Are algorithmic traders really distracted?

Evidence from Indian financial markets

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Outline

- Introduction
- Related Literature
- Research Questions
- Data and Methodology
- Results
Background

- Attention is a limited cognitive resource (Kahneman 1973)
  - Limited cognitive resource constraints human thinking capacity
- Cognitive sciences literature highlights that investor attention may be a source of underreaction to firm-specific news (Loh, 2010)
- Attention is an important factor in agents’ learning and decision-making process (Hou, Xiong & Peng, 2009)
- Limited attention can affect investor perception and market price as they fail to update their beliefs on arrival of earning news (Hirshleifer and Teoh 2003)
- Advancements in technological progress makes investors feel less cognitively challenged in decision making
- Prior studies look at indirect proxies of investor attention
  - Endogenous and noisy
  - External non-market events may act as better proxies
Literature

- Attention is a limited cognitive resource (Kahneman 1973)
- Limited attention can affect investor perception and market price as they fail to update their beliefs on arrival of earning news (Hirshleifer and Teoh 2003)
- Attention constraint leads investors to focus more on market and sector level information than firm specific information (Peng and Xiong 2006)
- Individual investors buy attention grabbing stocks following news arrival, on high-volume days and subsequent to stock posting extremely negative or positive single day return (Barber & Odean 2008)
- Investors underreact to relevant news because of distraction produced by extraneous news that competes for investor’s attention, Hirshleifer, Lim, and Teoh (2009)
Hypothesis Development

H1: Non-Algorithmic traders are more susceptible to extraneous distractions compared to Algorithmic traders

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

H3: Investors react differently to different categories of distraction

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

**Tick-by-tick (TBT) proprietary data**
- National Stock Exchange (NSE)
- Trades executed using algorithmic and non-algorithmic terminals
- 2011-2015

**Micro-level firm-specific sentiment scores**
- Thomson Reuters News Analytics (TRNA)
- Sentiment, relevance, novelty scores for firm-specific news
- 2004-2015

**Macro-level distraction news**
- Value-irrelevant (Non-market) events that act as competing stimuli
- Times of India & Factiva
- Google Search Volume Index (SVI)
- 2004-2015
Methodology

**Identification of distraction events**
- Headline Events from frontpage
- Media coverage
- Search Volume Index (SVI)

**Topic Modelling**
- Use machine learning technique
- Non-negative matrix factorization
- Assign distraction events into broad themes

**Look at trading activity of market participants**
- Algorithmic versus non-algorithmic facility
- Client (CLI), Proprietary (PROP) and non-client-non-proprietary (NC-NP)
- Positive versus negative news sentiment

**Look at news sentiment response coefficients (SRC’s)**
- Positive news sentiment versus negative news sentiment
- Control for relevance and novelty of firm specific news
Identification of Distraction Events

“An Attention-grabbing event is likely to be reported in the news. Investors’ attention could be attracted through other means, ......, but an event that attracts the attention of many investors is usually newsworthy”


- Scan newspaper headlines and bylines (Times of India\(^1\))
- Factiva is a global news database featuring nearly 33,000 sources including Dow Jones Newswires, The Wall Street Journal and Barron’s
- Simultaneously search keywords appearing in headline and bylines on Google Trends

Note:\(^1\)Times of India is the largest selling English language daily in the world (Audit Bureau of Circulations, 2015)
\(^1\)Ranked among the world’s six best newspapers (BBC, 1991)
Non-negative matrix factorization (NMF)

NMF assumes k number of topics exist for the entire corpus. Each of the k\textsuperscript{th} topic is a distribution of m keywords with probability \( p_{mi} \). These themes are mapped onto the document to assess the presence of k topics. \( W_i \)'s are words present in the document.

<table>
<thead>
<tr>
<th>Topics</th>
<th>Documents</th>
<th>Topic properties and assignments</th>
</tr>
</thead>
<tbody>
<tr>
<td>( K_{11} ) ( p_{11} )</td>
<td>( W_1 ) ( W_2 )</td>
<td>( T_1 )</td>
</tr>
<tr>
<td>( K_{12} ) ( p_{12} )</td>
<td>( W_3 ) ( \ldots )</td>
<td>( T_2 )</td>
</tr>
<tr>
<td>( K_{13} ) ( p_{13} )</td>
<td>( \ldots ) ( \ldots )</td>
<td>( \ldots )</td>
</tr>
<tr>
<td>( \ldots )</td>
<td>( \ldots ) ( \ldots )</td>
<td>( \ldots )</td>
</tr>
<tr>
<td>( K_{21} ) ( p_{21} )</td>
<td>( \ldots ) ( W_n )</td>
<td>( T_m )</td>
</tr>
<tr>
<td>( K_{22} ) ( p_{22} )</td>
<td>( \ldots )</td>
<td></td>
</tr>
<tr>
<td>( K_{23} ) ( p_{23} )</td>
<td></td>
<td></td>
</tr>
<tr>
<td>( \ldots )</td>
<td></td>
<td></td>
</tr>
<tr>
<td>( K_{m1} ) ( p_{m1} )</td>
<td>( \ldots )</td>
<td></td>
</tr>
<tr>
<td>( K_{m2} ) ( p_{m2} )</td>
<td>( \ldots )</td>
<td></td>
</tr>
<tr>
<td>( K_{m3} ) ( p_{m3} )</td>
<td>( \ldots )</td>
<td></td>
</tr>
</tbody>
</table>
Topic Modelling - Non Negative Matrix Factorization

