (non-algorithmic) system. For instance, the transaction record identifies machine traders through a separate algorithmic indicator that takes values 0,1,2, and 3. The indicator values 0 and 2[4] represent the trades that were initiated by members who are using the algorithmic trading facility, whereas values 1 and 3[5] identify trades executed by non-algorithmic terminals. The

[4] The algo indicator value two indicates trades are initiated by algorithmic traders using Smart Order Routing (SOR)

[5] The algo indicator value three indicates trades are initiated by non-algorithmic traders using Smart Order Routing (SOR)

trader's field in the database is particularly useful in determining the customer type on each side of the trade. The trader identity flag takes values 1, 2, and 3 for proprietary, client, and custodian trades respectively.

Second, we utilize the high-frequency sentiment scores data from the Thomson Reuters News Analytics (TRNA) database. TRNA provides comprehensive coverage of company-specific announcements on all the NSE listed firms. Reuters Data Feed (RDF) sources the data through news alerts, Reuters stories, and other third-party news sources. Using Lexalytics' natural language processing technology, each archived news item is scored along several dimensions. The analysis is primarily carried out at the sentence level[6].

Third, we avail the Times of India (TOI)[7] archives for the event headlines data to prepare the distraction events database. This unique database helps us systematically identify noisy days when investors may potentially be less attentive to financial markets. The Google Trends makes available the Search Volume Index (SVI) scores, which help in gauging the general interest level of individuals for the events. Further, we also collect the frequency count of the number of times a news event gets reported in other well-known media sources. The frequency count helps us filter out the regional or less distracting events from our database.

Many of the studies in the past consider indirect proxies for investor attention. These proxies are mostly endogenous and noisy, which may affect the reliability of the results. We propose that external non-market events that are value irrelevant may act as better proxies for investor distraction. Irrelevant stimuli are distracting, echo the essence of limited attention models deciphering the market underreaction anomalies (Hirshleifer, Lim, & Teoh, 2009). Our research setting offers an additional benefit that, unlike seasonal earnings announcements, firm-specific announcements occur throughout the year. Further, our choice of setting allows defined

---

[6] See (Hendershott, Livdan, & Schürhoff, 2015) for a more detailed description on TRNA database

[7] According to the Audit Bureau of Circulations, TOI is the largest selling English language daily in the world and has been ranked among the world's six best newspapers as per the BBC rankings in 1991. Such influential newspapers not only directly reach the readers, but also influence news coverage of smaller or regional newspapers across the country (Boykoff & Boykoff, 2007)

categories of investor distraction that also captures the interaction of investor biases and cognitive attention.

3.1 Identification of Distraction Events

We follow a novel approach to collect a list of irrelevant distraction events. We begin by scanning the news headlines and bylines of the TOI archives. Boulland, Degeorge, & Ginglinger (2016) note that an attention-grabbing event that attracts the attention of a large number of investors is usually newsworthy[8]. Selecting a media source such as TOI does not induce any biases as the speed of news dissemination does not drive investor attention (Da et al., 2011). We look up the keywords appearing in the TOI headlines on Google Trends to examine the nationwide relative popularity of the search term. The Search Volume Index (SVI) scores facilitate easier comparison across terms for search popularity on Google Search. The numbers are scaled on a range of zero to 100. A more significant score indicates the higher popularity of the phrase. This helps in assessing the general level of interest for particular news and gives a reasonable indication that individuals were actively searching for that news event. The choice of SVI is also motivated by Da et al. (2011), who argue that the score captures investor attention in a more timely fashion and represents a direct and unambiguous measure of attention.

We collect news headlines from the Times of India archives over twelve years from January 2004 through December 2015. The choice of the period was constrained by the availability of the records on the site. There were 49 holidays during the sample period when TOI was not issued. We examine headlines and bylines on the front page from the 4,334 available TOI editions. Since our goal is to construct a database of the primary distraction events, we filter out the news items where the Google SVI index is less than 100. This gives us a list of 368 key distraction events during the sample period. We apply a second filter to check if these incidents were sufficiently covered in other news media as well[9]. For this purpose, we remove the items which

[8] Although other channels may also distract investors, but events that distract a wide base of investors make it to the news (Barber & Odean, 2008).

[9] Media coverage may serve as a proxy for investors' attention. Peress (2008) quantifies this by the number of articles published in the Wall Street Journal (WSJ).

appeared for less than 50 times during the month in which the news made headlines. Using this procedure, we get a final list of 333 significant distraction events.

We start by breaking each sentence in the news articles into words, through a process called tokenization[10]. We subject the tokenized words through subsequent processing steps such as stemming and lemmatization. Stemming replaces each word with its root word, and lemmatization performs morphological analysis of words to return words in its base form, commonly referred to as lemma. One common goal of these preprocessing steps is to neutralize the jargon and acronyms and minimize the variation problems through a vocabulary control technique. The tokenized texts are assigned a part-of-speech tag using Stanford CoreNLP[11]. We also eliminate redundant entities such as proper nouns, dates, and digits as they do not convey extra information in classifying the text into different topics.

Researchers use linguistic-based analytical models to explore unstructured data in textual format. These analytical models have been used in extracting information in a non-conventional form from various channels and find a useful application in social media analytics (Liu, 2012; Pang & Lee, 2008), sentiment analysis (Blei, 2012) and topic modeling (Blei, 2012).

We use a nonparametric Bayesian model for eliciting the hidden themes in the text corpus. The basic structure resembles latent variable models. Studies in machine learning use probabilistic algorithms to unravel and annotate vast archives of documents with thematic information (Zhang et al., 2013).

Topic modeling relies on statistical techniques to examine the words of the original text to discern the significant themes hidden in the document. The algorithm does not require any prior labeling of the documents. One of the primary aims of this technique is to examine the topic coverage of the news text. We start with an n-gram based topic model to identify the specific

[10] Many text processing software have inbuilt functionality for text-processing. One such Python library is Natural Language ToolKit (NLTK) which is commonly used in text processing and analytics

[11] Stanford CoreNLP toolkit, is an extensible pipeline that provides core natural language analysis. This toolkit is quite widely used, both in the research NLP community and also among commercial and government users of open source NLP technology (Manning et al., 2014)

topic covered in the news. Finally, we use non-negative matrix factorization (Seung & Lee, 1999) to elicit the topic coverage over time[12].

We focus on news archives from print media due to their extensive circulation and content reliability. Barber and Odean (2008) argue that even though investors could be attracted through other means, but an event that draws the attention of a large population of investors is likely to be reported in the news. One principal argument for looking at the front page headline events is that only significant events appear in the headlines on the front page. Therefore these events concern a large population of a nation and immediately catch their attention. Using the NMF technique, we divide the distraction events into four sub-groups, namely —– Natural calamities & disasters, political, law & order, and sports & entertainment. Table 1 provides a year-wise, detailed breakup on each of the sub-categories. Sports & entertainment events form the most significant category with a count of 97, followed by political (89), natural calamities (82), and law & order (65).

