TEXTUAL DISCLOSURES AND RETAIL INVESTORS

Ankit Jain[1] (School of Business, University of Queensland)

Abdul Khizer[2] (Indian School of Business)

Ramabhadran S. Thirumalai[3] (Indian School of Business)

October 11, 2019

This is a preliminary draft. Please do not cite or distribute without the permission of authors.

[1] Email: a.jain@business.uq.edu.au, School of Business, University of Queensland, Room 403, Colin Clark Building, St. Lucia 4067, Brisbane, Australia
[2] Email: abdul_khizer@isb.edu, Indian School of Business, Gachibowli, Hyderabad 500111, India
[3] Email: ram_thirumalai@isb.edu, Indian School of Business, Knowledge City, Sector 81, Mohali 140306, India
We acknowledge the financial support from the NSE-NYU Stern Initiative on the Study of Indian Financial Markets and UQ Business School (BEL Faculty New Staff Research Start-Up Grant). We also thank Tuhin Harit for excellent research assistance. We remain responsible for all the errors in the paper.

TEXTUAL DISCLOSURES AND RETAIL INVESTORS

ABSTRACT

Using rich transaction-level data from the stock market, we examine how retail investors react to textual information. The unique dataset enables us to analyze the trading behavior of the same trader across stocks over the long horizon and how they interpret textual disclosures, which are a noisy signal about firm fundamentals. We examine if retail investors consider the credibility of managers when trading and learn from their past trading. This study will contribute to the growing literature on textual disclosures and improve our understanding of the secondary market consequences of such disclosures.

JEL Classification: M41, G14, G11

Keywords: narrative disclosures, tone management, conference calls, retail investors

INTRODUCTION

Prior evidence suggests that textual disclosures provide incremental information to investors as all value-relevant information cannot be presented in financial statements (Davis, Piger, and Sedor 2012; Li 2010). However, there is no formal external auditing requirement for these disclosures and it is difficult to regulate them (Cazier, Merkley, and Treu 2019). Thus, managers often mislead investors by increasing the complexity of the annual reports when the performance is poor (Li 2008) or engaging in tone management around important corporate events (Huang, Teoh, and Zhang 2014). The experimental evidence from Tan, Wang, and Zhou (2014) suggests that less sophisticated investors are more susceptible to the framing effects of language. The purpose of the current study is to empirically examine how less-sophisticated investors interpret textual information.

Most of the early evidence on the behavior of retail investors show that retail investors are unsophisticated, behaviorally biased, and otherwise uninformed. They argue that retail investors have lower ability to process information as compared to institutional investors (Tan, Wang, and Zhou 2014) and that they are more likely to be influenced by the poor readability of textual disclosures (Lawrence 2013). Thus, retail investors could make poor investment decisions by misinterpreting textual disclosures. However, the view that retail investors are unsophisticated and noise traders has been challenged by recent findings. Retail investors vastly outnumber institutions. They are not homogenous and some of them could be informed. Kelly and Tetlock (2013) and Kelly and Tetlock (2016) suggest that retail investors may have unique information about the firm either from geographical proximity, relationships with employers, or additional insights into customer tastes. Moreover, unlike institutional investors, retail investors do not suffer from principal-agent problems. Thus, it is possible that some retail investors are not prone to the framing effects of language. Therefore, it is not clear ex-ante if retail investors are influenced by textual disclosures.

Prior studies examining the trading of retail investors have employed data either from a single broker or used an indirect proxy. Lawrence (2013) employs data on the trades and portfolio positions of individual investors from a single broker for the period 1994 to 1996. Baginski, Demers, Kausar, and Yu (2018) use the trade size as a proxy for small investors. These proxies could lead to biased inferences about the population of retail investors (Kelly and Shue 2013). This concern is motivated by the fact that large investors split their orders into smaller trades (Loughran 2018), and therefore employing trade size to proxy investor category could lead to misclassification of traders. We use unique transaction-level data from the stock market in India that enables us to employ a much cleaner investors' classification scheme. Furthermore, the long duration of the dataset, from 2005 to 2017, enables us to analyze the trading behavior of the same trader across stocks over a long period.