Distraction Events

- Sports & Entertainment: 29.1%
- Politics: 26.7%
- Natural Calamities & Disasters: 24.6%
- Law & Order: 19.5%
- Distraction Events: 10%
Algorithmic trading – Milestones

- **SEBI allows Direct Market Access (DMA)**: Apr 2008
- **Smart Order Routing Introduced**: Aug 2010
- **SEBI issues broad guidelines for algorithmic trading**: March 2012
- **Forward Market Commission (FMC) issues guidelines for algorithmic trading in commodities**: Jan 2013

*Source: National Stock Exchange (NSE) of India*
Algorithmic Trading in India

Source: National Stock Exchange (NSE) of India
## Market Activity by Trader Type for news with positive sentiment

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

<table>
<thead>
<tr>
<th></th>
<th>Algorithmic</th>
<th></th>
<th></th>
<th>Non-Algorithmic</th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Client</td>
<td>Proprietary</td>
<td>Non-CP</td>
<td>Client</td>
<td>Proprietary</td>
</tr>
<tr>
<td>Natural Calamities &amp; Disaster</td>
<td>162.4</td>
<td>111.3</td>
<td>41.3</td>
<td>127.7</td>
<td>105.9</td>
<td>358.3</td>
</tr>
<tr>
<td>Political</td>
<td>381.6</td>
<td>272.0</td>
<td>98.3</td>
<td>225.8</td>
<td>162.7</td>
<td>532.3</td>
</tr>
<tr>
<td>Law &amp; Order</td>
<td>167.8</td>
<td>102.2</td>
<td>393.9</td>
<td>131.3</td>
<td>803.7</td>
<td>296.8</td>
</tr>
<tr>
<td>Sports &amp; Entertainment</td>
<td>347.4</td>
<td>185.8</td>
<td>84.8</td>
<td>189.2</td>
<td>112.4</td>
<td>434.9</td>
</tr>
<tr>
<td>All Distraction Days</td>
<td>353.0</td>
<td>213.7</td>
<td>88.5</td>
<td>217.0</td>
<td>126.7</td>
<td>473.9</td>
</tr>
<tr>
<td>Non-Distraction Days</td>
<td>338.1</td>
<td>171.7</td>
<td>78.6</td>
<td>253.3</td>
<td>145.0</td>
<td>542.1</td>
</tr>
<tr>
<td>Difference</td>
<td>14.9</td>
<td>42.0</td>
<td>9.9</td>
<td>-36.3</td>
<td>-18.3</td>
<td>-68.2</td>
</tr>
<tr>
<td>p-val</td>
<td>0.909</td>
<td>0.999</td>
<td>0.999</td>
<td>0.003</td>
<td>0.000</td>
<td>0.004</td>
</tr>
</tbody>
</table>

### Notes:
1) The figures indicate traded volume (INR million) by various categories of traders
2) The trading records were obtained using NSE tick-by-tick proprietary data and aggregated across various distraction days
### Market Activity by Trader Type for news with negative sentiment

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

<table>
<thead>
<tr>
<th>Event</th>
<th>Algorithmic Client</th>
<th>Algorithmic Proprietary</th>
<th>Algorithmic Non-CP</th>
<th>Non-Algorithmic Client</th>
<th>Non-Algorithmic Proprietary</th>
<th>Non-Algorithmic Non-CP</th>
</tr>
</thead>
<tbody>
<tr>
<td>Natural Calamities &amp; Disaster</td>
<td>243.4</td>
<td>143.9</td>
<td>53.9</td>
<td>186.9</td>
<td>127.4</td>
<td>437.2</td>
</tr>
<tr>
<td>Political</td>
<td>435.0</td>
<td>256.3</td>
<td>967.8</td>
<td>268.9</td>
<td>150.5</td>
<td>568.4</td>
</tr>
<tr>
<td>Law &amp; Order</td>
<td>233.8</td>
<td>131.4</td>
<td>47.3</td>
<td>170.8</td>
<td>98.6</td>
<td>349.0</td>
</tr>
<tr>
<td>Sports &amp; Entertainment</td>
<td>426.8</td>
<td>228.4</td>
<td>96.6</td>
<td>237.3</td>
<td>137.9</td>
<td>513.4</td>
</tr>
<tr>
<td>All Distraction Days</td>
<td>429.9</td>
<td>237.6</td>
<td>95.2</td>
<td>273.1</td>
<td>155.7</td>
<td>563.3</td>
</tr>
<tr>
<td>Non-Distraction Days</td>
<td>438.7</td>
<td>209.3</td>
<td>94.3</td>
<td>326.1</td>
<td>165.1</td>
<td>609.6</td>
</tr>
</tbody>
</table>