3.2 Company-Specific Sentiment Scores

Once we obtain the distraction events, our next task is to collect sentiment of firm-specific news. The sentiment scores for the firm-specific news are available from the Thomson Reuters News Analytics (TRNA)[13]. Using a sophisticated computational linguistic process, TRNA deciphers each news item and scores it for each asset appearing in the news. The primary attributes of the TRNA scores are categorized as follows:

- Relevance: Gives a quantitative measure of how relevant the news item is to the firm mentioned in the news. Each firm appearing in the news receives a score on a scale of zero to one. A higher score indicates that the news is highly relevant for the company.
- Sentiment: Indicates the tone of the news item. The field has three levels: 1,0 and -1 representing a positive, neutral and negative sentiment of the news.

---

[12] Non-negative matrix factorization (NMF) is an unsupervised machine learning algorithm for text classification. The algorithm arranges text in a document-term matrix (DTM), and the proximity between any two news items is assessed by calculating the Euclidean distance between two pairs of word frequencies

[13] We thank Thomson Reuters for providing the TRNA dataset

- Novelty: Shows whether the news item is unique or related to some previously seen news item. TRNA measures novelty as the number of times a news item is covered repetitively in a history window of 12 hours to seven days in one or more media sources.
- Headline Classification: Gives a brief analysis of the headline

We rely on TRNA for firm-specific news samples from 2004 to 2015. Our treatment sample consists of all firms for which sentiment scores and other metadata were available for matching companies in press releases archived on Reuters Data Feed (RDF).

Table 2 shows descriptive statistics of the firm-specific sentiment scores for Indian firms from January 2004 until December 2015. We have a total of 990,003 news releases over the period. Panel A shows that, on average, 11.2 percent[14] of the 1,789 Indian firms have some news available on TRNA. The daily news distribution has a standard deviation of 8.6. On the lower side of the distribution, there were days where only 0.168 percent of the total firms had some news releases. Whereas, on the higher end of the distribution, there were days where almost 36 percent of the firms had some announcements. The mean sentiment per news release is 0.091. Panel B, through D of Table 3, gives the breakup on the distribution of news releases by focusing on the predominant sentiment of the news. For example, Panel B presents the statistics on positive news sentiment, and Panel C shows the distribution of negative news sentiment.

3.3 High-Frequency Algorithmic Trading

We access the proprietary trading records maintained at NSE to decipher the market activity during our study period. Each transaction in the cash market segment is time-stamped, along with the particulars of the trade. Each row of the data represents a unique transaction history. The algorithmic trade indicator, as well as the client identity flag, makes this data particularly useful

---

[14] The average number of firm-specific news releases is 21.4 percent for Nifty 500 companies during distraction days and 21.3 percent during other days. A univariate t-statistic suggests no significant difference between the two periods. Therefore, it appears that journalists were not distracted. We rely on TRNA database for a comprehensive coverage on company news coverage

for our investigation. This segregates machine-initiated automated trades from those undertaken by human traders.

Contemporary research in finance examines the role of limited investor attention in asset pricing. Dellavigna and Pollet (2009) highlight that investors underreact to earnings announcements on Fridays compared to other weekdays. They predicate the findings on the assumption that investors are more likely to be inattentive on Fridays relative to other weekdays. Despite the widening appeal for cognitive factors such as limited attention playing a vital role in explaining asset pricing dynamics, empirical research has been scarce in this area (Dellavigna & Pollet, 2009).

Our study contributes to the existing literature on stock market underreaction by investigating the inattention phenomena and how it affects the decision making of investors. The idea resonates well with the hypothesis that inattention impacts the quality of decision making (Barber & Odean, 2008), determines stock buying decision of retail investors (Yuan, 2015), affect the trading behavior of investors and explains the market reaction to macroeconomic news announcements (Chen et al., 2016).

To further strengthen our point, we investigate the market response to firm-specific news announcements in various distraction periods. We collect firm related announcements from Dow Jones Factiva. Analysis of stock market reaction reveals that similar news announcements generate different market response during natural calamities & disaster situation as compared to the market reaction during a distraction triggered by an attention-grabbing law & order situation. This difference in stock return response cannot be ruled out as a non-significant aberration owing to the random walk movement of share prices. This differential response merits a detailed and more rigorous examination that can lead to sophisticated explanations of existing phenomena, for example, underreaction to earnings announcements on Fridays (Barber & Odean, 2008). The difference in stock return response also hints at the possibility of the nature of distraction itself affecting the decision-making behavior of investors.

Contemporary studies in finance look at both the indirect proxies of investor attention, such as trading volume (Barber & Odean, 2008), extreme returns (Barber & Odean, 2008), news headlines (Yuan, 2015)[15] as well as direct proxies such as Google Search Frequency (Drake et al., 2016). Most of the previous studies looked at proxies of investor attention without examining the source of distraction itself. We contribute to the existing investor attention literature by taking a more granular look into the nature of the systemic distractions and the investor's response to such nation-wide shocks. We hypothesize that the nature of distraction itself can have implications on the way investors react to irrelevant stimuli. Previous research suggests that the magnitude of inattention effect varies with the category of distraction and interacts with other behavioral biases such as investor mood (Baker & Wurgler, 2006).

4 Hypothesis and Research Design

4.1 Hypothesis Development

Earlier studies have examined how investor sentiment impacts stock prices and contributes to the mispricing of securities (Baker & Wurgler, 2007). Shleifer and Vishny (1997) investigate the effect of competing stimuli on markets during periods coinciding with the NCAA basketball tournament — commonly referred to as March Madness as it commences in March and generates "extraordinary levels of excitement." They find that March Madness veers investors' attention away from new earnings announcements. The number of trades is found to be significantly lower for firms announcing their earnings during the tournament periods compared to nontournament periods.

Behavioral finance studies highlight the distinctive trading behavior among different groups of investors. For example, the limits to arbitrage circumvent the arbitrageurs to trade on any market mispricing aggressively (Shleifer & Vishny, 1997). De Long, Shleifer, Summers, and Waldmann (1990a) posit that investors are vulnerable to sentiment, which reinforces their belief about future cash flows. However, traditional wisdom suggests that rational traders should be less sanguine in acting on any positive or negative news sentiment. Baker and Wurgler (2007) maintain that researchers now face the issue of measuring and quantifying the effects of sentiment and exploring the mechanism through which attentional constraints affect investors' trading activity. We mitigate this concern by using the TRNA database, which provides sentiment scores for each news in the database.

---

[15] See (Da et al., 2011) for a more detailed discussion

With advancements in technology, individuals have gradually transitioned towards the use of more algorithmic as opposed to manual trading strategies. Baker and Wurgler (2006) find that moving towards a more automated trading environment results in attenuating the effect of attentional constraints. Therefore, the cognitive constraint of investors, embracing mechanical trading strategies, should become less binding. We argue that the investor inattention hypothesis would not hold merit under such scenarios. The use of tick-level data from NSE helps us examine this issue in further detail. This tick-by-tick proprietary data flags the trades executed using machine algorithms vis-à-vis non-algorithmic trades and thus provide us opportunities for cleaner tests of the differential effects of external distractions.

