Are algorithmic traders really distracted ? Evidence from Indian financial markets

Kamran Quddus & Ashok Banerjee

NSE-NYU Conference 2018

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 decisionmaking 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"

– Barber, B. M., & Odean, T. (2007)

- Scan newspaper headlines and bylines (Times of India¹)
- 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:¹Times of India is the largest selling English language daily in the world (Audit Bureau of Circulations, 2015) ¹Ranked among the world's six best newspapers (BBC, 1991)

Figure 1: Topic Modelling

Non-negative matrix factorization (NMF)

NMF assumes k number of topics exist for the entire corpus. Each of the kth 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



Topic Modelling - Non Negative Matrix Factorization

Distraction Events



Algorithmic trading – Milestones



Source: National Stock Exchange (NSE) of India

Algorithmic Trading in India



■CM ■FAO ■CDS

Source: National Stock Exchange (NSE) of India

Market Activity by Trader Type for news with positive sentiment

Algorithmic traders are less sanguine in acting on any news Sentiment

□ Inattention effect is more pervasive for non-algorithmic trades

Empirical evidence shows that investors' reaction to news announcements remain muted

Panel A: Market Activity by Trader Type for news with positive sentiment										
		Algorithmic	0	N	mic					
	Client	Proprietary	/ Non-CP	Client	Proprietary	y 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				

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

Danal D: Market Activity by Trader Type for news with respirite continent

□ Machine traders are	•
not distracted by	
irrelevant stimuli	

□ Liquidity providers

Algorithmic trades provide support to price by pushing liquidity

		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	

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

Investigating Order Imbalance Around Distraction

 $NOI_{it} = \gamma_0 + \gamma_1 sent_pos_{it} + \gamma_2 sent_neg_{it} + \gamma_3 Dist_t + \gamma_4 Dist_t * sent_pos_{it} + \gamma_5 Dist_t * sent_neg_{it} + \sum_{k=1}^{5} \gamma_{6k} NOI_{i,t-k} + \gamma_7 Mkt_cap_{it} + (Industry Dummies)_i + (Year Dummies)_i + \varepsilon_{it}$

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_t is a dummy variable that takes value one if day t is a distraction day and zero otherwise

	Positiv	e news	Negative news				
	Algo	Non-algo	Algo	Non-algo			
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	Y	es	Y	es			
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.

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

 $D_t = \{D_{1t}, D_{2t}, D_{3t}, D_{4t}\}$ 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

 $\widehat{\epsilon_{it}} = \gamma_0 + \gamma_1 \operatorname{sent}_{\text{pos}_{it}} + \gamma_2 \operatorname{sent}_{\text{neg}_{it}} + \gamma_3 \operatorname{ILLIQ}_{it} + \gamma_4 \operatorname{IVOL}_{it} + \gamma_5 \operatorname{relevance}_{it} + \gamma_6 \operatorname{novelty}_{it} + \gamma_7 \operatorname{size}_{it} + \gamma_8 \operatorname{IMR}_{it}$

+ (Industry Dummies)_i + (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		Pa	Panel B Panel C Pan		nel D	Panel E		Panel F			
	All Distraction Days		Na Calar Dis	Natural Calamities & Political Law & Ord Disasters		& 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
- <u></u>												
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		es	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

Do stocks predominantly owned by retail investors exhibit higher underreaction

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

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

Dt= {D1b D2t, D3b D4t} are dummy variables for Monday through Thursday,

Qt = {Q1b Q2b Q3t, Q4t, Q5t} are dummy variables for days for which previous 1 through 5 days are non-weekend holidays

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

 $CAR[0,1]_{it}$ 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_{Remit} is a dummy variable that takes a value one if the retail ownership is above median and zero otherwise; ILLIQ and IVOL measure

 D_{Retail} is a dummy variable that takes a value of the in the retain ownership is above mechan and zero otherwise, include and in the measure

illiquidity and implied volatility respectively

	All Distraction Days Natural Calamities & Disasters			х́Р	olitical	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 _{Ret}	il 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 _{Rat}	_{ii1} 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 Dum	nies	Yes	Y	es	Yes			Yes	3	čes	3	es
Year		Vec	v		Vac			Vec		ac.	3	es
Dummies		105	1	60	1 65			105	1	60		
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

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!