We analyze the content of earnings conference calls because they are one of the most important avenues through which the management communicates significant information to investors (Brown, Call, Clement, and Sharp 2017; Li, Minnis, Nagar, and Rajan 2014; Frankel, Mayew, and Sun 2010). Although conference calls are voluntary in India, the number of Indian companies hosting these calls has risen significantly in recent years.[4] The Indian capital market regulator, Securities and Exchange Board of India (SEBI), mandates the disclosure of conference call transcripts to the public.[5] In addition to conference calls transcripts, we also plan to analyze

[4] "*Number of companies hosting earnings calls rises by 40% in five years to FY18*" – By Kiran Kabtta Somvanshi, Economic Times (November 27, 2018). (Link: https://economictimes.indiatimes.com/markets/stocks/news/number-of-companies-hosting-earnings-calls-rises-by-40-in-fy18/articleshow/66820555.cms?from=mdr)

[5] Provisions of Regulation 30 of Listing Obligations and Disclosure Requirements Regulations, 2015

more formal disclosures such the management discussion and analysis (MD&A) in the annual report.

We operationalize the textual content of earnings conference call transcripts by capturing the sentiment of the management. We calculate *TONE* as the difference in the frequency of optimistic and pessimistic words and scale this measure by the total number of words. Then, we examine how different classes of investors interpret *TONE*.

Using a sample of 3,172 quarterly earnings conference call transcripts from 201 unique firms from 2005 to 2017, we find that the market reacts positively to optimistic *TONE* over the short-window around the earnings announcement date when the transcripts are made available publically. However, we find that in the long-run, the association of *TONE* and cumulative abnormal returns in negative. These findings of short-term and long-term market reaction suggest that management employs tone management to mislead investors and investors are misled in the short-term. However, the market corrects these mistakes in the long-run.

As a robustness test, we decompose *TONE* into two components, *NTONE* and *ABTONE* (Huang, Teoh, and Zhang 2014) and separately examine the market reaction to these components. *NTONE* captures a part of *TONE* that can be justified by the underlying firm fundamentals and *ABTONE* is a discretionary part. We find that investors find *NTONE* to be useful and there is a positive association between *NTONE* and future returns but this association is negative for *ABTONE*. These findings are consistent with (Huang, Teoh, and Zhang 2014) and strengthen the argument that management employs tone management to mislead investors.

In the next step, we analyze the trading activities of retail and institutional investors separately. There are more than 18 million unique traders in the Bombay Stock Exchange transaction data during the period 2005 to 2011. We will analyze the trading activities of retail and institutional investors separately and examine their gains. The work is in progress and we aim to investigate the following research questions in our study:

1. How do different classes of investors react to textual information?
2. Is there a wealth transfer from retail investors to institutional investors?
3. Do retail investors take into account the credibility of management when interpreting textual information?
4. Do retail investors learn from their mistakes and become careful in buying the stocks of firms with overly optimistic managers when they were misled by the same manager in the past?
5. Which section of the earnings conference call is more useful to retail investors i.e., the presentation section or the Q&A section?
6. Are textual disclosures more informative for firms with good corporate governance?
7. Are misleading textual disclosures intentional or unintentional i.e. is there a systematic association between textual disclosures and subsequent insider trading?
8. Are there systematic differences between formal communication (Management Discussion and Analysis) and information communication (Earnings conference calls)? Are retail investors able to understand these differences?
9. Are the results driven by the attention of retail investors[6]?
10. What are the characteristics (e.g. size) of firms where the retail investors are less prone to the framing effect?

[6] We plan to employ events such as Cricket World Cup as exogenous events that could reduce the attention of retail investors.