**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

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**Notes:**
1) The figures indicate traded volume (INR million) by various categories of traders.
2) The trading records were obtained using NSE tick-by-tick proprietary data and aggregated across various distraction days.
NOI\textsubscript{it} = \gamma\textsubscript{0} + \gamma\textsubscript{1}sent\textsubscript{pos}\textsubscript{it} + \gamma\textsubscript{2}sent\textsubscript{neg}\textsubscript{it} + \gamma\textsubscript{3}Dist\textsubscript{t} + \gamma\textsubscript{4}Dist\textsubscript{t}*sent\textsubscript{pos}\textsubscript{it} + \gamma\textsubscript{5}Dist\textsubscript{t}*sent\textsubscript{neg}\textsubscript{it} + \sum\textsubscript{k=1}^{5} \gamma\textsubscript{6k}NOI\textsubscript{i,t-k} + \gamma\textsubscript{7}Mkt\_cap\textsubscript{it} + (Industry\_Dummies)\textsubscript{i} + (Year\_Dummies)\textsubscript{i} + \epsilon\textsubscript{it}

NOI is the net order imbalance, calculated as the net buyer-initiated less the seller-initiated trades, sent\_pos and sent\_neg are the probability that the sentiment of the news was positive or negative respectively; Dist\textsubscript{t} is a dummy variable that takes value one if day t is a distraction day and zero otherwise

<table>
<thead>
<tr>
<th></th>
<th>Positive news</th>
<th>Negative news</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Algo</td>
<td>Non-algo</td>
</tr>
</tbody>
</table>
| sent\_pos       | 0.804 (0.356***) | 0.178 (0.088**) | -0.272 (0.151*) | 0.828 (0.246***)
| sent\_neg       | 1.089 (0.838) | -0.004 (0.112) | -0.141 (0.082*) | 0.657 (0.351*)
| Dist            | 0.668 (0.418) | 0.279 (0.092****) | -0.089 (0.065) | 0.793 (0.273***)
| Dist*sent\_pos  | -0.797 (0.413*) | -0.240 (0.109**) | 0.302 (0.133**) | -1.060 (0.312***)
| Dist*sent\_neg  | -0.342 (1.243) | -0.086 (0.141) | 0.143 (0.081**) | -0.859 (0.347***)
| Mkt\_cap        | 0.001 (0.024) | 0.035 (0.005****) | 0.003 (0.002) | 0.024 (0.009***)
| Intercept       | -0.851 (0.557) | -0.429 (0.107***) | 0.096 (0.067) | -0.767 (0.238***)
| Industry\_Dummies | Yes | Yes |
| N               | 9,132 | 11,517 | 6,957 | 7,801 |

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.
Asymmetric investor reaction to firm specific announcements during various distraction events

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

\[ R_t = \beta_0 + \beta_1 D_t + \beta_2 R_{it-1} + \beta_3 D_{it} + \beta_4 Q_t + \varepsilon_t, \]

and

\[ \varepsilon_{it} = \gamma_0 + \gamma_1 \text{sent_pos}_{it} + \gamma_2 \text{sent_neg}_{it} + \gamma_3 \text{ILLIQ}_{it} + \gamma_4 \text{IVOL}_{it} + \gamma_5 \text{relevance}_{it} + \gamma_6 \text{novelty}_{it} + \gamma_7 \text{size}_{it} + \gamma_8 \text{IMR}_{it} + (\text{Industry Dummies})_i + (\text{Year Dummies})_t + \nu_i. \]

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.
Do stocks predominantly owned by retail investors exhibit higher underreaction