H1: Non-Algorithmic traders are more susceptible to extraneous distractions compared to Algorithmic traders in reacting to any news sentiment

We examine whether irrelevant stimuli triggered by critical non-market distraction events, hinder market reaction to firm-specific announcements. Given the cognitive and temporal limits to the information processing capacity of individuals, we hypothesize that market reaction to any firm-specific announcements during such distraction periods will elicit a muted response. Therefore, we hypothesize that the strength of the relationship between the sentiment of any firm-specific announcement to the stock return will be weaker during periods marked by distraction compared to regular periods.

H2: News carrying positive or negative sentiment will elicit a muted response during distraction periods relative to average trading days.

Our third hypothesis is motivated by studies that argue that investors react differently to positive and negative news. For example, Hirshleifer et al. (2009) indicate that investors respond differently to positive and negative earnings surprises by firms. We also contemplate that all kinds of distractions do not trigger similar levels of underreaction. The differences in investor behavior may partly account for the fact that various categories of distraction may induce different kinds of biases on individual investors. Our natural experiment setup, therefore, allows us to delineate the interactions of investor biases with news sentiment.

One commonly reported investor bias is conservatism, characterized by the slow updating of opinions in the light of new information. Edwards (1968) states that human disaggregation of data may explain why individuals fail to combine the diagnostic meaning of one piece of information with another when revising their opinions. Various idiosyncracies in noises characterize different categories of distraction. Baker and Wurgler (2007) posit that an individual's capability to integrate information into investment decision making is psychological. The state of mind, feelings, and attitudes contaminate human decisions. Also, some biases, including availability bias and conservatism may distort judgments of probability, variance or even correlation. Our experimental settings allow us to delineate the interactions of investor biases with news sentiment unambiguously.

H3: Investors react differently to different categories of distraction

We take the "bottom-up" approach suggested in (Barberis et al., 1998) by highlighting the individual differences in biases among different groups of investors. Various psychological biases such as conservatism (Daniel et al., 1998), representativeness, and overconfidence (Miller, 1977) may induce predictive ability in explaining the differences in underreaction or overreaction exhibited by investors.

We distinctly bring out the differentiation that even within non-algorithmic transactions, less sophisticated traders would be more inattentive compared to institutional traders. Our proposition tests the psychological biases arising from the differences of opinion (De Long et al., 1990a) among various categories of investors. The behavioral finance literature model investors as either rational arbitrageurs who are less susceptible to changes in sentiment or as irrational traders, who are more prone to fluctuating sentiments (De Long et al., 1990a).

H4: Less sophisticated (retail) traders are more affected by distractions as compared to institutional investors

4.2 **Research Design**

4.2.1 Asymmetric Reaction Around Distraction Events

To examine investor behavior during distraction periods, we investigate the abnormal stock return around the news announcement dates. We use distraction events as a proxy for investor inattention. The investor inattention hypothesis argues that these developments inhibit the ability of market participants to react to the firm-specific news. We use the model (equation (1)) to estimate the stock returns. In the first stage, stock returns are regressed on its one-period lagged return, market return, and a set of variables to control for the day of the week effect and non-weekend effect.

$$R_{it} = \beta_0 + \beta_{1i} R_{it-1} + \beta_{2i} R_{Mt} + \beta_{3i} D_t + \beta_{4i} Q_t + \varepsilon_{it}, \quad (1)$$

$D_t = \{D_{1t}, D_{2t}, D_{3t}, D_{4t}\}$ are dummy variables for Monday through Thursday,
$Q_t = \{Q_{1t}, Q_{2t}, Q_{3t}, Q_{4t}, Q_{5t}\}$ are dummy variables for days for which previous 1 through 5 days are non-weekend holidays

In the second stage, we take the residuals from regression (1) and regress it on sentiment scores of news releases. Positive and negative sentiment scores are represented by sent_pos and sent_neg respectively. The sentiment scores range from zero to one, and hence can also be interpreted as the probability of news carrying positive and negative sentiment respectively. Edwards et al. (1968) argue that smaller firms exhibit larger underreaction during distraction phases. We control for the size of the business to check for this variation in the distraction effect.

$$\hat{\epsilon}_{it} = \gamma_0 + \gamma_1 \text{ sent\_pos}_{it} + \gamma_2 \text{ sent\_neg}_{it} + \gamma_3 \text{ ILLIQ}_{it} + \gamma_4 \text{ IVOL}_{it} + \gamma_5 \text{ relevance}_{it} + \gamma_6 \text{ novelty}_{it} + \gamma_7 \text{ size}_{it} + \gamma_8 \text{ IMR}_{it} + (\text{Industry Dummies})\text{i} + (\text{Year Dummies})_t + v_{it} \quad (2)$$

$\hat{\epsilon}_{it}$ are the residuals derived from the previous regression, sent_posit and sent_negit are the probability that the sentiment of the news was positive and negative respectively; relevanceit measures the pertinence of the asset reported in the news and novelty is the measure of the uniqueness of the news being reported.

4.2.2 Order Imbalance Analysis by Trader Type

We analyze the tick-by-tick (TBT) proprietary dataset that provides complete order and trade description on all NSE listed stocks. This unique TBT data reveal identifiers that enable the segregation of algorithmic traders from non-algorithmic traders. The trades are chronologically arranged according to clock time. An advantage of using this data is that it gives a comprehensive picture regarding the type of transaction (buy/sell), order type (market/ limit), and the exact time at which the order arrived and the time at which it got executed. We would classify a trade as buyer-initiated if the prior order on the stock was on the buy-side. Similarly, we classify a trade as seller-initiated if the previous order for the stock was on the sell-side. We measure net order imbalance (NOI) across each trader category as the total buyer-initiated traded volume minus total seller initiated traded volume within that trade group, scaled by the total traded volume for the stock on that day.

$$NOI_{it} = \gamma_0 + \gamma_1 \text{ sent\_pos}_{it} + \gamma_2 \text{ sent\_neg}_{it} + \gamma_3 \text{ Dist}_t + \gamma_4 \text{ Dist}_t * \text{sent\_pos}_{it} + \gamma_5 \text{ Dist}_t * \text{sent\_neg}_{it} + \sum_{k=1}^{5} \gamma_{6k} NOI_{i-t-k} + \gamma_7 \text{ size}_{it} + (\text{Industry Dummies})_i + (\text{Year Dummies})_t + \varepsilon_{it} \quad (3)$$

$Dist_t$ is a dummy variable that takes a value of one, on distraction days, and zeroes otherwise.

NOI calculated separately for algorithmic traders, and non-algorithmic traders are regressed on news sentiment, lagged NOI, the distraction dummy, and its interaction with the sentiment variables.