Our study will make multiple contributions. First, it will contribute to the growing literature on textual disclosures by providing additional evidence on the secondary market consequences of these disclosures and improve our understanding of reaction to textual disclosures by different classes of investors. Furthermore, we resolve the trader's classification issue in the prior literature (Baginski, Demers, Kausar, and Yu 2018) by employing rich transaction-level data from the Bombay Stock Exchange (BSE).

Second, this study will contribute to a growing literature on trading by retail investors (Lawrence 2013; Ben-David, Birru, and Prokopenya 2018; Kelley and Tetlock 2016; Kelley and Tetlock 2013) and examine if retail investors consider the credibility of managers when trading and learn from their past trading activities. The novel and rich transaction-level data also allows us to examine the trading behavior of the same trader across stocks over the long horizon and how they interpret textual disclosures which are a noisy signal about firm fundamentals.

DATA

We employ a rich tick-by-tick transaction data from the Bombay Stock Exchange (BSE)[7] in India. The dataset has all orders and trades during the period from 2005 to 2017. It also contains the categories of traders and their masked identity. This allows us to identify trades of different categories of investors easily. This dataset also enables us to analyze the trading behavior of the same trader across stocks over a long period. We combine this transaction-level data with the earnings conference call data. We hand-collect the transcripts of earnings conference calls from ProwessIQ, Capital IQ, and Researchbyte[8] website. We include firms that were a part of the S&P

[7] The Bombay Stock Exchange (BSE) is the world's tenth-largest stock exchange in terms of market capitalization.
[8] Researchbyte (Link: https://www.researchbytes.com/) is one of leading websites that provides information on annual reports, earnings conference calls, management interviews, and investor presentations for Indian companies.

BSE 200 index between 2005 and 2017. Finally, we collect accounting and daily stock trading data from Prowessdx.

We parse conference call transcripts by writing Python programs and calculate *LENGTH* (total number of words) and count the frequency of optimistic and pessimistic words. For this purpose, we employ a financial dictionary of optimistic and pessimistic words from Loughran and McDonald (2011).[9] We define *TONE* as the difference between the count of optimistic words and pessimistic words and scale it by the total number of words in the transcript. We also plan to hand-collect the annual reports and management discussion and analysis (MD&A) from ProwessIQ and Capital IQ.

RESULTS AND DISCUSSION

The summary statistics of the BSE transaction data are presented in Table 1(A).[10] During 2005 to 2011, there are more than 1.19 billion trades executed on the BSE by more than 18 million unique investors. There are approximately 10.3 million unique retail investors and 38 thousand unique institutional investors in the sample. The summary statistics of trading from retail investors is presented in Table 1(B). We find that on average, there are more than 84,000 unique retail investors who are daily involved in more than 400,000 trades on BSE. The total value of these trades is 9,164 million rupees.

The summary statistics of earnings conference calls and firm characteristics are presented in Table 1(C). There are 3,172 quarterly earnings conference call transcripts from 201 unique firms

---

[9] This financial dictionary contains 354 optimistic words (e.g. "*achieve*", "*benefit*", "*enhance*") and 2,355 pessimistic words (e.g. "*adverse*", "*damage*").
[10] These summary statistics of transaction-level data are based on the sample from 2005 to 2011. The work is in progress to get the data ready from 2012 to 2017 for analysis as well.

from 2005 to 2017. We winsorize all variables at 1 percent and 99 percent level. As seen in Table 1(C), we find that on an average there are 7,441 words (*LENGTH*) in the earnings conference calls out of which 84 words are optimistic and 59 words are pessimistic. Thus, *TONE* on average is optimistic.