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

\[
R_{it} = \beta_0 + \beta_1 R_{it-1} + \beta_2 R_{it} + \beta_3 D_{it} + \beta_4 Q_i + \varepsilon_{it}
\]

\[ D_{it} = \{D_{1t}, D_{2t}, D_{3t}, D_{4t}\} \] are dummy variables for Monday through Thursday,

\[ Q_i = \{Q_{1i}, Q_{2i}, Q_{3i}, Q_{4i}, Q_{5i}\} \] are dummy variables for days for which previous 1 through 5 days are non-weekend holidays

\[ CAR_{[0,1]}_{it} = \gamma_0 + \gamma_1 \text{sent_pos}_{it} + \gamma_2 \text{sent_neg}_{it} + \gamma_3 \text{relevance}_{it} + \gamma_4 \text{novelty}_{it} + \gamma_5 \text{size}_{it} + \gamma_6 (P/B)_{it} + \gamma_7 (D_{Retail})_{it} + \gamma_8 \text{sent_pos}_{it} * D_{Retail}_{it} + \gamma_9 \text{sent_neg}_{it} * D_{Retail}_{it}
\]

\[ CAR_{[0,1]}_{it} \] are the cumulative abnormal returns over day 0 to +1; \text{sent_pos}_{it} and \text{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; \text{D_{Retail}} is a dummy variable that takes a value one if the retail ownership is above median and zero otherwise; \text{ILLIQ} and \text{IVOL} measure illiquidity and implied volatility respectively.

<table>
<thead>
<tr>
<th>All Distraction Days</th>
<th>Natural Calamities &amp; Disasters</th>
<th>Political</th>
<th>Law &amp; Order</th>
<th>Sports &amp; Entertainment</th>
<th>Attention Days</th>
</tr>
</thead>
<tbody>
<tr>
<td>Coef.</td>
<td>Robust Std Error</td>
<td>Coef.</td>
<td>Robust Std Error</td>
<td>Coef.</td>
<td>Robust Std Error</td>
</tr>
<tr>
<td>Sent_pos</td>
<td>0.522</td>
<td>0.142***</td>
<td>0.611</td>
<td>0.375</td>
<td>0.059</td>
</tr>
<tr>
<td>Sent_neg</td>
<td>-0.143</td>
<td>-0.147</td>
<td>-0.602</td>
<td>0.336</td>
<td>-0.285</td>
</tr>
<tr>
<td>ILLIQ</td>
<td>0.007</td>
<td>0.042</td>
<td>0.004</td>
<td>0.030</td>
<td>-0.029</td>
</tr>
<tr>
<td>IVOL</td>
<td>-0.023</td>
<td>0.008**</td>
<td>-0.007</td>
<td>0.003***</td>
<td>-0.031</td>
</tr>
<tr>
<td>Relevance</td>
<td>0.046</td>
<td>0.098</td>
<td>-0.226</td>
<td>0.225</td>
<td>-0.276</td>
</tr>
<tr>
<td>Novelty</td>
<td>-0.001</td>
<td>0.016</td>
<td>-0.002</td>
<td>0.033</td>
<td>0.035</td>
</tr>
<tr>
<td>Size</td>
<td>-0.083</td>
<td>0.026***</td>
<td>-0.304</td>
<td>0.093***</td>
<td>-0.205</td>
</tr>
<tr>
<td>P/B</td>
<td>0.005</td>
<td>0.003</td>
<td>0.016</td>
<td>0.009</td>
<td>0.013</td>
</tr>
<tr>
<td>D_{Retail}</td>
<td>-0.221</td>
<td>0.245</td>
<td>-0.321</td>
<td>0.491</td>
<td>0.332</td>
</tr>
<tr>
<td>sent_pos*D_{Retail}</td>
<td>0.282</td>
<td>0.501</td>
<td>0.193</td>
<td>0.968</td>
<td>-0.621</td>
</tr>
<tr>
<td>sent_neg*D_{Retail}</td>
<td>0.309</td>
<td>0.457</td>
<td>-0.345</td>
<td>0.824</td>
<td>-0.625</td>
</tr>
<tr>
<td>IMR</td>
<td>-0.052</td>
<td>0.149</td>
<td>-0.248</td>
<td>0.487</td>
<td>-0.577</td>
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<tr>
<td>Intercept</td>
<td>1.139</td>
<td>0.581</td>
<td>3.853</td>
<td>1.620**</td>
<td>2.522</td>
</tr>
<tr>
<td>Industry Dummies</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Year</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Dummies</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>N</td>
<td>24,838</td>
<td>15,398</td>
<td>16,302</td>
<td>10,826</td>
<td>13,908</td>
</tr>
</tbody>
</table>

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.
Findings

Trading behavior varies across different group of investors
- Algorithmic traders are less sanguine in acting on any news sentiment
- Inattention effect dominant for client non-algorithmic trades
- Traded volume falls during distraction periods for non-algorithmic trades
- Use of algorithmic trading helps in mitigating the effects of attention constraints

Trading behavior varies across different categories of distraction
- Turnover and number of transactions are lowest during sports and entertainment events
- Political events are least distractive
- Underreaction to both positive and negative news sentiment

Cumulative abnormal returns
- Sentiment response coefficients of negative news sentiment not statistically significant
- Even relevant news are overlooked
- Novelty of news not significant

Ownership of stock matters
- Level of ownership by retail investors correlated with abnormal returns
- Less sophisticated investors moderate the negative returns on negative news sentiment
- Lack of buying on positive news sentiment
THANK YOU!