5 Results

5.1 Client-wise Activity on Distraction Days

Table 3 gives a breakup of trading activity by client type. We use trade records from the NSE's tick-by-tick proprietary data in the cash market segment. The algorithmic indicator in the data allows us to identify the trades executed by algorithmic terminals as well as the non-algorithmic facilities[16]. Further, we use the client identity flag to segregate trading data based on whether the trade is proprietary, done on behalf of a client, or a non-client, non-proprietary trade. Panel A shows the trading activity by trader type for positive news sentiment. Consistent with H1, we find statistical evidence that the inattention effect is more pervasive for non-algorithmic trades compared to algorithmic trades. The difference in trading volume between distraction days and normal days is 14.9 ($p > 0.9$) for algorithmic trading on behalf of the client. The corresponding

[16] The Algo indicator takes values zero through three for Algo, Non-Algo, Algo through SOR, and Non-Algo through SOR respectively. We combine the categories zero and two to represent the algorithmic trades. Similarly, we combine the categories one and three to represent non-algorithmic trades. Trades through Smart Order Routing (SOR) represent a small fraction in both algo and non-algo transactions.

difference is -36.3 ($p < 0.01$) for non-algorithmic client trades. We find no statistical difference in trading volume during distraction days for different categories of algorithmic traders.

The differences in the response of the underlying information processing system can also explain the differences in trading behavior between machine and human traders. Automated decision-making system circumvents conservatism in information processing (Hong et al., 2000). This conservatism may account for the inability of human traders to revise their opinions as much as a rational Bayesian agent would. Computer-assisted decisions enable the algorithmic traders to precisely reflect the impact of all available information in updating their beliefs[17]. The results are similar for news with negative sentiment.

Our results, therefore, suggest that machine traders are not distracted by irrelevant stimuli and act as liquidity providers. Algorithmic traders, in general, provide support to price by pushing liquidity. The participation of algorithmic traders, therefore, contributes to higher quality markets by offering liquidity.

5.2 **Order Imbalance on Distraction Days**

Table 4 shows order imbalance around firm-specific news releases. We also introduce up to one-week lagged values in our regression model to account for any residual serial correlation. However, we only report the coefficients of interest in Table 4. We find the reaction of order imbalance to positive news sentiment goes down on distraction days. The coefficient -0.240 ($p < 0.05$) suggests that the reaction of non-algorithmic traders declines on distraction days. The similar coefficient for algorithmic traders is -0.797 ($p < 0.1$), which indicates that the results are weakly significant for algorithmic traders. The empirical evidence concurs with our initial hypothesis that algorithmic traders are not as distracted by external non-market events. A similar order imbalance scenario for negative news releases is shown in Panel B.

---

[17] Algorithmic and manual traders differ in the underlying mechanism that processes the available information. Algorithmic traders use artificial intelligence that incorporates Bayes' rule into posterior distribution encompassing the impact of all available information. Human brain may not be able to estimate likelihood ratios or aggregate all available information into their posterior. See Edwards et al. (1968) for a more detailed discussion.

5.3 **Price impact on distraction days**

Table 5 presents our empirical findings exhibiting the asymmetric response of investors to firm-specific announcements during different categories of distraction periods. Panel A shows the response coefficients to positive and negative sentiment news during all distraction periods. Overall the results indicate that the investors are distracted by irrelevant stimuli. The beta coefficient, γ_2 for announcements carrying negative sentiment is -0.024 ($p > 0.10$), suggesting that investors underreact to any negative corporate announcements during distraction phases. The results are consistent with the notion that any negative company news diffuses only slowly across the investors (De Long, Schleifer, Summers, & Waldmann, 1990b). Surprisingly, γ_1 signifying the response coefficient for positive news is 0.386 ($p < 0.01$) and statistically significant. Panels B through E presents the results across various distraction categories. We find empirical evidence of underreaction to negative sentiment news during all distraction periods, consistent with H3. However, the coefficient γ_1 of positive sentiment is economically and statistically significant in the overall distraction period as well as in different categories of distractions, except political events (Panel C). Positive news triggers positive feedback trading among traders (Peng & Xiong, 2006), which justifies the economic significance of coefficients in case of positive news. The γ_1 coefficients also vary from 0.4 ($p < 0.10$) in Panel B to 0.507 ($p < 0.05$) in Panel D, validating our H3. In other words, the results indicate that investors' response to positive sentiment news differs across various categories of distraction. The relevance of the news announcement has no statistical significance across distraction categories, excepting Panel B, where γ_3 is -0.290 ($p < 0.10$). This supports the investor inattention hypothesis that investors fail to react to any relevant news during distraction periods adequately.

The counter-intuitive results for positive news during the distraction period may be due to aggregating the reaction of algorithmic with non-algorithmic traders. This further highlights that our study offers a better explanation of traders’ behavior during distraction periods.

6 **Robustness Tests and Additional Analyses**

For further robustness, additional tests are performed on the entire dataset that includes both algorithmic and non-algorithmic traders.

6.1 **Investor sophistication and distraction**

We further check whether the retail ownership in a particular stock is significantly correlated with the cumulative abnormal returns. Hendershott et al. (2015) argue that limited attention compels investors to overlook useful firm-specific information. Less attentive investors fail to incorporate the news into prices resulting in underreaction. Our primary results establish that human traders are more prone to underreaction. Further, as a robustness check, we examine whether stocks predominantly held by less sophisticated (retail investors) weakly respond to any positive or negative news sentiment during short periods of distraction. The results (Table 6) show that retail investors are less attentive during periods of distraction. This is true for both positive and negative sentiment news. This is consistent with H4 that retail investors are more distracted by irrelevant external stimuli than sophisticated institutional investors.

Standard empirical finance literature measures underreaction using the ex-post abnormal returns having the same sign as the event. Behavioral researchers postulate that this return drift may result from investors' lack of attention. Peress (2008) argues that the post-event continuations in returns may occur because of the gradual learning of inattentive investors. The presence of market frictions may prevent attentive investors from taking advantage of these temporal arbitrage opportunities.

6.2 News arrival during trading hours

We examine whether the inattention effect is accentuated if the firm-specific news arrives during trading hours. We construct a dummy variable Open that takes a value one if news comes during trading hours and zero otherwise. We regress trading volume (TdVal) on distraction dummy and its interaction with Open variable, and other controls as shown in the model (4)

$$TrdVal_{it} = \beta_0 + \beta_1{*}Distraction_t + \beta_2{*}Open_{it}{*}Distraction_t + \beta_3{*}IVOL_{it} + \beta_4{*}MktCap_{it} + \beta_5{*}ShrsOut_{it} + \text{Industry dummies} + \text{Year dummies} + \varepsilon_{it} \quad (4)$$

As shown in Panel A in Table 7, the β_1 coefficient is negative and statistically significant. This suggests that there is a significant drop in trading volume during distraction days. Furthermore, the coefficient of interaction term β_2 is negative and significant which indicates that the effect of inattention is more pronounced if firm news arrives during trading hours.