We calculate abnormal returns as the difference between daily stock returns from Prowess and market returns. We use the BSE Sensex returns as a proxy for market returns. We calculate cumulative abnormal returns (CAR) across different windows around the earning announcement date. We start by examining the effect of *TONE* on investors' reaction. We run the following specification:

$$CAR[-1,+T] = \alpha + \beta_1 * TONE + \beta_2 * ROA + \beta_3 * \Delta\, ROA + \beta_4 * \frac{P}{B} + \beta_5 * SIZE + \beta_6 * STDDEV\ RETURNS + \beta_7 * STD\ DEV\ ROA + Fixed\ effects + \text{€} \tag{1}$$

We analyze investors' reaction during the two short-term windows [-1, +1] and [-1, +5] where 0 is the earnings announcement date when the conference call is hosted. Our main coefficient of interest is β_1. We control for earnings (*ROA*), performance benchmark (*ΔROA*), log of market capitalization at the time of earnings announcement (*SIZE*), price-to-book ratio (*P/B*), and measures of information uncertainty *(STD DEV RETURNS* and *STD DEV ROA*) and include industry and quarter fixed effects. The results from equation (1) are presented in Table 2. We find a positive association between *TONE* and CAR, which is statistically significant at the 1 percent level in specifications (1)-(2). We find that as *TONE* increases from 25th percentile to 75th percentile, *CAR[-1, +1]* increases by 1.2 percent. Thus, the association is also economically meaningful. This shows that investors react positively to optimistic *TONE*.

If positive *TONE* captures some good aspects of future firm fundamentals that cannot be captured by the quantitative disclosures such as ROA, then the increase in stock price should be permanent. However, if the management is trying to mislead investors by employing an overly optimistic *TONE*, there will be a price reversal after some time. To examine if *TONE* is informative about future performance or misleading to investors, we examine the association between *TONE* and investors' reaction over a long-term window of [+6, +250] after the earnings announcement. We run the following specification:

$$CAR[+6,+250] = \alpha + \beta_1 * TONE + \beta_2 * ROA + \beta_3 * \Delta\, ROA + \beta_4 * \frac{P}{B} + \beta_5 * SIZE + \beta_6 * STDDEV\ RETURNS + \beta_7 * STD\ DEV\ ROA + Fixed\ effects + \epsilon \quad \textbf{(2)}$$

Our main coefficient of interest is β_1. If *TONE* is informative about future firm fundamentals, then β_1 will be positive and significant. If *TONE* is misleading then investors will react negatively in the long-term after realizing their mistake, the stock price will revert, and β_1 will be negative and significant. The results are shown in the specification (3) in Table 2. We find a negative association between *TONE* and *CAR[+6, +250]*, which is significant at the 10 percent level. Thus, we find that *TONE* is misleading and stock prices revert in the long-term.

In the next step, following prior literature (Huang, Teoh, and Zhang 2014), we decompose *TONE* into *NTONE* and *ABTONE*. *NTONE* is a component of *TONE* that can be justified by the underlying firm fundamentals and *ABTONE* is a discretionary component of *TONE*. Specifically, we run the following regression:

$$TONE = \alpha + \beta_1 * ROA + \beta_1 * \Delta\, ROA + \beta_3 * \frac{P}{B} + \beta_4 * SIZE + \beta_5 * STDDEV\ RETURNS + \beta_6 * STD\ DEV\ ROA + \epsilon \quad \textbf{(3)}$$

In equation (3), we control for similar variables which are used in equations (1) and (2). The estimated value of *TONE* from equation (3) is *NTONE* and residual from this regression is *ABTONE*. We separately examine the market reaction to *NTONE* and *ABTONE* using the similar specifications as in equations (1) and (2). Instead of using its raw values, we use the yearly decile rankings, *D_ABTONE* and *D_NTONE*, of *ABTONE* and *NTONE*, respectively, as the independent variables (Huang, Teoh, and Zhang 2014). The results are presented in Table 3. We find that in the short-term the market's reaction to *ABTONE* is positive and statistically significant (specifications (1)-(2)) but the long-term reaction is negative (specification (3)). On the contrary, long-term reaction to *NTONE* is positive and significant. Thus, investors find *NTONE* to be informative but *ABTONE* to be misleading. These findings are consistent with that of Huang, Teoh, and Zhang (2014).