6.3 Half-Life

In this section, we investigate the persistence of news sentiment on stock return series. If market participants are distracted by irrelevant events, they may not immediately react to firm-specific news during those periods. However, as the effect of any disturbance dissipates investors start focusing on financial markets again. If our hypothesis holds, this will manifest in the adjustment time that it takes for any news to reflect in prices. We conjecture that the half-life of firm information would be different for distracted versus attentive investors.

We test the difference in the average half-life of firm news during both distraction and attention days. The results in Table 7 panel B, shows that the average half-life of news impact is higher during distraction days. The higher half-life during distraction periods suggests that when market participants are inattentive, the impact of material information takes a longer time to reflect in prices fully. Our results concur with the investor attention hypothesis, which postulates that less attentive investors would cause the news to reflect in prices slowly, and hence the adjustment would be delayed.

6.4 Trading in Cross-listed stocks

We test whether the inattention-induced drop in liquidity is observed for stocks cross-listed on foreign exchanges. If the source of distraction is local, then we may conjecture that the domestic inattention effect should not influence outside investors. Thus we investigate whether trading activities in stocks cross-listed at a foreign exchange experience similar drop in trading during distraction days. Table 7, panel C shows that while the stocks listed on local bourses experience a statistically significant decline in trading activity, there is no such drop in trading activity on stock listed on foreign exchanges.

7 Conclusion

The main findings of the study highlight that investors underreact to both positive and negative sentiment during distraction periods. Our empirical results highlight that investors do not behave homogeneously in all categories of distraction. The underreaction is more pronounced during distraction periods triggered by natural calamities & disasters and political events compared to distraction in other periods. We also examine the trading pattern of investors during these periods. Consistent with our hypothesis, we find a statistically significant drop in the number of transactions undertaken by the market participants. This decline in both the turnover and traded quantity indicates that investor participation drops significantly during distraction periods. Further, our results suggest that retail traders are more distracted by external distractions as compared to institutional investors. This underreaction holds for both positive and negative sentiment news. Minor underreaction by institutional investors could be due to the adoption of more sophisticated quantitative trading strategies and increased reliance on technology. Our results have possible managerial implications regarding timing the release of voluntary disclosures to manage investor expectations.

References

Bagnoli, M. E., Clement, M. B., Watts, S. G., 2005. Around-the-clock media coverage and the timing of earnings announcements. McCombs Research Paper Series No. ACC-02-06. Available at SSRN: https://ssrn.com/abstract=570247 [Accessed 29th July, 2018].

Baker, M., Wurgler, J., 2006. Investor sentiment and the cross-section of stock returns. The Journal of Finance 61, 1645–1680. https://doi.org/10.1111/j.1540-6261.2006.00885

Baker, M., Wurgler, J., 2007. Investor sentiment in the stock market. Journal of Economic Perspectives 21, 129–152. https://doi.org/10.1257/jep.21.2.129

Barber, B. M., Odean, T., 2008. All that glitters: The effect of attention and news on the buying behavior of individual and institutional investors. The Review of Financial Studies 21, 785–818. https://doi.org/10.1093/rfs/hhm079

Barberis, N., Shleifer, A., Vishny, R., 1998. A model of investor sentiment. Journal of Financial Economics 49, 307–343. https://doi.org/10.1016/S0304-405X(98)00027-0

Blei, D. M., 2012. Probabilistic topic models. Communications of the ACM 55, 77–84. https://doi.org/10.1145/2133806.2133826

Boulland, R., Degeorge, F., Ginglinger, E., 2016. News dissemination and investor attention. Review of Finance 21, 761–791. https://doi.org/10.1093/rof/rfw018

Boykoff, M. T., Boykoff, J. M., 2007. Climate change and journalistic norms: A case-study of US mass-media coverage. Geoforum 38, 1190–1204. https://doi.org/10.1016/j.geoforum.2007.01.008

Chakrabarty, B., Moulton, P. C., 2012. Earnings announcements and attention constraints: The role of market design. Journal of Accounting and Economics 53, 612–634. https://doi.org/10.1016/j.jacceco.2012.01.001

Chen, J., Liu, Y.-J., Lu, L., Tang, Y., 2016. Investor attention and macroeconomic news announcements: Evidence from stock index futures. Journal of Futures Markets 36, 240–266. https://doi.org/10.1002/fut.21727

Da, Z., Engelberg, J., Gao, P., 2011. In search of attention. The Journal of Finance 66, 1461–1499. https://doi.org/10.1111/j.1540-6261.2011.01679.x

Daniel, K. D., Hirshleifer, D., Subrahmanyam, A., 1998. Investor psychology and security market under-and overreactions. The Journal of Finance 53, 1839–1885. https://doi.org/10.1111/0022-1082.00077

De Long, J. B., Shleifer, A., Summers, L. H., Waldmann, R. J., 1990a. Noise trader risk in financial markets. Journal of Political Economy 98, 703–738. https://doi.org/10.1086/261703

De Long, J. B., Shleifer, A., Summers, L. H., Waldmann, R. J., 1990b. Positive feedback investment strategies and destabilizing rational speculation. The Journal of Finance 45, 379–395. https://doi.org/10.1111/j.1540-6261.1990.tb03695.x

Dellavigna, S., Pollet, J. M., 2009. Investor inattention and friday earnings announcements. The Journal of Finance 64, 709–749

Drake, M. S., Gee, K. H., Thornock, J. R., 2016. March market madness: The impact of value-irrelevant events on the market pricing of earnings news. Contemporary Accounting Research 33, 172–203. https://doi.org/10.1111/1911-3846.12149

Edmans, A., García, D., Norli, Ø., 2007. Sports sentiment and stock returns. The Journal of Finance 62, 1967–1998. https://doi.org/10.1111/j.1540-6261.2007.01262.x

Edwards, W., 1968. Conservatism in human information processing. In: Kleinmutz, B. (Ed.). Formal Representation of Human Judgment. New York, NY: John Wiley and Sons, 17–52.

Edwards, W., Phillips, L. D., Hays, W. L., Goodman, B. C., 1968. Probabilistic information processing systems: Design and evaluation. IEEE Transactions on Systems Science and Cybernetics 4, 248–265. https://doi.org/10.1109/TSSC.1968.300119

Egeth, H., Kahneman, D., 1975. Attention and effort. The American Journal of Psychology 88, 339.

Francis, J., Pagach, D., Stephan, J., 1992. The stock market response to earnings announcements released during trading versus nontrading periods. Journal of Accounting Research 30, 165–184

Hendershott, T., Livdan, D., Schürhoff, N., 2015. Are institutions informed about news? Journal of Financial Economics 117, 249–287. https://doi.org/10.1016/j.jfineco.2015.03.007

Hirshleifer, D., Teoh, S. H., 2003. Limited attention, information disclosure, and financial reporting. Journal of Accounting and Economics 36, 337–386. https://doi.org/10.1016/j.jacceco.2003.10.002

Hirshleifer, D., Lim, S. S., Teoh, S. H., 2009. Driven to distraction: Extraneous events and underreaction to earnings news. The Journal of Finance 64, 2289–2325. https://doi.org/10.1111/j.1540-6261.2009.01501.x

Hong, H., Lim, T., Stein, J., 2000. Bad news travels slowly: Size, analyst coverage and the profitability of momentum strategies. The Journal of Finance 55, 265–295. https://doi.org/10.1111/0022-1082.00206

Hou, K., Xiong, W., Peng, L., 2009. A tale of two anomalies: The implications of investor attention for price and earnings momentum. Available at SSRN: https://ssrn.com/abstract=976394 [Accessed 29th July, 2018].

Lamoureux, C. G., & Lastrapes, W. D. (1990). Persistence in Variance, Structural Change, and the GARCH Model. *Journal of Business & Economic Statistics*, *8*(2), 225–234. https://doi.org/10.1080/07350015.1990.10509794

Liu, B., 2012. Sentiment analysis and opinion mining. Synthesis Lectures on Human Language Technologies 5, 1–167. https://doi.org/10.2200/s00416ed1v01y201204hlt016

Loh, R. K., 2010. Investor inattention and the underreaction to stock recommendations. Financial Management 39, 1223–1252. https://doi.org/10.1111/j.1755-053X.2010.01110.x

Manning, C., Surdeanu, M., Bauer, J., Finkel, J., Bethard, S., Mcclosky, D., 2014. The Stanford CoreNLP natural language processing toolkit. In: Proceedings of 52nd Annual Meeting of the Association for Computational Linguistics: System Demonstrations. Baltimore, Maryland, USA, 55–60.

Miller, E. M., 1977. Risk, uncertainty, and divergence of opinion. The Journal of Finance 32, 1151–1168. https://doi.org/10.1111/j.1540-6261.1977.tb03317.x

Odean, T., 1999. Do investors trade too much? American Economic Review, 89, 1279–1298. https://doi.org/10.1257/aer.89.5.1279

Pang, B., Lee, L., 2008. Opinion mining and sentiment analysis. Foundations and Trends® in Information Retrieval 2, 1–135. https://doi.org/10.1561/1500000011

Peng, L., Xiong, W., 2006. Investor attention, overconfidence and category learning. Journal of Financial Economics 80, 563–602. https://doi.org/10.1016/j.jfineco.2005.05.003

Peress, J., 2008. Media coverage and investors' attention to earnings announcements. Available at SSRN: https://ssrn.com/abstract=2723916 [Accessed 29th July, 2018].

Seung, H. S., Lee, D. D., 1999. Learning the parts of objects by non-negative matrix factorization. Nature 401, 788–791.

Shleifer, A., Vishny, R. W., 1997. The limits of arbitrage. The Journal of Finance 52, 1, 35–55. https://doi.org/10.1111/j.1540-6261.1997.tb03807.x

Stancati, M., Pokharel, K., 2011. Why was hazare such a media hit? Available at: https://blogs.wsj.com/indiarealtime/2011/09/05/why-was-hazare-such-a-media-hit/ [Accessed 1 Jul. 2018]

Yuan, Y., 2015. Market-wide attention, trading, and stock returns. Journal of Financial Economics 116, 548–564. https://doi.org/10.1016/j.jfineco.2015.03.006

Zhang, J., Zhang, L., Yang, G., Wu, D., Jiang, L., Huang, L., Wen, Z., Li, M., 2013. Nonnegative matrix factorization for the improvement in sensitivity of discovering potentially disease-related genes. Chemometrics and Intelligent Laboratory Systems 126, 100–107. https://doi.org/10.1016/j.chemolab.2013.05.004

Tables

Table 1. Descriptive Statistics on Distraction Events

Yearly distribution of the number of event days of each category of distraction events during the period 2004 – 2015. The news headlines have been collected from the Times of India archives and categorized using Non-negative matrix factorization algorithm

	Group				
	(1)	(2)	(3)	(4)	
Year	Natural Calamities	Political	Law & Order	Sports &	Total
2004	9	11	6	11	37
2005	5	3	3	4	15
2006	4	5	9	3	21
2007	3	7	4	11	25
2008	12	1	7	6	26
2009	23	11	6	13	53
2010	7	10	11	11	39
2011	5	8	6	5	24
2012	4	6	2	6	18
2013	1	4	6	8	19
2014	3	14	2	9	28
2015	6	9	3	10	28
Total	82	89	65	97	333

Table 2. Descriptive Statistics on Firm-Specific Sentiment Scores.

	Mean	**S.D.**	**1%**	**50%**	**99%**
Panel A: All News Releases and sentiment (990,003 observations)					
News stocks per day (% of 1,789 firms)	11.189	8.634	0.168	9.558	36.054
News days per stock (% of 4,479 days)	4.469	3.448	0.067	3.818	14.401
Stocks per news release	4.523	5.960	2.000	2.000	30.000
Sentiment per news release	0.091	0.386	-0.763	0.093	0.820
Panel B: News releases with dominant Positive Sentiment (339,706 observations)					
News stocks per day (% of 1,780 firms)	3.723	2.892	0.056	3.146	12.472
News days per stock (% of 4,265 days)	1.554	1.207	0.023	1.313	5.205
Stocks per news release	4.212	4.944	2.000	2.000	26.000
Sentiment per news release	0.456	0.238	0.018	0.481	0.826
Panel C: News releases with dominant Negative Sentiment (248,166 observations)					
News stocks per day (% of 1,756 firms)	3.226	2.593	0.057	2.620	10.592
News days per stock (% of 4,182 days)	1.355	1.089	0.024	1.100	4.448
Stocks per news release	4.616	5.316	2.000	2.000	26.000
Sentiment per news release	-0.425	0.224	-0.764	-0.503	-0.014
Panel D: News releases with Neutral Sentiment (402,131 observations)					
News stocks per day (% of 1,782 firms)	5.315	4.388	0.056	4.265	18.687
News days per stock (% of 4,056 days)	2.335	1.928	0.025	1.874	8.210
Stocks per news release	2.755	2.743	2.000	2.000	16.000
Sentiment per news release	0.102	0.101	-0.134	0.077	0.445

Table 3. Comparison of Market Activity by Trader Type.