After documenting the short-term and long-term reactions of investors and thus validating our *TONE* measures, we analyze the reaction of retail investors and institutional investors separately. We run the following specifications separately for retail investors and institutional investors:

$$NET\ BUY = \alpha + \beta_1 * TONE + \beta_1 * ROA + \beta_3 * \frac{P}{B} + \beta_4 * SIZE + \beta_5 * STDDEV\ RETURNS + Fixed\ effects + \epsilon \qquad \textbf{(4)}$$

We use *NET BUY* during the event window [-1, +5] as the dependent variable to analyze the net buying activities of investors in response to *TONE*. We compute the following proxies for *NET BUY* separately for retail and institutional investors:

- (number of shares bought – number of shares sold)/(number of shares bought + number of shares sold)
- (number of shares bought – number of shares sold)/(total shares outstanding)
- (number of buy orders – number of sell orders)/(number of buy orders + number of sell orders)

- (dollar amount of shares bought - dollar amount of shares sold)/(dollar amount of shares bought + dollar amount of shares sold)

Next, we investigate the profitability of trades of investors for multiple holding periods – 30, 90, 120, 250 days and run the following specification:

$$TRADING\ GAIN = \alpha + \beta_1 * TONE + \beta_1 * ROA + \beta_3 * \frac{P}{B} + \beta_4 * SIZE + \beta_5 * STDDEV\ RETURNS + \beta_6 * Prior\ RETURNS + Fixed\ effects + € \quad \textbf{(5)}$$

We compute trading gains separately for retail investors and institutional investors by multiplying daily net buys during the event window [-1, +5] with the change in price over subsequent holding periods. The analysis for empirical specification in equations (4) and (5) is in process.

FURTHER WORK

The analysis of transaction-level data from the Bombay Stock Exchange (BSE) is in process. This dataset provides us the masked identity of all investors. This will allow us to employ investor fixed effects that will control for all time-invariant characteristics at the investor level. We will investigate if retail investors take into consideration the credibility of the management when making investment decisions based on textual disclosures. We are also hand-collecting the exact time during the day when the earnings conference calls are held and then will analyze the intra-day trading behavior of retail and institutional investors.

CONCLUSION

Most of the early evidence on the behavior of retail investors show that retail investors are unsophisticated, behaviorally biased, and otherwise uninformed. Using rich and transaction-level data from the stock market, we examine how retail investors react to textual information which is a noisy signal about firm fundamentals. We find that management employs tone management to mislead investors in the short-term. However, stock prices revert in the long-term. We are currently investigating the trading activities of retail and institutional investors separately.

REFERENCES

Baginski, S. P., Demers, E., Kausar, A., & Yu, Y. J. “Linguistic tone and the small trader.” *Accounting, Organizations and Society* (2018).

Barber, Brad M., Yi-Tsung Lee, Yu-Jane Liu, and Terrance Odean. "How Much Do Individual Investors Lose by Trading." *The Review of Financial Studies* 22, no. 2 (2009): 609-632.

Ben-David, Itzhak, Justin Birru, and Viktor Prokopenya. "Uninformative feedback and risk taking: Evidence from retail forex trading." *Review of Finance* 22, no. 6 (2018): 2009-2036.

Brown, Lawrence D., Andrew C. Call, Michael B. Clement, and Nathan Y. Sharp. "Managing the narrative: Investor relations officers and corporate disclosure☆." *Journal of Accounting and Economics* 67, no. 1 (2019): 58-79

Cazier, Richard A., Kenneth J. Merkley, and John S. Treu. "When are Firms Sued for Qualitative Disclosures? Implications of the Safe Harbor for Forward-Looking Statements." *The Accounting Review* (2019).

Davis, Angela K., Jeremy M. Piger, and Lisa M. Sedor. "Beyond the numbers: Measuring the information content of earnings press release language." *Contemporary Accounting Research* 29, no. 3 (2012): 845-868.

Frankel, Richard, William J. Mayew, and Yan Sun. "Do pennies matter? Investor relations consequences of small negative earnings surprises." *Review of Accounting Studies* 15, no. 1 (2010): 220-242.

Garfinkle, J. 2009. Measuring investors’ opinion divergence. *Journal of Accounting Research* 47 (5): 1317-1348.

Huang, Xuan, Siew Hong Teoh, and Yinglei Zhang. "Tone management." *The Accounting Review* 89, no. 3 (2014): 1083-1113.

Kelley, Eric K., and Paul C. Tetlock. "How wise are crowds? Insights from retail orders and stock returns." *The Journal of Finance* 68, no. 3 (2013): 1229-1265.

Kelley, Eric K., and Paul C. Tetlock. "Retail short selling and stock prices." *The Review of Financial Studies* 30, no. 3 (2016): 801-834.

Lawrence, Alastair. "Individual investors and financial disclosure." *Journal of Accounting and Economics* 56, no. 1 (2013): 130-147.

Li, Feng. "Annual report readability, current earnings, and earnings persistence." *Journal of Accounting and Economics* 45, no. 2-3 (2008): 221-247.

Li, Feng. "The information content of forward-looking statements in corporate filings—A naïve Bayesian machine learning approach." *Journal of Accounting Research* 48, no. 5 (2010): 1049-1102.

Li, Feng, Michael Minnis, Venky Nagar, and Madhav Rajan. "Knowledge, compensation, and firm value: An empirical analysis of firm communication." *Journal of Accounting and Economics* 58, no. 1 (2014): 96-116.

Loughran, Tim, and Bill McDonald. "When is a liability not a liability? Textual analysis, dictionaries, and 10-Ks." *The Journal of Finance* 66, no. 1 (2011): 35-65.

Loughran, Tim. "Linguistic tone and the small trader: Measurement issues, regulatory implications, and directions for future research." *Accounting, Organizations and Society* (2018).

Tan, Hun-Tong, Elaine Ying Wang, and B. O. Zhou. "When the use of positive language backfires: The joint effect of tone, readability, and investor sophistication on earnings judgments." *Journal of Accounting Research* 52, no. 1 (2014): 273-302.

Table 1: Summary Statistics

This table provides summary statistics of our sample. Panel A shows the trade summary of the BSE transaction dataset. Panel B shows the characteristics of daily trades from retail investors. Finally, Panel C shows the summary statistics of the sample used in the regression analysis. All continuous variables are winsorized at top and bottom 1% to mitigate the effect of outliers.

Table 1(A)

Bombay Stock Exchange- Trade Summary (2005-2011)	
Total trades (millions)	1,190
Number of unique traders (millions)	18.5
Number of unique retail traders (millions)	10.3
Number of unique institutional traders	38,000

Table 1(B)

Retail traders daily characteristics	**(1) Mean**	**(2) SD**	**(3) Min**	**(4) Max**
Count of daily trades	437,280	258,699	13,373	1,725,000
Trade value (in million Rupees)	9164	5004	248.1	32020
Trade volume (in millions)	38.36	26.10	633,368	199.1
Unique traders	84,246	44,991	4,302	330,030

Table 1(C)

VARIABLES	(1) N	(2) Mean	(3) SD	(4) p25	(5) p75
TOTAL WORDS	3,172	7,441	2,256	6,115	8,529
OPTIMISTIC WORDS	3,172	84.48	38.91	58	105
PESSIMISTIC WORDS	3,172	58.89	27.13	40	72
TONE	3,172	0.0029	0.0048	-0.0003	0.0060
D_ABTONE	3,171	5.485	2.872	3	8
D_NTONE	3,172	5.480	2.873	3	8
SIZE	3,172	11.94	1.347	11.01	12.90
ROA	3,172	0.186	0.144	0.0638	0.255
ΔROA	3,172	-0.0229	0.117	-0.0557	0.0240
STD DEV RETURNS	3,172	0.0205	0.00732	0.0154	0.0238
STD DEV ROA	3,172	7.882	1.277	6.991	8.787
P/B	3,172	4.682	4.877	1.767	5.597
CAR [-1, +1]	3,172	-0.193	5.646	-3.406	3.107
CAR [-1, +5]	3,172	-0.480	7.289	-4.942	3.987
CAR [+6, +250]	2,679	-0.927	34.84	-20.52	20.67