The figures indicate traded volume (INR million) by various categories of traders. The trading records were obtained using NSE tick-by-tick proprietary data and aggregated across various distraction days. The client identity was flagged using an indicator variable

Panel A: Market Activity by Trader Type for news with positive sentiment

	Algorithmic			Non-Algorithmic		
	Client	Proprietary	Non-CP	Client	Proprietary	Non-CP
	(1)	(2)	(3)	(4)	(5)	(6)
Natural Calamities & Disaster	162.4	111.3	41.3	127.7	105.9	358.3
Political	381.6	272.0	98.3	225.8	162.7	532.3
Law & Order	167.8	102.2	393.9	131.3	803.7	296.8
Sports & Entertainment	347.4	185.8	84.8	189.2	112.4	434.9
All Distraction Days	353.0	213.7	88.5	217.0	126.7	473.9
Non-Distraction Days	338.1	171.7	78.6	253.3	145.0	542.1
Difference	14.9	42.0	9.9	-36.3	-18.3	-68.2
p-val	0.909	0.999	0.999	0.003	0.000	0.004

Panel B: Market Activity by Trader Type for news with negative sentiment

	Algorithmic			Non-Algorithmic		
	Client	Proprietary	Non-CP	Client	Proprietary	Non-CP
	(1)	(2)	(3)	(1)	(2)	(3)
Natural Calamities & Disaster	243.4	143.9	53.9	186.9	127.4	437.2
Political	435.0	256.3	967.8	268.9	150.5	568.4
Law & Order	233.8	131.4	47.3	170.8	98.6	349.0
Sports & Entertainment	426.8	228.4	96.6	237.3	137.9	513.4
All Distraction Days	429.9	237.6	95.2	273.1	155.7	563.3
Non-Distraction Days	438.7	209.3	94.3	326.1	165.1	609.6
Difference	-8.8	28.3	0.9	-53.0	-9.4	-46.3
p-val	0.245	0.999	0.625	0.000	0.021	0.019

Table 4. Investigating Order Imbalance Around Distraction.

	Positive news		Negative news	
	Algorithmic	Non-Algorithmic	Algorithmic	Non-Algorithmic
sent_pos	0.804	0.178	-0.272	0.828
	(0.356)***	(0.088)**	(0.151)	(0.246)***
sent_neg	1.089	-0.004	-0.141	0.657
	(0.838)	(0.112)	(0.082)	(0.351)
Dist	0.668	0.279	-0.089	0.793
	(0.418)	(0.092)***	(0.065)	(0.273)***
Dist*sent_pos	-0.797	-0.240	0.302	-1.060
	(0.413)	(0.109)**	(0.133)**	(0.312)***
Dist*sent_neg	-0.342	-0.086	0.143	-0.859
	(1.243)	(0.141)	(0.081)**	(0.347)**
Mkt_cap	0.001	0.035	0.003	0.024
	(0.024)	(0.005)***	(0.002)	(0.009)***
Intercept	-0.851	-0.429	0.096	-0.767
	(0.557)	(0.107)***	(0.067)	(0.238)***
Industry Dummies	Yes		Yes	
N	9,132	11,157	6,957	7,801

$$NOI_{it} = \gamma_0 + \gamma_1\, sent\_pos_{it} + \gamma_2\, sent\_neg_{it} + \gamma_3\, Dist_t + \gamma_4\, Dist_t{*}sent\_pos_{it} + \gamma_5\, Dist_t{*}sent\_neg_{it} + \sum_{k=1}^{5} \gamma_{6k}\, NOI_{i,\, t-k} + \gamma_7\, size_{it} + (IndustryDummies)_i + (YearDummies)_t + \varepsilon_{it}$$

NOI is the net order imbalance, calculated as net buyer-initiated trades less the seller-initiated trades, $sent\_pos_{it}$, and $sent\_neg_{it}$ are the probability that the sentiment of the news was positive and negative respectively; $Dist_t$ is a dummy variable that takes value one if day t is a distraction day and zeroes otherwise

Notes: Industries are defined by the Fama-French 48-industry classification. Variables are winsorized at the 1 percent and 99 percent levels. Standard errors are clustered by the news announcement date. *, **, and *** indicate significance at the $p < 0.10$, $p < 0.05$, and $p < 0.01$ levels respectively

Table 5. Asymmetric Investor Reaction to Firm Specific Announcements during Various Distraction Events.

$$R_{it} = \beta_0 + \beta_{1i} R_{it-1} + \beta_{2i} R_{Mt} + \beta_{3i} D_t + \beta_{4i} Q_t + \varepsilon_{it},$$

$D_t = \{D_{1t}, D_{2t}, D_{3t}, D_{4t}\}$ are dummy variables for Monday through Thursday,

$Q_t = \{Q_{1t}, Q_{2t}, Q_{3t}, Q_{4t}, Q_{5t}\}$ are dummy variables for days for which previous 1 through 5 days are non-weekend holidays

$$\widehat{\epsilon_{it}} = \gamma_0 + \gamma_1 \text{sent\_pos}_{it} + \gamma_2 \text{sent\_neg}_{it} + \gamma_3 \text{ILLIQ}_{it} + \gamma_4 \text{IVOL}_{it} + \gamma_5 \text{relevance}_{it} + \gamma_6 \text{novelty}_{it} + \gamma_7 \text{size}_{it} + \gamma_8 \text{IMR}_{it} + (\text{Industry Dummies})_i + (\text{Year Dummies})_t + v_i$$

$\widehat{\epsilon_{it}}$ are the residuals derived from previous regression, sent_pos_{it} and sent_neg_{it} are probability that the sentiment of the news was positive and negative respectively; relevance_{it} measures the pertinence of the asset reported in the news; novelty is the measure of uniqueness of the news being reported; ILLIQ and IVOL measure illiquidity and implied volatility respectively

	Panel A		Panel B		Panel C		Panel D		Panel E		Panel F	
	All Distraction Days		**Natural Calamities & Disasters**		**Political**		**Law & Order**		**Sports & Entertainment**		**Attention Days**	
	Coef.	Robust Std. Error	Coef.	Robust Std. Error	Coef.	Robust Std. Error	Coef.	Robust Std. Error	Coef.	Robust Std. Error	Coef.	Robust Std. Error
Sent_pos	0.358	0.111***	0.501	0.282*	0.128	0.172	0.339	0.229	0.604	0.199***	0.363	0.131***
Sent_neg	-0.070	0.100	-0.132	0.247	-0.067	0.182	0.198	0.235	0.028	0.182	-0.478	0.149***
ILLIQ	-0.012	0.026	-0.029	0.020	-0.022	0.095	-0.028	0.068	-0.006	0.033	0.554	0.282**
IVOL	-0.185	0.202	-0.596	0.531	-0.425	0.337	-0.123	0.064	-0.007	0.049	-0.004	0.037
Relevance	-0.099	0.069	-0.261	0.161	-0.209	0.094	0.151	0.142	-0.081	0.147	-0.142	0.079*
Novelty	0.001	0.009	-0.013	0.020	0.012	-0.009	0.022	0.024	0.002	0.016	0.002	0.024
Size	-0.028	0.012**	-0.099	0.032***	-0.087	0.032**	-0.069	0.048	-0.123	0.045***	-0.063	0.019***
IMR	-0.049	0.094	0.057	0.272	-0.437	0.184**	-0.466	0.387	-0.852	0.243***	-0.616	0.122***
_Cons	0.626	0.392	1.064	0.773	1.954	1.024*	0.629	0.794	1.279	0.531**	0.982	0.349***
Industry Dummies	Yes		Yes		Yes		Yes		Yes		Yes	
Year Dummies	Yes		Yes		Yes		Yes		Yes		Yes	
N	24,838		15,398		16,302		10,826		13,908		44,288	

Notes: Industries are defined by the Fama-French 48-industry classification. Variables are winsorized at the 1 percent and 99 percent levels. Standard errors are clustered by the news announcement date. *, **, and *** indicate significance at the $p < 0.10$, $p < 0.05$, and $p < 0.01$ levels respectively

Table 6. Do Stocks Predominantly Owned by Retail Investors Exhibit Higher Underreaction.

$R_{it} = \beta_0 + \beta_{1i} R_{it-1} + \beta_{2i} R_{Mt} + \beta_{3i} D_t + \beta_{4i} Q_t + \varepsilon_{it}$,

$D_t = \{D_{1t}, D_{2t}, D_{3t}, D_{4t}\}$ are dummy variables for Monday through Thursday,

$Q_t = \{Q_{1t}, Q_{2t}, Q_{3t}, Q_{4t}, Q_{5t}\}$ are dummy variables for days for which previous 1 through 5 days are non-weekend holidays

$$\widehat{\boldsymbol{CAR}[\mathbf{0},\mathbf{1}]}_{it} = \gamma_0 + \gamma_1 \text{sent\_pos}_{it} + \gamma_2 \text{sent\_neg}_{it} + \gamma_3 \text{relevance}_{it} + \gamma_4 \text{novelty}_{it} + \gamma_5 \text{size}_{it} + \gamma_6 (P/B)_{it} + \gamma_7 (D_{Retail})_{it} + \gamma_8 \text{sent\_pos}_{it} * D_{Retail,it} + \gamma_9 \text{sent\_neg}_{it} * D_{Retail,it} + \gamma_{10} \text{ILLIQ}_{it} + \gamma_{11} \text{IVOL}_{it} + \gamma_{13} \text{IMR}_{it} + (\text{Industry Dummies})_i + (\text{Year Dummies})_t + v_{it}$$

$\widehat{\boldsymbol{CAR}[\mathbf{0},\mathbf{1}]}_{it}$ are the cumulative abnormal returns over day 0 to +1; sent_pos_{it} and sent_neg_{it} are probability that the sentiment of the news was positive and negative respectively; relevance_{it} measures the pertinence of the asset reported in the news; novelty is the measure of uniqueness of the news being reported; D_{Retail} is a dummy variable that takes a value one if the retail ownership is above median and zero otherwise; ILLIQ and IVOL measure illiquidity and implied volatility respectively

	All Distraction Days		**Natural Calamities & Disasters**		**Political**		**Law & Order**		**Sports & Entertainment**		**Attention Days**	
	Coef.	Robust Std Error	Coef.	Robust Std Error	Coef.	Robust Std Error	Coef.	Robust Std Error	Coef.	Robust Std Error	Coef.	Robust Std Error
Sent_pos	0.522	0.142***	0.611	0.375	0.059	0.287	0.621	0.324*	0.690	0.268**	0.651	0.195***
Sent_neg	-0.143	0.147	-0.602	0.336	-0.285	0.266	0.182	0.332	0.256	0.338	-0.480	0.207**
ILLIQ	0.007	0.042	0.004	0.030	-0.029	0.139	-0.011	0.094	0.055	0.072	0.795	0.442*
IVOL	-0.023	0.008**	-0.007	0.003***	-0.031	0.014**	-0.002	0.001	-0.306	0.265	-0.048	0.053
Relevance	0.046	0.098	-0.226	0.225	-0.276	0.201	0.262	0.235	0.155	0.192	-0.135	0.118**
Novelty	-0.001	0.016	-0.002	0.033	0.035	0.022	-0.012	0.027	-0.017	0.024	-0.055	0.036
Size	-0.083	0.026***	-0.304	0.093***	-0.205	0.067***	0.044	0.076	-0.146	0.097	-0.049	0.032
P/B	0.005	0.003	0.016	0.009	0.013	0.007*	0.005	0.003	-0.005	0.004	-0.013	0.005***
D_{Retail}	-0.221	0.245	-0.321	0.491	0.332	0.555	-0.242	0.543	-0.758	1.097	0.265	0.475
sent_pos*D_{Retail}	0.282	0.501	0.193	0.968	-0.621	0.999	0.370	0.978	1.716	2.170	0.165	0.812**
sent_neg*D_{Retail}	0.309	0.457	-0.345	0.824	-0.625	1.069	0.449	1.101	1.778	1.690	-0.767	0.836
IMR	-0.052	0.149	-0.248	0.487	-0.577	0.342*	-0.105	0.542	-0.847	0.405*	-0.683	0.194***
Intercept	1.139	0.581	3.853	1.620**	2.522	1.395*	-0.539	1.291	1.919	1.186	0.839	0.521
Industry Dummies	Yes		Yes		Yes		Yes		Yes		Yes	
Year Dummies	Yes		Yes		Yes		Yes		Yes		Yes	
N	24,838		15,398		16,302		10,826		13,908		44,288	

Notes: Industries are defined by the Fama-French 48-industry classification. Variables are winsorized at the 1 percent and 99 percent levels. Standard errors are clustered by the news announcement date. *, **, and *** indicate significance at the p < 0.10, p < 0.05, and p < 0.01 levels respectively

Table 7. Investigating trading activity in different scenarios

Panel A: Comparing changes in market activity during trading versus outside trading hours

$$TrdVal_{it} = \beta_0 + \beta_1{*}Distraction_t + \beta_2{*}Open_{it}{*}Distraction_t + \beta_3{*}IVOL_{it} + \beta_4{*}MktCap_{it} + \beta_5{*}ShrsOut_{it} + \text{Industry dummies} + \text{Year dummies} + \varepsilon_{it}$$

Distraction is an indicator variable that takes a value one during distraction days and zero otherwise; Open is a dummy which assumes a value one if news arrives during trading hours and zero otherwise; ShrsOut represents outstanding shares and TrdVal measures the trading volume. The remaining variables are as defined earlier

	Coefficient	t-value
Distraction	-0.024	-6.05****
Open*Distraction	-0.009	-2.15**

Panel B: Comparing mean half-life during two periods

The table shows the half-life variance of news released on distraction versus attention days. Following Lamoureux & Lastrapes (1990), the half-life is calculated as 1- [ln(2)/ln(α_1+β_1)]

Average half-life			
Distraction	Attention	Difference	t-stat
4.45	4.05	0.40	9.09***

Panel C: Comparing changes in trading on cross-listed stocks

The table shows the average trading volume of shares listed on domestic and foreign exchange during distraction versus attention days

Change in liquidity on cross-listed stocks during different periods				
Exchange	Distraction	Attention	Difference	t-stat
Domestic	8.58	6.86	-1.72	-6.97 ***
Foreign	2.89	2.81	-0.08	-0.49