Table 2: The market reaction to *TONE*

This table presents investors' reaction to *TONE* from the earnings conference calls around earnings announcements based on the equation **(1)**. The dependent variables are cumulative market-adjusted abnormal returns (in percent) around different windows. The control variables include earnings (*ROA*), performance benchmark (*ΔROA*), log of market capitalization at the time of earnings announcement (*SIZE*), price-to-book ratio (*P/B*), and measures of information uncertainty (*STD DEV RETURNS* and *STD DEV ROA*). Standard errors (in brackets) are based on heteroscedasticity-robust standard errors that are clustered at the two digits NIC (industry) level. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1) ***CAR [-1, +1]***	**(2)** ***CAR [-1, +5]***	**(3)** ***CAR [+6, +250]***
TONE	188.0***	230.6***	-389.4*
	(31.37)	(42.94)	(199.5)
SIZE	0.0350	0.113	-2.833
	(0.229)	(0.270)	(2.108)
P/B	0.00479	-0.0404	-0.535
	(0.0274)	(0.0513)	(0.428)
ROA	1.438	4.189*	58.25***
	(1.798)	(2.379)	(11.75)
ΔROA	0.422	-0.329	-25.56***
	(1.022)	(0.979)	(7.696)
STD DEV ROA	-0.293	-0.241	-1.165
	(0.175)	(0.236)	(1.255)
STD DEV RETURNS	-12.78	24.82	106.4
	(28.19)	(33.97)	(178.4)
INTERCEPT	1.117	-1.689	32.06
	(2.248)	(2.242)	(21.83)
Observations	3,172	3,172	2,677
R-squared	0.045	0.042	0.126
Industry FE	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes

Table 3: The market reaction to AB*TONE* and *NTONE*

This table presents investors' reaction to *D_ABTONE and D_NTONE* from the earnings conference calls around earnings announcements based on the equation **(1)**. The dependent variables are cumulative market-adjusted abnormal returns (in percent) around different windows. The control variables include earnings (*ROA*), performance benchmark (*ΔROA*), log of market capitalization at the time of earnings announcement (*SIZE*), price-to-book ratio (*P/B*), and measures of information uncertainty (*STD DEV RETURNS* and *STD DEV ROA*). Standard errors (in brackets) are based on heteroscedasticity-robust standard errors that are clustered at the two digits NIC (industry) level. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1) ***CAR [-1, +1]***	**(2)** **CAR *[-1, +5]***	**(3)** ***CAR [+6, +250]***
D_ABTONE	0.255***	0.306***	-0.581**
	(0.0486)	(0.0671)	(0.282)
D_NTONE	-0.0638	-0.111	1.672**
	(0.0748)	(0.144)	(0.817)
SIZE	0.226	0.394	-5.485**
	(0.299)	(0.356)	(2.342)
P/B	0.0133	-0.0270	-0.715
	(0.0257)	(0.0530)	(0.487)
ROA	1.447	4.254*	56.10***
	(1.808)	(2.368)	(11.45)
ΔROA	-0.0468	-1.033	-18.13**
	(0.989)	(1.103)	(7.676)
STD DEV ROA	-0.567**	-0.648	2.848
	(0.280)	(0.397)	(2.038)
STD DEV RETURNS	-24.12	8.404	241.7
	(26.87)	(35.56)	(192.2)
INTERCEPT	0.681	-1.979	23.57
	(2.070)	(2.371)	(22.36)
Observations	3,171	3,171	2,676
R-squared	0.043	0.040	0.128
Industry FE	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes