The Information Content of Tone Dispersion: Evidence from Earnings Conference Call Q&As*

Jyun-Ying Fu† Alan Huang‡ Russell Wermers§ Jingyu Zhang¶

Yuxin Zhang ‖

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†Department of International Business, National Taiwan University. Email: jyunfu@ntu.edu.tw

‡School of Accounting and Finance, University of Waterloo. Email: aghuang@uwaterloo.ca

§Robert H. Smith School of Business, University of Maryland. Email: wermers@umd.edu

¶Stephen J.R. Smith School of Business, Queen's University. Email: jingyu.zhang@queensu.ca

‖University of Nottingham (Ningbo Campus). Email: Yuxin.Zhang@nottingham.edu.cn

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Abstract

We show that the dispersion of tone "sentiment" in conference calls amounts to information production. Using question-and-answer (Q&A) sessions of earnings conference calls, we measure tone level and dispersion with the FinBERT model, and informativeness with a computational topic modeling approach aided by human interpretation. Tone dispersion is highly significantly related to the information quantities embodied in earnings calls. More tone-dispersed calls exhibit a larger sensitivity of price response to earnings news, as well as a higher trading volume. Moreover, it is the topic-related component of tone dispersion that drives such capital market outcomes, with analyst tone dispersion playing a larger role therein than that of executives. Our research contributes by documenting the information value of tone dispersion in corporate communications.

JEL Classification: G14, G23, M12

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1 Introduction

Text is data (Gentzkow et al. (2019)). Extant literature has extensively examined financial texts, such as regulatory filings, corporate news articles, and conference calls, with a pronounced focus on the tone level or sentiment of these texts.[1] Textual sentiment is often determined by occurrences of sentiment words using lexicons (e.g., Loughran and McDonald (2011)) or by machine-reading sentiments of sentences (e.g., Azimi and Agrawal (2021); Huang et al. (2023)).

The dispersion of tone level is, however, less studied. Tone dispersion captures the degree to which tone is spread across a document. Given the conventional nature of tone being negative, neutral, or positive, the same tone level of a document may result from starkly different tone dispersion at the micro-level of the document. Consider Figure 1, where two tone-neutral, equally-sized documents each feature an equal number of negative and positive sentences, but one document has substantially more toned sentences than the other. Despite being classified with the same tone level, the latter is more tone-dispersed: It has more toned sentences (either negative or positive), and hence contains larger intensity of information about sentiment. Reflecting such intensity, we argue that tone dispersion measures information production in this paper.

[Insert Figure 1 Here]

We employ earnings conference calls to test the information production hypothesis of tone dispersion. Earnings calls typically take place shortly after quarterly earnings announcements, last for one to one and a half hours, and consist of a prepared management

[1] See, e.g., reviews by Loughran and McDonald (2016) and Loughran and McDonald (2020).

presentation session reviewing the quarterly results, followed by a Questions and Answers (Q&A) session where analysts verbally interact with the management. The Securities and Exchange Commission (SEC) enacted Regulation Fair Disclosure (Reg FD) in 2000, preventing public companies from selectively disclosing material, nonpublic information to investors and market professionals. Earning calls have since become the dominant form for analysts to interact with corporate management to explore and derive value-relevant information. We specifically focus on the interactive Q&A sessions where exchanges of conversation allow us to separately examine tone dispersions of executives and analysts. The importance of earnings calls as a dominant communication channel for market participants, combined with the limited length of earnings calls, results in opportunity costs such that these Q&A exchanges are meaningful and informative, hence rendering earnings call Q&A's an ideal testing ground for our hypothesis.

We establish the link between tone dispersion and information quantity using a large sample of earnings calls from 2006 to 2023. We capture tone dispersion by Bachmann et al.'s (2013) uncertainty quantification method for qualitative survey data, measuring the dispersion of tone across sentences in each Q&A session for executives and analysts, respectively. We in turn measure the sentence tone using FinBERT, a Bidirectional Encoder Representations from Transformers (BERT) model trained with financial corpora that outperforms a number of lexicon-based approaches and other machine learning methods (Huang et al. (2023)).[2] To measure the intensity of information, we utilize Non-negative Matrix Factorization (NMF), a topic modelling approach in computational linguistics that describes and

[2]BERT is the state-of-the-art machine learning method for large language modelling, include tone classification (e.g., Devlin, Chang, Lee, and Toutanova (2019)).

quantifies text clusters in each call (e.g., Lee and Seung (1999)). We manually verify the NMF topics and classify the topics into financial, operational, and industry-specific groups. NMF topic loadings capture the information exposures of the call to the topics. We find that both analyst and executive tone dispersions are positively and significantly associated with the overall topic loadings. While analyst tone dispersion is significantly related to financial, operational, and industry-specific topic loadings, executive tone dispersion is significantly related to financial topic loadings. These findings therefore confirm that tone dispersion is related to information production; in particular, analyst tone dispersion is related to multiple aspects of firm information.

We also verify the information production by tone dispersion through capital market outcomes. If tone dispersion is indicative of information production, this relation would manifest itself through sensitivities of price responses and trading volume. We confirm that, for earnings conference calls with higher analyst (executive) tone dispersion, immediate post-call share prices respond 28.2% (23.3%) more sensitively to earnings surprises, and the abnormal stock trading volume is 2.64% (2.03%) higher. That analyst and executive tone dispersions are associated with higher sensitivities of stock prices to earnings news and larger trading volumes is consistent with elevated trading on and price responsiveness to information production via more dispersed tone in corporate communication.

We investigate the information mechanism of tone dispersion by decomposing it into a component related and a component orthogonal to topic loadings. We find that the differential price response and trading volume of calls with high tone dispersion are primarily and persistently driven by the topic-related component of tone dispersion, regardless of the topic classification scheme that we use. Furthermore, when comparing the relative significance between analyst and executive tone dispersions, the topic-related component of analyst tone dispersion plays a larger role in these relations than that of executive tone dispersion, highlighting the diverse nature of analyst participants in calls and the informativeness of wide array of analyst questioning in the Q&A sessions.

Our paper contributes to the literature by proposing that tone dispersion, a measure generally regarded as measuring uncertainty, is related to the amount of information production, in particular in the setting of conference calls—an interactive environment where communicating formally takes place in a limited time frame and is therefore associated with significant opportunity costs for parties involved. Allee and DeAngelis (2015) define a measure of tone dispersion, respectively, for negative and positive words in Loughran and McDonald (2011) as the degree that these sentiment words are evenly spread within a call, and find that such dispersion is related to firm performance and managers' financial reporting decisions; for example, the dispersion of positive (negative) words in the prepared remarks section of conference calls is positively (negatively) associated with firm performance. Different from Allee and DeAngelis (2015), we apply FinBERT—a machine learning method—to classify the sentence-level sentiment and aggregate positive and negative sentiments into a combined dispersion measure. We show that tone dispersion is associated with information production, offering a potential channel to explain the findings of Allee and DeAngelis (2015) that tone dispersion is related to metrics such as firm performance. Moreover, we show that tone dispersion is different from uncertainty: Not only do our results remain robust to the controls of ex-ante information asymmetry measures of idiosyncratic return volatility and analyst forecast dispersion, these ex-ante information asymmetry measures also come no way close to producing post-call differential price response to earnings and trading volume.

We also contribute to the literature on the information content of earnings conference calls. Earlier work argues that conference calls deliver share-price-relevant information to the stock markets.[3] Recent research empirically explores the implications of analysts' sentiment or managers' sentiment during earnings conference calls.[4] Our paper focuses on the largely ignored dimension of a text's verbal features: tone dispersion. Specifically, we use the FinBERT model to quantify two verbal features of earnings conference call Q&A sessions, namely, tone level and tone dispersion, and empirically explore their implications from an information production perspective.

Our paper is related to the literature on unexpected earnings news and share price responses. This literature focuses on earnings response coefficient (ERC) that captures the sensitivity of share price responses to firm earnings news. Collins and Kothari (1989) document the cross-sectional heterogeneity and time-series variation in ERC. Following Collins

[3]Bowen, Davis, and Matsumoto (2002) and Kimbrough (2005) find that earnings conference calls are associated with improved accuracy of analyst forecasts. Their findings suggest that new information, beyond what is already disclosed in legally required corporate filings and announcements, has been revealed to analysts via earnings conference calls. Frankel, Johnson, and Skinner (1999) and Bushee, Matsumoto, and Miller (2003) find heightened levels of trading activity and return volatility during earnings conference calls, supporting the view that stock markets extract incremental information from earnings conference calls.

[4]At the individual firm level, Price, Doran, Peterson, and Bliss (2012) find that sentiment measures of earnings conference calls significantly predict abnormal return, trading volume, and post-earnings announcement drift; Borochin, Cicon, DeLisle, and Price (2018) examine how linguistic sentiment measures of managers and analysts distinctly affect how investors assess firm value uncertainty; Chen, Nagar, and Schoenfeld (2018) find that investors also respond differently to the tone levels of managers and analysts. At the aggregate market level, Jiang, Lee, Martin, and Zhou (2019) find that manager tone levels of earnings conference calls significantly predict future aggregate stock market returns. Furthermore, Larcker and Zakolyukina (2012) find that extremely positive managerial tone levels in conference calls predict financial restatement, suggesting that manager tone levels can be used to identify firms' deceptive behavior. Huang, Teoh, and Zhang (2014) argue that the firms with an abnormal positive tone level in earnings press releases are associated with negative future earnings and cash flows. Blaua, DeLisle, and Price (2015) argue that short sellers incorporate managerial tones in conference calls into their trading decisions. In particular, their evidence suggests that short sellers target firms with unusually positive managerial tones.

and Kothari (1989), many papers document the factors that affect the relationship between abnormal returns and unexpected earnings.[5] Notably, Matsumoto, Pronk, and Roelofsen (2011) and Chen, Nagar, and Schoenfeld (2018) find that the disclosure tone in a conference call affects ERC. Our paper joins this literature and employs ERC as the main test field to examine the information production hypothesis. We argue that the incremental information content of highly tone-dispersed Q&As is captured by the enhanced sensitivity of immediate share price responses to firm earnings news.

2 Information Content of Tone Dispersion

2.1 Data Sources

We extract quarterly earnings conference call transcripts from Standard & Poor's Capital IQ from 2006 to 2023.[6] A conference call typically consists of a management presentation session and a Questions and Answers (Q&A) session. The presentation session usually contains prepared remarks or comments by the management team, while the Q&A session contains spontaneous responses by managers to analysts' questions and remarks. The Q&A session therefore captures material information on how managers verbally interacts with the participating analysts. In our textual analyses, we only focus on the Q&A sessions (including analyst questions and executive responses) of earnings conference calls, which typically take

[5]These factors include, among others, firm audit qualifications (Choi and Jeter (1992)), auditor's reputation (Teoh and Wong (1993)), change of firm auditor (Hackenbrack and Hogan (2002)), uncertainty in analyst earnings forecasts (Imhoff and Lobo (1992)), the default risk in firm debt (Dhaliwal and Reynolds (1994) and Billings (1999)), market-wide investor sentiment (Mian and Sankaraguruswamy (2012)), and many others (Ghosh, Gu, and Jain (2005), Keung, Lin, and Shih (2010), Chi and Shanthikumar (2017)).

[6]Large quantity of Capital IQ calls start to exist from 2006. See also Huang and Wermers (2024).

place right after firms' quarterly earnings announcements. Analyst earnings forecasts are from I/B/E/S. Share price, number of shares outstanding, and other stock trading variables are from CRSP. Data of firm characteristics are from Compustat. Quarterly data of 13(f) institutional share ownership at the individual firm level are from Thomson/Refinitiv. Our regression sample consists of 116,670 quarterly earnings conference calls for 5,005 unique companies.

2.2 The FinBERT Model for Textual Tone

Natural Language Processing (NLP) provides a strong and effective way to understand the large body of conference calls. NLP's most revolutionary stream is Bidirectional Encoder Representations from Transformers, the BERT model (Devlin, Chang, Lee, and Toutanova (2019)). Its key technical innovation is applying the bidirectional training of Transformer, a popular attention model, to language modeling. Unlike directional models which read the text input sequentially (left-to-right or right-to-left), BERT is bidirectional: It can learn the context of a word based on its surroundings or context (left and right of the word).

Building upon the BERT model, Yang et al. (2020) and Huang et al. (2023) propose FinBERT, a specialized BERT for financial communications.[7] Specifically, FinBERT is trained on a large volume of financial corpora, consisting of 2.5 billion tokens (word units) of annual and quarterly reports, 1.3 billion tokens of earnings call transcripts, and 1.1 billion tokens of analyst reports. FinBERT results in state-of-the-art performance on sentiment classification for financial communications. Huang et al. (2023) report that FinBERT summarizes contex-

[7]FinBERT is open-source and can be downloaded from: https://github.com/yya518/FinBERT

tual information in financial text well, and outperforms Loughran and McDonald's (2011) dictionary-based approach and a number of other machine learning methods in sentiment classification for blocks of text.

We utilize FinBERT to classify every sentence in the Q&A sessions of quarterly earnings conference call transcripts as positive (coded as "+1"), negative (coded as "−1"), or neutral (coded as "0"). We then aggregate a tone measure for analysts (executives) in each call by taking the simple average of the tones of the sentences belonging to analysts (executives) in the Q&A session, and denote it as A_Tone (E_Tone). Panel A of Table 1 provides the summary statistics of these two measures. Executives are much more optimistic than analysts, as the mean of E_Tone is positive and is about four times of that of A_Tone, consistent with the literature that documents that management tends to be overly optimistic in conference calls (e.g., Brockman et al. (2015)). Appendix A1 provides definitions for all variables employed in our empirical analyses.

[**Insert Table 1 Here**]

Panel B of Table 1 presents the correlation between tone level measures of analysts and executives and shows that analyst tone level A_Tone and executive tone level E_Tone are positively correlated. For the whole sample, the correlation is 0.330. We also examine the correlations between A_Tone and E_Tone across different levels of unexpected earnings. Standardized unexpected earnings (SUE) are calculated as the difference between actually announced earnings per share and analyst forecast consensus, and then scaled by share price at the previous quarter end. Following Dellavigna and Pollet (2009), we sort all $SUEs$ into 11 quantiles where quantile 6 is for zero earnings surprises, quantiles 1-5 for negative earnings surprises, and quantiles 7-11 for positive earnings surprises. The correlation between A_Tone and E_Tone ranges from 0.275 to 0.339 across all the SUE ranks and remains fairly close to the full sample correlation. Overall, these correlations are consistent with the premise that the way how analysts put their questions can verbally stimulate how the executives reply to their questions.

Prior studies typically construct the document-level tone measures using simple counts of negative and positive words using, for example, sentiment words of Loughran and McDonald (2011) (e.g., Henry (2008), Price et al. (2012), Blaua et al. (2015), Jiang et al. (2019), among others). For our sample of conference calls, Appendix A2 provides an example of Apple, Inc.'s call where there are sentences that the Loughran and McDonald's (2011) dictionary-based approach misses but FinBERT correctly classifies the sentiment. Untabulated, the full sample correlation between the Loughran and McDonald sentiment and FinBERT sentiment is 0.516 (0.692) for analysts (executives), indicating that the FinBERT sentiment measure is correlated with, but different from, the Loughran and McDonald measure.

2.3 Measurement of Tone Dispersion

Following Bachmann et al.'s (2013) standard quantification method for qualitative survey data, we define the tone dispersion of a conference call as:

$$TD_t = \sqrt{Frac_t^+ + Frac_t^- - \left(Frac_t^+ - Frac_t^-\right)^2} \tag{1}$$

where $Frac_t^+$ ($Frac_t^-$) is the fraction of positive (negative) sentences, as classified by FinBERT, out of all sentences in a call. This measure is bounded between 0 (e.g., when the call have zero positive and 100% negative sentences)—the most clear, and 1 (e.g., when 50% of the call sentences are positive and the rest 50% are negative)—the most dispersed. For simplicity, if we assume there are no neutral sentences in the text, we can visualize the hump-shaped relation between TD and the fraction of the positive sentences in a text in Figure 2, where the peak takes place at 50% of the fraction and the bottom takes place at both ends.

[Insert Figure 2 Here]

We separate executives from analysts in the Q&A session and calculate a TD measure for executives (analysts) as ETD (ATD). The correlation between ETD and ATD is modest. Panel B of Table 1 shows that the correlation is 0.489 the full sample. The correlation between ETD and ATD across all the SUE ranks varies from 0.438 to 0.493 and remains fairly close to the full sample correlation.

2.4 Topic Modelling for Information

A higher dispersion in tone, we argue, results from a larger intensity of information. In this section, we establish evidence for this assertion via a topic modelling approach in computational linguistics. Specifically, we use a variant of Latent Dirichlet Allocation (LDA) called Non-negative Matrix Factorization (NMF) to determine the topics of a call, and show that tone dispersion relates with the degree of exposures to the topics. NMF is a machine-learning topic modeling algorithm that describes data clusters of related documents. For a given number of topics, it outputs the cluster of key word tokens (word units) for each topic and the amounts of topic exposures that the corpus of interest carries. It is a linear dimensionality reduction technique and is particularly useful in sparse documents (e.g., Lee and Seung (1999)). Different from LDA, which typically outputs relative amounts (probabilities) of exposures of each corpus to linguistic topics, NMF captures the absolute amounts. The Online Appendix to this paper details our application of NMF in conference calls.

As earnings conference calls involve a heavy component of industry-specific discussion (e.g., Tang and Huang (2024)), we execute the NMF topic modelling for each 4-digit GICS industry following Huang et al. (2018). Consistent with the sentence-level analysis for FinBERT, we similarly calculate a topic loading for each sentence of the call (within each industry), and aggregate the topic loadings within each conference call for executives and analysts, respectively.[8]

The key input for NMF is the number of topics. A large number of topics increases the overlap in content, whereas a smaller number of topics may fall short of specificity. We follow Cai et al.'s (2024) analysis of topic modelling in risk disclosures in bond prospectuses and choose 10 topics for a given industry. As earnings calls typically discuss firms' financial performance and operation, compared with general computational linguistic model, the sample is relatively homogeneous, and hence a smaller number of topics offers a reasonable approximation to topic exposures.

The concentration of discussion in earnings conference calls in financial and operating issues also aids us to "label" each topic, so that we can assign an economic interpretation to a topic. We categorize the topics into financial and non-financial topics and further categorize

[8]Since NMF outputs the absolute topic exposures, here by simple aggregation we capture the overall topic exposures of executives and analysts, respectively. Normalization by length of speech is less of a concern as earnings calls typically last for one to one and a half hours and hence the length of the Q&A session is largely comparable across calls.

the latter into operational, industry-specific topics using the top 10 words from each topic. We manually read through the keywords of each topic, categorize these topics industry by industry, and also use ChatGPT 4.0 to verify our categorizations. Briefly, we provide ChatGPT 4.0 with the keywords of each topic in a particular industry and ask ChatGPT 4.0 which of the following categories a topic belongs to: financial, operational, and industry-specific. ChatGPT 4.0 returns the requested categorizations with explanations. That is, the NMF topic output captures meaningful and interpretable economic content highly related to the nature of earnings conference calls. Appendix A3 provides examples of the topics output and categorization.

Panel A of Table 2 provides the summary statistics for the topic exposures. On average overall, analyst questions have about the same (albeit slightly lower) exposures as executive replies, indicating that both parties discuss about the same amount of issues. Both parties discuss more on non-financial topics (i.e., operational and industry-specific topics) than on financial topics, on a roughly 2:1 ratio. Lastly, the topic exposures have a large dispersion across calls, in particular for executives: The coefficient of variation (i.e., the ratio of standard deviation to mean) of the overall topic loading for executives (analysts) is 130% (50%), suggesting that analysts are more homogeneous, across calls, than executives in the issues discussed. This is consistent with the notion that the nature of the job of analysts is more singular than that of the cross-section of executives.

[Insert Table 2 Here]

Panel B of Table 2 presents the correlation matrix of these variables. We note that the correlation of the overall topic loading between analysts ($A\_TopicExposure$) and executives

($E\_TopicExposure$) is moderate at 0.275—indicating that although both parties discuss roughly the same amount of issues, they do not tend to closely follow each other on themes of discussion. This moderate level of correlation necessiates separating analysts' topic loading from that of executives. While the correlation between the financial and non-financial topic loadings by executives is rather high (0.698)—indicating that executives tend to discuss a similar amount of financial and non-financial contents in calls, such correlation for analysts is rather moderate (0.237), consistent with the fact that questions are fielded by a diverse set of analysts from different institutions.

We argue that tone dispersion is related to information intensity; specifically, we conjecture that Q&A sessions with a higher tone dispersion are associated with greater quantities of incremental information being delivered. That is, we expect our tone dispersion measures to be positively correlated with information quantities. To test this information production hypothesis, we execute a correlation test between tone dispersion and topic loading. We run Fama-MacBeth regressions of tone dispersion measures onto topic loading for each quarterly cross-section. We present the results in Table 3. The first three columns regress ATD onto $A\_TopicExposure$ while the last three columns regress ETD onto $E\_TopicExposure$. We control for analyst and executive tone levels. To accommodate the potential interaction effects between analysts and executives, we further include ATD (ETD) as an explanatory variable for ETD (ATD).[9] We also control for autocorrelations in coefficient estimates from cross-sectional regressions with Newey-West adjusted standard errors at 4 quarters or 8 quarters.

[9]For example, one may argue that the way the analysts ask the questions can potentially stimulate how the executives answer questions. Our results are robust if drop all of the control variables in Table 3.

[Insert Table 3 Here]

We note that the coefficients for both $A\_TopicExposure$ and $E\_TopicExposure$ are positively and statistically significant at the 1% level, regardless of model specifications. These results suggest that higher analyst and executive tone dispersion is both associated with greater quantity of analyst information, consistent with our information production hypothesis. Using Column (1) (or (2)) for ATD as a benchmark, one standard deviation increase in analyst topic exposure is associated with a 1.80 (or 1.33) increase in ATD, representing a 18.90% (or 13.97%) fraction of ATD's standard deviation. Analogously, using Column (4) for ETD as a benchmark, one standard deviation increase in executive topic exposure is associated with a increase in ATD, representing a 6.23% fraction of ETD's standard deviation. Overall, these results suggest that our measures of tone dispersion positively capture information quantities and that the economic significance of one standard deviation change in analyst topic exposure is substantial.

3 Capital Market Informativeness of Tone Dispersion

3.1 Return Response to Tone Dispersion

We next examine the price informativeness of tone dispersion. If tone dispersion is indicative of information production, we expect that this relation will manifest itself through differential price response to earnings. To this end, we employ the following specification for the price informativeness of analyst tone dispersion:

$$CAR_{i,t}\left(t_1,t_2\right) \;=\; \phi_0+\phi_1 SUE_{i,t}+\phi_2 SUE_{i,t}\times ATD\_High_{i,t}+\phi_3 ATD\_High_{i,t}+\Phi_4' X_{i,t}+\epsilon_{i,t}$$

where $CAR_{i,t}\left(t_1,t_2\right)$ is the cumulative DGTW-adjusted return of Daniel et al. (1997) in percentage points over (trading) day t_1 to day t_2 relative to the earnings announcement date of firm i for quarter t, and $X_{i,t}$ is the vector of covariates.

We include several sets of covariates as control variables: i) tone level measures for analysts and executives to absorb the effects of sentiment on share prices; ii) two proxies for investor attention (Dellavigna and Pollet (2009), Hirshleifer et al. (2009)): whether the quarterly earnings are announced on a Friday, and the total number of all other firms announcing their quarterly earnings on the same day; iii) firm characteristics at the quarterly frequency: firm size as measured by a firm's market capitalization, book-to-market ratio (for firm growth), firm leverage, stock turnover, and momentum as measured by a stock's holding period return for the previous quarter and also, prior to that, its nine-month holding period return; iv) ex-ante volatility: idiosyncratic return volatility as constructed as the standard deviation in a firm's stock returns in the past quarter, and analyst forecast dispersion as constructed as the standard deviation of analyst earnings forecasts for the quarter; and, v) other related variables of institutional ownership and following analysts. The Online Appendix to this paper provides the summary statistics and correlation matrix for these variables.

To aid interpretation, we convert the continuous tone dispersion variable to ATD_High (ETD_High), an indicator variable that equals one if the Q&A session of a conference call has a value of ATD (ETD) that is higher than the quarterly cross-sectional median, and zero otherwise.[10] Our main coefficient of interest is ϕ_2, indicating whether a differential exists in the sensitivity of $CAR(t_1, t_2)$ to SUE between conference calls with and without a highly tone-dispersed Q&A session. We may take the ratio of ϕ_2 over ϕ_1 to assess the economic significance of the sensitivity differential (Hershleifer, Lim and Teoh, 2009; DellaVigna and Pollet, 2009). We also replace ATD_High with or add ETD_High to examine the effects of executive tone dispersion on share price responses to earnings news.

Table 4 shows the results for whether tone dispersion matters for share price response to SUE. Following Hirshleifer et al. (2009) and Hirshleifer and Sheng (2022), we examine two CAR windows: days [0, 1], and days [2, 61]; the former examines the immediate price response to unexpected earnings and the latter examines whether there exists a post-earnings-announcement-drift (PEAD). Column (1) shows that immediate share price response to SUE is positive and statistically significant, confirming that positive earnings surprises lead to higher returns. Since we use 11 quantiles for SUE, the coefficient estimate for SUE of 0.723 indicates that as SUE increases by one rank, $CAR(0, 1)$ will increase by 0.723 percentage points (pps) on average. More importantly, the coefficient of the interaction term $SUE \times ATD\_High$ is positive and statistically significant at 0.204, indicating that one rank increase in SUE would additionally lead to 0.204 pps increase in $CAR(0, 1)$ for calls with high analyst tone dispersion. The economic significance is substantial as well: The differential effect on immediate share price response by ATD_High increases the sensitivity of $CAR(0, 1)$ to SUE by 28.2% (i.e., 0.204/0.723). In sum, earnings conference calls with higher analyst tone dispersion during the Q&A sessions have larger immediate price

[10]Our findings remain qualitatively the same if we instead use the continuous tone dispersion variables; see the Online Appendix.

impacts per unit of earnings surprise. Column (2) shows that the coefficients for SUE and $SUE \times ATD\_High$ are both statistically insignificant for $CAR(2, 61)$, suggesting no PEAD and no differential effect of ATD for PEAD in our sample period.[11]

[Insert Table 4 Here]

Columns (3) and (4) in Table 4 conduct the same exercises but for ETD_High. We find that executive tone dispersion also affects immediate share price responses to earnings news. The coefficient of the interaction term $SUE \times ETD\_High$ for $CAR(0, 1)$ is positive and statistically significant, indicating that earnings conference calls with high ETD have incremental sensitivity of CAR to SUE. Again, the economic significance is substantial as well: The relative increment in sensitivity is 23.3% (i.e., 0.171/0.733), which is somewhat smaller than that of ATD. Again, the coefficients for SUE and $SUE \times ETD\_High$ $CAR(2, 61)$ are both statistically insignificant, similarly suggesting no differential in PEAD across high and low ETD groups.

To mitigate concerns that ETD simply captures the variations in ATD (and vice versa), we run a horserace that includes both ATD and ETD (and their interactions with SUE) into Columns (5) and (6). We find that the incremental price effects of both analyst and executive tone dispersion remain statistically significant for $CAR(0, 1)$. That is, earnings calls with higher analyst or executive tone dispersion are associated with larger immediate price responses to earnings surprise. Consistent with the earlier results, the incremental price response to SUE by ATD is somewhat higher than that by ETD. Overall, the findings in

[11] PEAD is no longer statistically significant in recent research using recent data. Cite Charlse Martineau's paper. In untabulated results, we also experiment with alternative return windows of [2, 30] and [2, 45] and find similar results for PEAD.

Table 4 suggest that both analyst tone dispersion and executive tone dispersion matter for how sensitively share prices respond to earnings surprises, consistent with our information production story.

3.2 The Information Mechanism

In this section, we further decompose tone dispersion into two components: one that is related to topic exposures, and the unrelated component. Bushee, Gow, and Taylor (2018) project analyst language complexity (measured by the fog index—or the level of readability of the text—of analyst questions) on executive language complexity. They argue that the projection component of analyst language complexity on executive language reflects the information content of analyst questions, and the residual from the projection reflects the degree of managerial obfuscation. In Bushee et al. (2018), the former component helps reduce information asymmetry of the firm, whereas the latter component increases information asymmetry. We similarly decompose ATD (ETD) into two components based on Column (2) ((5)) of Table 3: ATD_Info (ETD_Info), the projection of analyst (executive) tone dispersion on information quantity, and ATD_Res (ETD_Res), the residual from the projection. While the residual—reflecting topic-unrelated tone dispersion—may still play a role in the information mechanism, we expect that it is the topic-related tone dispersion component that drives the return response of tone dispersion.[12]

[12] Table 2 provides the summary statistics and correlation matrix of these components. Since ATD_Info results from a projection of ATD on ETD (among other variables), it therefore has a high correlation with the ETD components of ETD_Info and ETD_Res; the analogous applies to ETD_Info. If we instead use Columns (1) and (4) of Table 3 that remove the cross-dependence between ATD and ETD for projection, the above correlations would be much reduced, and at the same time, our conclusions remain qualitatively the same.

We repeat the Table 4 regressions with these tone dispersion components. As with ATD_High, we generate an indicator variable ATD_Info_High (ETD_Info_High) that equals one if the value of ATD_Info (ETD_Info) is higher than the quarterly cross-sectional median, and zero otherwise. Similarly, ATD_Res_High (ETD_Res_High) is an indicator variable that equals one if the value of ATD_Res (ETD_Res) is higher than the quarterly cross-sectional median, and zero otherwise. Table 5 presents the results.

[**Insert Table 5 Here**]

We first examine separately the role of each decomposition. The first two columns in Table 5 show that our main results in Table 4 are driven by both components of analyst tone dispersion. Specifically, the coefficients for $SUE \times ATD\_Info\_High$ and $SUE \times ATD\_Res\_High$ are positive and statistically significant at the 1% level for $CAR(0, 1)$ in Column (1), but statistically insignificant for $CAR(2, 61)$ in Column (2). The magnitude of coefficient estimate for $SUE \times ATD\_Info\_High$ is about twice as large as that for $SUE \times ATD\_Res\_High$, suggesting that the price response to SUE is higher for the topic-related ATD component than for the topic-unrelated ATD component. Columns (3) and (4) show similar patterns for ETD components—the immediate price response to SUE is higher for the topic-related ETD component than for the topic-unrelated ETD component.

We pool both decompositions and compare the relative importance of all components in Columns (5) and (6). In this horse race test, we find that $SUE \times ATD\_Info\_High$ has the largest coefficient estimate towards explaining $CAR(0, 1)$, followed by $SUE \times ETD\_Info\_High$ (with only about half of the magnitude of coefficient estimate), $SUE \times ATD\_Res\_High$, and finally, an insignificant $SUE \times ETD\_Res\_High$ term. These results indicate that the price response differs across information components, highlighting the relative importance of topic-related components (relative to topic-unrelated components) as well as the role of ATD (relative to ETD). Overall, these results support our information production hypothesis for tone dispersion.

3.3 Finer Partition of Information Content

The previous section uses the overall topic exposure. We now replicate the previous results in Tables 3 and 5 using finer classifications of information topics. Specifically, instead of directly using total information quantity for the projection of ATD and ETD, we use the finer topic partitions of financial vs. non-financial topics in columns (1) and (3), and the group of financial, operational, and industry-specific topics in columns (2) and (4). Column (1) shows that ATD is positively and statistically significantly correlated with both financial and non-financial topic loadings. Column (2) shows that ATD is positively and statistically significantly correlated with both financial, operational, and industry-specific topic loadings. Regarding economic significance, a one-standard-deviation increase in analyst financial, operational, and industry-specific exposure is associated with an increase of 0.95, 0.78, 0.18 in ATD, respectively. Overall, these results indicate all three topic categories substantially contribute to analyst tone dispersion while financial topics seem to lead, followed by operational and industry-specific topics. In contrast, ETD is positively and statistically significantly associated with only the financial topic loading, but not with those of the non-financial topics or its components of operational and industry-specific topics. The findings that ATD is related to all aspects of topic loadings but ETD is constrained to only financial-related topics suggest that analyst tone dispersion is more diverse than executive tone dispersion.

[Insert Table 6 Here]

Panel B of Table 6 confirms the information channel of Table 5 using the classification of financial, operational, and industry-specific topic groups; that is, we project tone dispersion to these finer topic loadings and decompose tone dispersion again to topics- and non-topics-related components. Our findings in Panel B are highly consistent with those in Table 5: topics-related components are more important than topics-unrelated components, and ATD components are more important than ETD components in explaining the differential short-term price response to earnings surprise.

3.4 Abnormal Trading Volume

Prior literature has also examined stock trading volume upon earnings announcements or other events as part of their analyses on stock market reactions to corporate news.[13] For example, Hirshleifer, Lim, and Teoh (2009) find that the trading volume upon a firm's earnings announcement is lower when there is a greater number of other firms announcing their earnings on the same day. In this section, we provide additional evidence on abnormal trading volume to support our information production story. We conjecture that highly tone-dispersed Q&A sessions are associated with greater quantity of incremental information beyond financial numbers and therefore result in greater trading volume upon earnings

[13]See, e.g., Pevzner et al. (2015); Hirshleifer et al. (2009); Dellavigna and Pollet (2009); Barber and Odean (2008); Copper and Lewis (2001); Barber and Douglas (1993); among others.

announcements. This positive association should hold after controlling for the magnitude of unexpected earnings news.

Following Hirshleifer et al. (2009), we employ $AbVol(0,1)$, the abnormal trading volume averaged over the earnings announcement day and the very next day as the dependent variable. Daily abnormal trading volume is constructed as the difference between the natural log of daily trading volume and the 30-day average of log daily trading volume from day -40 to day -11. $AbVol(0,1)$ is the two-day average of daily trading volume on the earnings announcement date and the very next day. We include the same set of covariates here as in our previous analyses. Following Hirshleifer et al. (2009), we also control for the absolute magnitude of standardized unexpected earnings.[14]

The first column in Table 7 shows that Q&A sessions with high ATD tend to experience high levels of abnormal trading volume. The coefficient for ATD_High is positive and statistically significant at the 1% level. This coefficient is of economic significance as well: The differential in abnormal trading volume between Q&A sessions with ATD higher and lower than its cross-sectional median is 1.691, or 2.61% relative to sample mean.[15] Column (2) decomposes ATD into 10-topics-related and unrelated components, and the results show that the topics-related component has a much larger coefficient estimate than the topics-unrelated component; that is, the topics-related component of ATD has a larger explanatory power

[14] Since $SUE = 6$ stands for zero earnings surprises, we take the absolute value of $SUE - 6$ as the absolute magnitude of SUE.

[15] This percentage differential is sizable indeed. According to Hirshleifer et al. (2009)'s formula, the log of daily trading volume is compared with the average of log daily trading volume from day -40 to day -11. A daily abnormal trading volume taking the value of 0 means a stock's current trading volume is equal to the geometric mean of trading volumes over the day -40 to day -11 window. The sample mean of $AbVol(0,1)$ takes the magnitude of 64.1 percentage points, indicating that stock trading volumes over the two-day window upon earnings announcement (i.e. day 0 and day 1) are substantially higher than stock trading volumes from day -40 to day -11. Therefore, the 2.61% differential relative to the sample mean of 64.1 percentage points is actually based on a figure that is already substantially sizable.

on trading volume. In Column (3) we decompose ATD to the explained and unexplained components by financial, operational, and industry-specific topics, and find that only the topics-related component is statistically significant. Columns (4)-(6) repeat the same exercise for ETD, and the results similarly show that ETD explains stock trading volume upon earnings news, and that it is the topics-related component that persistently carries such explanatory power.

[**Insert Table 7 Here**]

Column (7) includes both ATD and ETD into the regression and the results show that albeit analyst and executive tone dispersion both have positive effects on trading volume, the coefficient estimate of the ATD dummy (ATD_High) is larger than that of the ETD dummy (ETD_High). Columns (8) and (9) repeat the decomposition analyses accordingly. The results indicate that the informative components of our tone dispersion measures have stronger effects on abnormal trading volume than the residual components. Interestingly, the effects of executive tone dispersion's informative component turn statistically insignificant when running a horserace with that of analyst tone dispersion. Overall, these results support our information production hypothesis for tone dispersion. Overall, these results support the notion that compared to ETD, ATD is relatively more informative on trading volume; and that within ATD, the topics-related component plays a larger role in predicting trading volume (relative to the topicc-unrelated components). These results are highly consistent with the role of ATD and ETD on the return response to earnings surprise.

4 Robustness Checks and Discussions

4.1 Alternative Measures of Tone Dispersion and Return Windows

Earlier, we use the dispersion measure in Bachmann et al. (2013), which the authors use to capture ex ante disagreement and uncertainty in business survey opinions. A similar, yet popular measure to capture uncertainty is standard deviation. In Panel A of Table 8, we instead measure tone dispersion as the standard deviation of the tones of sentences by analysts or executives. Untabluated, Bachmann et al. (2013)-based and standard deviation-based ATD's (ETD's) have a correlation coefficient of 0.995 (0.983), showing that they are highly correlated but still distinct. Panel A continues to show that, for the standard deviation-based tone dispersion, both return response to earnings surprise and the trading volume are more pronounced in high ATD and ETD and in topic information-related components of ATD and ETD, and that analyst tone dispersion carries higher significance than executive tone dispersion therein. These results are highly consistent with our earlier conclusions.

[Insert Table 8 Here]

We also conduct robustness checks by employing alternative windows the measures of stock market responses. Specifically, we replicate our main findings on share price responses to earnings news using $CAR(-1, 1)$ following Mian and Sankaraguruswamy (2012), Hartzmark and Shue (2018), and many others. We similarly apply this alternative window to the measure of abnormal stock trading volume. The first (last) two columns in Panel B confirm that our main findings on share price responses to earnings news (abnormal stock trading volme) are robust to this alternative window.

4.2 Robustness to Ex-Ante Information Asymmetry

We have argued and showed evidence that tone dispersion is related to information production. Yet it is possible that tone dispersion, as it also serves to measure uncertainty, is related to and driven by other uncertainty aspects of the firm. While we have controlled for idiosyncratic return volatility and analyst dispersion for these other aspects of ex-ante firm information asymmetry, our results of incremental role of tone dispersion on the return response to earnings surprise may be subsumed by ex-ante information asymmetry. To ameliorate this problem, in Table 9 we include interaction terms of earnings surprise and ex-ante information asymmetry measures idiosyncratic return volatility and analyst dispersion, along side with the interaction term of earnings surprise and tone dispersion.

We find that the interaction terms of earnings surprise and idiosyncratic return volatility does not explain $CAR(0,1)$, and that opposite to the sign of the interaction term of earnings surprise and tone dispersion, the interaction terms of earnings surprise and analyst dispersion is negatively and significantly related to $CAR(0,1)$. In contrast, after controlling for these other interaction terms, our conclusion that tone dispersion and topic-information-related component of tone dispersion, in particular, those by analysts, positively drive the earnings surprise-return relation remains qualitatively the same. In untabluated results, we also partition the sample into low and high idiosyncratic return volatility, or into low and high analyst dispersion, and find our conclusions remain. In sum, our results are unlikely to be driven by ex-ante information asymmetry as measured by return volatility or analyst dispersion.

[Insert Table 9 Here]

5 Conclusion

The illegalization of selective disclosure, formalized by Regulation Fair Disclosure (Reg FD) in 2000, has established earnings calls as one of the most dominant means for analysts to interact with corporate management and obtain value-relevant information. While the literature has focused on a multitude of capital market implications of such interactions, particularly on the tone "sentiment" of earnings calls, less attention has been paid to tone dispersion, or the degree to which executive or analyst tone is spread throughout the call. This paper attempts to fill this gap in the literature.

Everything else being equal, a less evenly spread tone would contain a larger (absolute) amount of toned information; we therefore argue that tone dispersion indicates information production. We measure tone sentiments of executives and analysts, respectively, for Q&A sessions of earnings calls using FinBERT, a state-of-the-art machine learning method for computational linguistics, and capture tone dispersion by Bachmann et al.'s (2013) uncertainty quantification from tone sentiments of analyst questions or executive answers. We measure the amount of information in a given call segment with Non-negative Matrix Factorization (NMF), a topic modeling approach that describes text clusters, and subsequently classify topics to meaningful business labels of financial, operational, and industry-specific groups. We show that tone dispersion is related to information quantities (the amount of topic loadings) embodied in earnings calls; in particular, analyst tone dispersion is significantly related to financial, operational, and industry-specific topic loadings, whereas executive tone dispersion is significantly related to financial topic loadings.

The capital market outcomes also lend support to the information production hypothesis of tone dispersion. We find that analyst and executive tone dispersions are both associated with higher sensitivities of stock prices to earnings news and larger trading volumes. Other measures of ex-ante information asymmetry, such as idiosyncratic return volatility and analyst forecast dispersion, do not give rise to such results, suggesting that it is the information contained in tone dispersion that drives the elevated responsiveness of trading outcomes.

Lastly, we confirm the information mechanism of tone dispersion by decomposing dispersion into a topic-related and an orthogonal component. We find that the differential price response to earnings and trading volume associated with calls of high tone dispersion is primarily driven by the topic-related component of tone dispersion. In particular, the topic-related component of analyst tone dispersion plays a larger role in these relations than that of executive tone dispersion, highlighting the informativeness of analyst inquiries in calls. Overall, our paper contributes by documenting the information value of tone dispersion in corporate communications.

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Appendices

A1 Variable Definitions

Variable Name	Definition
$CAR(0,1)$	The cumulative DGTW-adjusted return in percentage points over the earnings announcement date and the very next day.
$CAR(2,61)$	The cumulative DGTW-adjusted return in percentage points from 2 days to 61 trading days after earnings announcement.
$AbVol(0,1)$	The two-day average of daily trading volume on the earnings announcement date and the very next day. Following Hershleifer, Lim, and Teoh (2009), daily abnormal trading volume is constructed as the difference between the natural log of daily trading volume and the 30-day average of log daily trading volume from day -40 to day -11.
SUE	Standardized unexpected earnings calculated as the difference between actually announced earnings per share and analyst forecast consensus, and then scaled by share price at the previous quarter end. Following Dellavigna and Pollet (2009), we sort all SUEs into 11 quantiles where quantile 6 is for zero earnings surprises, quantiles 1-5 for negative earnings surprises, and quantiles 7-11 for positive earnings surprises.
ATD	Analyst tone dispersion calculated using the dispersion measure in Bachmann et al. (2013) over what the analysts say during the Q&A session of an earnings conference call.
ETD	Executive tone dispersion calculated using the dispersion measure in Bachmann et al. (2013) over what the executives say during the Q&A session of an earnings conference call.
A_Tone	Analyst tone level calculated for analysts as the differential between the numbers of positive and negative sentences scaled by the number of total sentences.
E_Tone	Executive tone level calculated for executives as the differential between the numbers of positive and negative sentences scaled by the number of total sentences.
$Friday$	An indicator variable that equals one if a firm announces its quarterly earnings on a Friday.
$Sameday\_EAs$	The natural log of the total number of all other firms announcing their quarterly earnings on the same day.
$MarketCap$	The natural log of a firm's market capitalization.
BM	The book-to-market ratio.
$Leverage$	The ratio of total liabilities over total assets.
$Turnover$	The ratio of trading volume over number of shares outstanding at the previous quarter end.
Ret_l3m	The holding period return for the previous quarter.
$Momentum$	The nine-month holding period return before Ret_l3m.
$IdioVol$	The standard deviation of a firm's daily stock returns in the past quarter.
$InstOwn$	A firm's percentage ownership by 13f institutional investors.
$FollowingAnalysts$	The natural log of total number of estimates to form a firm's analyst consensus for its to-be-announced quarterly earnings.
$AnaDispersion$	The standard deviation of analyst earnings forecasts.

A2 An Example to Compare FinBERT and Loughran and McDonald (2011)

This section compares tone classifications by the FinBERT model and the Loughran and McDonald (2011) ("LM2011") method for an excerpt of conversation between executives and an analyst from the quarterly earnings conference call of Apple, Inc. on November 2nd, 2017.

Speaker	Sentence	FinBERT	LM2011
Tim Cook (CEO)	Not today, not the apps that you'll see on the App Store today, but what it will be, what it can be, I think its profound and I think Apple is in a really unique position to lead in this area.	Positive	NULL
Tim Cook (CEO)	It's having the right product lineup for the market.	Positive	NULL
Amit Jawaharlaz Daryanani (RBC Capital Markets)	And are yield and efficiencies broadly much more severe this time versus what you've seen historically?	Negative	Neutral*
Luca Maestri (CFO)	As I mentioned, particularly on the App Store, which is very important to us, the number of paying accounts has grown a lot.	Positive	NULL
Luca Maestri (CFO)	But we also have other businesses that are growing very, very fast and actually accelerating year-ago quarter.	Positive	NULL

*Note: The word "efficiency" is classified as positive in Loughran and McDonald (2011) and "severe" as negative. "NULL" means the sentence does not contain any word listed in Loughran and McDonald (2011) dictionaries.

A3 Topic Examples and Categorizations

This section presents two examples of topics classifications that are employed in the empirical analyses. Specifically, Panel A lists the topics classifications for the industry with GIC4 code 2550 (Consumer Discretionary Distribution & Retail) and Panel B GIC4 code 3030 (Household & Personal Products).

Panel A: Topics Classifications for GIC4=2550

Topics	Keywords	Financial	Operational	Industry-Specific
Topic 01	market, expect, growth, impact, price, increase, sale, cost, margin, high	1		
Topic 02	store, sale, new, open, market, mean, great, point, comp, product		1	
Topic 03	car, vehicle, market, inventory, unit, new, use, sell, business, service			1
Topic 04	interpret, platform, user, service, product, revenue, business, growth, china, increase	1		
Topic 05	business, inventory, comp, category, point, trend, feel, line, half, margin		1	
Topic 06	brand, product, new, growth, consumer, expect, opportunity, great, strong, partner			1
Topic 07	inventory, product, sale, line, company, new, tag, increase, cost, end		1	
Topic 08	customer, marketing, growth, business, new, category, gross_margin, spend, high, product			1
Topic 09	business, company, market, revenue, work, margin, opportunity, people, mean, service	1		
Topic 10	growth, seller, marketing, revenue, rate, buyer, market, mobile, new, consumer	1		

Panel B: Topics Classifications for GIC4=3030

Topics	Keywords	Financial	Operational	Industry-Specific
Topic 01	category, business, pricing, growth, expect, share, price, innovation, consumer, line			1
Topic 02	product, new, customer, revenue, forward, line, sale, company, launch, great		1	
Topic 03	brand, growth, new, consumer, sale, channel, market, product, launch, store			1
Topic 04	market, china, growth, business, grow, share, impact, strong, brazil, mean			1
Topic 05	price, market, increase, cost, capacity, line, product, private_label, machine, business		1	
Topic 06	business, margin, mean, great, start, sale, work, end, sell, line		1	
Topic 07	fund, business, capital, opportunity, company, cost, synergy, forward, management, transaction	1		
Topic 08	study, product, patient, market, use, muscle, great, start, company, people			1
Topic 09	sale, production, product, increase, company, bulk, customer, inventory, cash, revenue	1		
Topic 10	line, day, sale, business, event, distributor, member, new, incentive, people		1	

Figure 1: Comparing Texts with the Same Tone

This figure compares tone-neutral texts with different levels of tone dispersion. Panel A presents a text that has ten sentences in total, out of which 2 are positive, 2 are negative, and the remaining 6 sentences are neutral. Panel B presents a text that has ten sentences in total, out of which 4 are positive, 4 are negative, and the remaining 2 sentences are neutral.

Panel A. Less tone-dispersed **Panel B. More tone-dispersed**

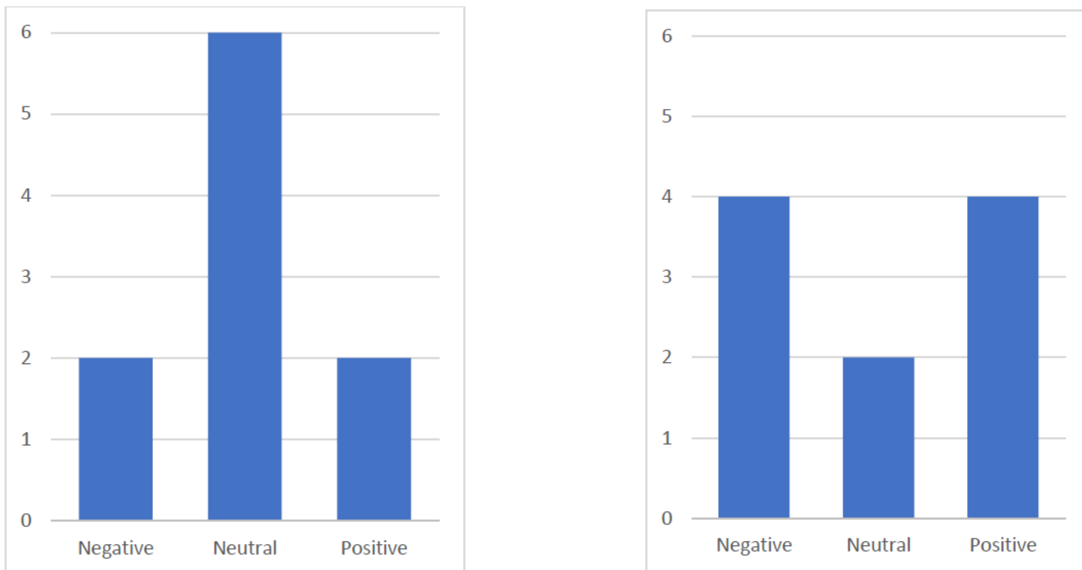

Figure 2: Tone Dispersion

This figure visualizes tone dispersion (TD, the y-axis) as a function of the fraction of positive sentences in a text (the x-axis), by assuming no neutral sentences for simplicity. The hump-shaped relation between TD and the fraction of the positive sentences in a text in this figure indicates that the peak takes place at 50% of the fraction and the bottom takes place at both ends.

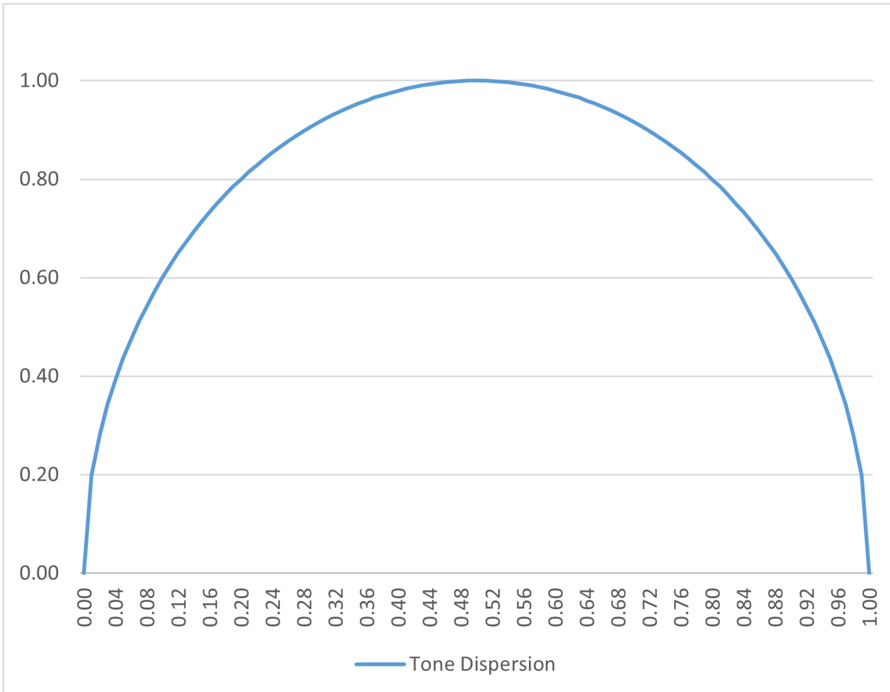

Table 1: Comparing Analyst and Executive Verbal Features

This table presents the summary statistics and correlations between measures of analyst and executive tone level and between measures of analyst and executive tone dispersion, respectively. All measures of tone level and tone dispersion are constructed using the FinBERT model. Analyst tone level (A_Tone) and executive tone level (E_Tone) are calculated separately for analysts and executives as the differential between the numbers of positive and negative sentences scaled by the number of total sentences. ATD (ETD) is analyst (executive) tone dispersion calculated using the dispersion measure in Bachmann et al. (2013) over what the analysts (executives) say during the Q&A session of an earnings conference call. We provide the full-sample correlation as well as subsample correlations depending on the level of unexpected earnings. Standardized unexpected earnings (SUE) are calculated as the difference between actually announced earnings per share and analyst forecast consensus, scaled by share price at the previous quarter end. Following Dellavigna and Pollet (2009), we sort all SUEs into 11 quantiles where quantile 6 is for zero earnings surprises, quantiles 1-5 for negative earnings surprises, and quantiles 7-11 for positive earnings surprises.

Panel A: Summary statistics of tone dispersion and tone measures

	N Obs	Mean	SD	P10	P25	Median	P75	P90
A_Tone	116,670	0.048	0.066	-0.032	0.000	0.045	0.088	0.131
E_Tone	116,670	0.173	0.091	0.059	0.110	0.169	0.233	0.294
ATD	116,670	0.366	0.095	0.258	0.319	0.377	0.428	0.472
ETD	116,670	0.490	0.080	0.399	0.451	0.498	0.540	0.577

Panel B: Correlations between analyst and executive measures

	Correlation between	
	A_Tone and E_Tone	ATD and ETD
Full Sample	0.330	0.489
SUE Group		
$SUE = 1$	0.275	0.477
$SUE = 2$	0.276	0.468
$SUE = 3$	0.286	0.493
$SUE = 4$	0.283	0.490
$SUE = 5$	0.291	0.484
$SUE = 6$	0.296	0.483
$SUE = 7$	0.339	0.474
$SUE = 8$	0.335	0.461
$SUE = 9$	0.321	0.482
$SUE = 10$	0.310	0.438
$SUE = 11$	0.312	0.488

Table 2: The Topics Model

This table describes the variables constructed via the Topics Model in Huang et al. (2018). Panel A presents the summary statistics, and Panel B provides the correlation matrix.

Panel A: Summary statistics of topics model measures

Variable	N Obs	Mean	SD	P10	P25	Median	P75	P90
A_TopicExposure	115,778	5.208	2.598	2.227	3.327	4.826	6.663	8.704
A_TopicExposure_Fin	115,778	1.953	1.268	0.566	0.990	1.691	2.644	3.715
A_TopicExposure_NonFin	115,778	3.246	1.966	1.078	1.795	2.879	4.278	5.875
E_TopicExposure	116,293	5.567	7.227	0.232	0.434	1.088	10.064	16.642
E_TopicExposure_Fin	116,293	1.981	2.838	0.028	0.119	0.426	3.132	6.211
E_TopicExposure_NonFin	116,293	3.561	4.890	0.117	0.249	0.715	5.990	10.917
ATD_Info	115,778	0.369	0.049	0.307	0.340	0.372	0.402	0.428
ATD_Res	115,778	0.000	0.075	-0.086	-0.043	0.002	0.047	0.089
ETD_Info	116,293	0.492	0.045	0.436	0.464	0.493	0.521	0.546
ETD_Res	116,293	0.000	0.060	-0.066	-0.036	-0.001	0.036	0.072

Panel B: Correlation matrix of topics model measures

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
(1) *A_TopicExposure*	1.000									
(2) *A_TopicExposure_Fin*	0.669	1.000								
(3) *A_TopicExposure_NonFin*	0.878	0.237	1.000							
(4) *E_TopicExposure*	0.275	0.181	0.244	1.000						
(5) *E_TopicExposure_Fin*	0.214	0.341	0.062	0.872	1.000					
(6) *E_TopicExposure_NonFin*	0.275	0.066	0.319	0.957	0.698	1.000				
(7) *ATD_Info*	0.351	0.285	0.275	0.129	0.131	0.112	1.000			
(8) *ATD_Res*	0.000	0.041	-0.025	0.004	0.021	-0.007	0.000	1.000		
(9) *ETD_Info*	0.148	0.165	0.087	0.131	0.145	0.106	0.474	0.583	1.000	
(10) *ETD_Res*	0.017	0.043	-0.006	-0.003	0.015	-0.013	0.681	-0.435	-0.003	1.000

Table 3: Statistical Association between Tone Dispersion and Topic Loading

This table examines the statistical association between tone dispersion measures and information quantities. We run Fama-MacBeth regressions where tone dispersion measures are regressed onto information quantities for each cross-section. In this table, we multiply ATD and ETD by 100 to make the coefficients easier to read. Newey-West corrected standard errors for 4 quarters are reported in columns (1), (2), (4) and (5) and for 8 quarters in columns (3) and (6), and t-statistics are reported with coefficients. ***, **, and * stand for statistical significance at the 1%, 5%, and 10% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
		ATD			ETD	
$A\_TopicExposure$	0.691***	0.511***	0.511***			
	(21.78)	(20.41)	(19.39)			
$E\_TopicExposure$				0.069***	0.037***	0.037***
				(7.67)	(4.51)	(4.00)
A_Tone	23.498***	31.351***	31.351***	-13.697***	-22.878***	-22.878***
	(10.83)	(16.03)	(13.44)	(-10.16)	(-29.83)	(-31.93)
E_Tone	13.492***	-7.530***	-7.530***	38.888***	33.883***	33.883***
	(26.82)	(-12.13)	(-10.13)	(20.64)	(23.66)	(19.71)
ATD					0.351***	0.351***
					(36.46)	(37.46)
ETD		0.571***	0.571***			
		(22.08)	(17.74)			
Observations	115,206	115,206	115,206	115,718	115,718	115,718
Number of Groups	72	72	72	72	72	72
Adjusted R-squared	0.106	0.283	0.283	0.191	0.363	0.363
Standard Errors	NW 4	NW 4	NW 8	NW 4	NW 4	NW 8

Table 4: Tone Dispersion and Share Price Responses to Earnings News

This table examines how tone dispersion matters for share price responses to unexpected earnings news. All variables are defined in Appendix A1. Standard errors are double-clustered at the industry and year levels, and t-statistics are reported with coefficients. ***, **, and * stand for statistical significance at the 1%, 5%, and 10% level, respectively.

	(1) $CAR(0,1)$	(2) $CAR(2,61)$	(3) $CAR(0,1)$	(4) $CAR(2,61)$	(5) $CAR(0,1)$	(6) $CAR(2,61)$
SUE	0.723***	0.012	0.733***	-0.031	0.686***	-0.004
	(10.70)	(0.15)	(10.23)	(-0.39)	(9.47)	(-0.05)
$SUE \times ATD\_High$	0.204***	-0.075			0.165***	-0.092
	(3.92)	(-0.91)			(4.19)	(-1.09)
ATD_High	-1.789***	0.741			-1.432***	0.897
	(-4.66)	(1.23)			(-4.80)	(1.42)
$SUE \times ETD\_High$			0.171***	0.021	0.118**	0.051
			(2.93)	(0.27)	(2.55)	(0.61)
ETD_High			-1.843***	-0.363	-1.419***	-0.619
			(-4.52)	(-0.59)	(-4.43)	(-0.93)
A_Tone	18.896***	4.426***	18.370***	4.408**	18.466***	4.234**
	(10.31)	(2.90)	(10.43)	(2.78)	(10.24)	(2.63)
E_Tone	7.816***	5.289***	8.576***	5.550***	8.510***	5.600***
	(9.45)	(3.43)	(9.84)	(3.74)	(9.75)	(3.76)
$Friday$	0.044	-0.507	0.041	-0.503	0.045	-0.507
	(0.32)	(-1.29)	(0.28)	(-1.30)	(0.32)	(-1.33)
$Sameday\_EAs$	-0.032	-0.097	-0.031	-0.094	-0.028	-0.096
	(-0.83)	(-0.64)	(-0.84)	(-0.60)	(-0.73)	(-0.61)
$MarketCap$	-0.804***	-4.227***	-0.818***	-4.229***	-0.816***	-4.232***
	(-5.27)	(-8.43)	(-5.29)	(-8.45)	(-5.35)	(-8.44)
BM	0.141***	0.209	0.139***	0.205	0.137***	0.207
	(3.06)	(1.09)	(3.01)	(1.07)	(2.96)	(1.08)
$Leverage$	-0.302	-1.169	-0.299	-1.178	-0.314	-1.172
	(-1.02)	(-0.92)	(-0.99)	(-0.90)	(-1.04)	(-0.89)
$Turnover$	-0.028	0.013	-0.027	0.009	-0.030	0.012
	(-0.77)	(0.07)	(-0.77)	(0.05)	(-0.85)	(0.07)
Ret_l3m	-0.456	-0.962	-0.470	-0.985	-0.484	-0.974
	(-1.18)	(-0.81)	(-1.22)	(-0.84)	(-1.26)	(-0.82)
$Momentum$	-0.756***	-0.971	-0.770***	-0.990	-0.781***	-0.983
	(-4.32)	(-1.46)	(-4.30)	(-1.49)	(-4.35)	(-1.48)
$IdioVol$	18.878**	20.823	18.706**	20.474	18.474**	20.632
	(2.34)	(0.65)	(2.34)	(0.64)	(2.31)	(0.64)
$InstOwn$	0.372	-2.720*	0.408	-2.717*	0.394	-2.709*
	(0.78)	(-2.06)	(0.84)	(-2.01)	(0.82)	(-2.00)
$FollowingAnalysts$	-0.062	-1.091*	-0.064	-1.081*	-0.055	-1.088*
	(-0.45)	(-2.00)	(-0.48)	(-1.96)	(-0.40)	(-1.98)
$AnaDispersion$	0.708*	-1.665	0.732*	-1.695	0.698*	-1.669
	(1.80)	(-1.20)	(1.91)	(-1.21)	(1.78)	(-1.20)
Firm FE & YQ FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	92,262	90,202	92,262	90,202	92,262	90,202
Adjusted R-squared	0.172	0.044	0.172	0.044	0.173	0.045

Table 5: Decomposing Tone Dispersion

This table explores how the informative and residual components of tone dispersion matter for share price responses to unexpected earnings news. We first decompose ATD (ETD) into two components: ATD_Info (ETD_Info), the part of analyst (executive) tone dispersion that is explained by information quantity, and ATD_Res (ETD_Res), the unexplained part. ATD_Info_High (ETD_Info_High) is an indicator variable that equals one if the Q&A session of a conference call has a level of ATD_Info (ETD_Info) that is higher than the quarterly cross-sectional median, and zero otherwise. ATD_Res_High (ETD_Res_High) is an indicator variable that equals one if the Q&A session of a conference call has a level of ATD_Res (ETD_Res) that is higher than the quarterly cross-sectional median, and zero otherwise. All other variables are defined in Appendix A1. The same covariates are included as with Table 4. Standard errors are double-clustered at the industry level and year level, and t-statistics are reported with coefficients. ***, **, and * stand for statistical significance at the 1%, 5%, and 10% level, respectively.

	(1) $CAR(0,1)$	(2) $CAR(2,61)$	(3) $CAR(0,1)$	(4) $CAR(2,61)$	(5) $CAR(0,1)$	(6) $CAR(2,61)$
SUE	0.669***	-0.029	0.698***	-0.044	0.655***	-0.035
	(9.59)	(-0.33)	(9.31)	(-0.47)	(8.50)	(-0.29)
$SUE \times ATD\_Info\_High$	0.209***	0.070			0.173***	0.066
	(3.65)	(1.28)			(3.64)	(1.60)
ATD_Info_High	-1.989***	-0.381			-1.467***	-0.121
	(-5.02)	(-0.86)			(-4.34)	(-0.36)
$SUE \times ATD\_Res\_High$	0.112***	-0.045			0.073***	-0.029
	(5.23)	(-0.66)			(3.35)	(-0.38)
ATD_Res_High	-0.965***	0.403			-0.735***	0.233
	(-5.95)	(0.81)			(-4.83)	(0.51)
$SUE \times ETD\_Info\_High$			0.186***	-0.021	0.107***	-0.028
			(4.27)	(-0.27)	(3.77)	(-0.44)
ETD_Info_High			-1.731***	0.032	-1.012***	0.003
			(-5.71)	(0.05)	(-5.16)	(0.01)
$SUE \times ETD\_Res\_High$			0.071*	0.063	0.006	0.024
			(2.06)	(0.79)	(0.18)	(0.23)
ETD_Res_High			-0.981***	-0.733	-0.494**	-0.581
			(-4.24)	(-1.25)	(-2.13)	(-0.87)
Covariates	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE & YQ FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	92,262	90,202	92,262	90,202	92,262	90,202
Adjusted R-squared	0.173	0.044	0.173	0.044	0.174	0.045

Table 6: Decomposing Tone Dispersion: Finer Topic Groups

This table replicates previous tables using finer topic groups. Specifically, Panel A replicates Table 3 by classifying all topics into financial and non-financial topics in columns (1) and (3), and into financial, operational, and industry-specific topics in columns (2) and (4). Newey-West corrected standard errors for 4 quarters are reported in all columns. Panel B replicates Table 5 by classifying all topics into financial, operational, and industry-specific topics. t-statistics are reported with coefficients. ***, **, and * stand for statistical significance at the 1%, 5%, and 10% level, respectively.

Panel A: Fama-MacBeth Regressions with Finer Topic Groups

	(1)	(2)	(3)	(4)
	ATD		*ETD*	
A_TopicExposure_Fin	0.804***	0.745***		
	(16.16)	(14.27)		
A_TopicExposure_NonFin	0.384***			
	(20.10)			
A_TopicExposure_Op		0.665***		
		(12.28)		
A_TopicExposure_IS		0.143***		
		(4.07)		
E_TopicExposure_Fin			0.136***	0.133***
			(9.66)	(9.84)
E_TopicExposure_NonFin			-0.015	
			(-1.20)	
E_TopicExposure_Op				-0.007
				(-0.42)
E_TopicExposure_IS				-0.022
				(-1.04)
A_Tone	31.420***	31.202***	-22.756***	-22.733***
	(16.07)	(16.49)	(-29.61)	(-29.64)
E_Tone	-7.601***	-7.881***	33.786***	33.754***
	(-12.20)	(-12.65)	(23.41)	(23.20)
ATD			0.350***	0.349***
			(36.16)	(36.22)
ETD	0.567***	0.564***		
	(22.18)	(22.49)		
Observations	115,206	115,206	115,718	115,718
Number of groups	72	72	72	72
Adjusted R-squared	0.285	0.287	0.364	0.364

Panel B: The Information Channel with Financial, Operational, and Industry-Specific Topic Groups

	(1) $CAR(0,1)$	(2) $CAR(2,61)$	(3) $CAR(0,1)$	(4) $CAR(2,61)$	(5) $CAR(0,1)$	(6) $CAR(2,61)$
SUE	0.675***	-0.029	0.698***	-0.054	0.661***	-0.046
	(9.37)	(-0.33)	(9.36)	(-0.57)	(8.57)	(-0.39)
$SUE \times ATD\_Info\_High$	0.208***	0.066			0.169***	0.048
	(3.41)	(1.23)			(3.20)	(1.00)
ATD_Info_High	-1.951***	-0.378			-1.421***	-0.067
	(-4.53)	(-0.86)			(-3.69)	(-0.17)
$SUE \times ATD\_Res\_High$	0.101***	-0.041			0.060**	-0.024
	(4.53)	(-0.65)			(2.49)	(-0.34)
ATD_Res_High	-0.866***	0.301			-0.618***	0.122
	(-4.88)	(0.64)			(-3.41)	(0.28)
$SUE \times ETD\_Info\_High$			0.186***	-0.010	0.112***	-0.014
			(4.08)	(-0.13)	(3.97)	(-0.23)
ETD_Info_High			-1.712***	-0.012	-1.053***	-0.009
			(-5.41)	(-0.02)	(-5.58)	(-0.02)
$SUE \times ETD\_Res\_High$			0.071**	0.075	0.006	0.046
			(2.11)	(0.92)	(0.18)	(0.41)
ETD_Res_High			-0.972***	-0.748	-0.489*	-0.663
			(-4.37)	(-1.29)	(-2.03)	(-0.93)
Covariates	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE & YQ FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	92,262	90,202	92,262	90,202	92,262	90,202
Adjusted R-squared	0.173	0.044	0.173	0.044	0.174	0.044

Table 7: Abnormal Trading Volume

This table presents the effects of analyst and executive tone dispersion on stock trading volume upon earnings announcements. Following Hirshleifer, Lim, and Teoh (2009), daily abnormal trading volume is constructed as the difference between current daily trading volume and the average of daily trading volume over the past 30 days from day -40 to day -11. The dependent variable across all columns, $AbVol(0,1)$, is the two-day average abnormal trading volume over the earnings announcement date and the next day. The same covariates are included as with Table 4. $AbsSUE$, the absolute value of "SUE - 6", is further included into all regressions as an additional covariate. Standard errors are double-clustered at the industry level and year level, and t-statistics are reported with coefficients. ***, **, and * stand for statistical significance at the 1%, 5%, and 10% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
ATD_High	1.691***						1.551***		
	(3.21)						(3.08)		
ATD_Info_High		2.502***						2.402***	
		(5.69)						(4.38)	
ATD_Res_High		0.838*						0.663	
		(1.76)						(1.43)	
$ATD\_Info\_High(3TGs)$			2.398***						2.305***
			(4.34)						(3.35)
$ATD\_Res\_High(3TGs)$			0.789						0.624
			(1.71)						(1.40)
ETD_High				1.304**			1.059**		
				(2.89)			(2.55)		
ETD_Info_High					1.330**			0.546	
					(2.73)			(1.26)	
ETD_Res_High					0.754			0.020	
					(1.74)			(0.04)	
$ETD\_Info\_High(3TGs)$						1.260**			0.516
						(2.61)			(1.06)
$ETD\_Res\_High(3TGs)$						0.705			0.015
						(1.62)			(0.03)
Covariates	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE & YQ FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	92,263	92,263	92,263	92,263	92,263	92,263	92,263	92,263	92,263
Adjusted R-squared	0.364	0.364	0.364	0.364	0.364	0.364	0.364	0.364	0.364

Table 8: Alternative Measures as Robustness Checks

This table employs alternative measures and examines the robustness of main findings in previous tables. Panel A employs an alternative measure of tone dispersion. Specifically, we employ the FinBERT model and classify each sentence into either positive, negative, or tone-neutral categories and have them numerically labeled as 1, -1, and 0, accordingly. Then, instead of using the dispersion measure in Bachmann et al. (2013), we measure tone dispersion via calculating the standard deviation of a Q&A session's all sentences by analysts and executives, respectively. In Panel A, ATD_High (ETD_High) is defined as equal to one if the alternative measure of analyst (executive) tone dispersion is greater than its quarterly cross-sectional median, and zero otherwise. The "$Info$" and "Res" variables are constructed accordingly. Panel B employs measures of immediate share price responses to unexpected earnings using alternative windows: $CAR(-1,1)$ and $AbVol(-1,1)$ are employed to replace $CAR(0,1)$ and $AbVol(0,1)$. Standard errors are double-clustered at the industry and year levels, and t-statistics are reported with coefficients. ***, **, and * stand for statistical significance at the 1%, 5%, and 10% level, respectively.

Panel A: Alternative measures of tone dispersion

	(1) $CAR(0,1)$	(2) $CAR(0,1)$	(3) $AbVol(0,1)$	(4) $AbVol(0,1)$
SUE	0.688***	0.661***		
	(9.53)	(8.41)		
$SUE \times ATD\_High$	0.159***			
	(4.38)			
ATD_High	-1.400***		1.547***	
	(-5.10)		(3.163)	
$SUE \times ETD\_High$	0.124**			
	(2.61)			
ETD_High	-1.462***		1.043**	
	(-4.40)		(2.643)	
$SUE \times ATD\_Info\_High$		0.158***		
		(3.38)		
ATD_Info_High		-1.354***		2.202***
		(-3.92)		(3.48)
$SUE \times ATD\_Res\_High$		0.069***		
		(3.66)		
ATD_Res_High		-0.698***		0.572
		(-4.78)		(1.37)
$SUE \times ETD\_Info\_High$		0.109***		
		(3.93)		
ETD_Info_High		-1.046***		0.516
		(-5.36)		(1.02)
$SUE \times ETD\_Res\_High$		0.012		
		(0.35)		
ETD_Res_High		-0.534**		-0.193
		(-2.32)		(-0.40)
Covariates	Yes	Yes	Yes	Yes
Firm FE & YQ FE	Yes	Yes	Yes	Yes
Observations	92,726	92,726	92,727	92,727
Adjusted R-squared	0.173	0.174	0.364	0.364

Panel B: Alternative windows of outcome variables

	(1) $CAR(-1,1)$	(2) $CAR(-1,1)$	(3) $AbVol(-1,1)$	(4) $AbVol(-1,1)$
SUE	0.724***	0.690***		
	(9.08)	(8.06)		
$SUE \times ATD\_High$	0.176***			
	(4.05)			
ATD_High	-1.539***		0.977**	
	(-4.82)		(2.59)	
$SUE \times ETD\_High$	0.137**			
	(2.71)			
ETD_High	-1.592***		0.727**	
	(-4.53)		(2.15)	
$SUE \times ATD\_Info\_High$		0.193***		
		(3.87)		
ATD_Info_High		-1.657***		1.766***
		(-4.76)		(3.91)
$SUE \times ATD\_Res\_High$		0.079***		
		(3.90)		
ATD_Res_High		-0.811***		0.405
		(-5.69)		(1.03)
$SUE \times ETD\_Info\_High$		0.117***		
		(3.64)		
ETD_Info_High		-1.071***		0.215
		(-4.59)		(0.53)
$SUE \times ETD\_Res\_High$		0.009		
		(0.25)		
ETD_Res_High		-0.505*		-0.066
		(-2.09)		(-0.15)
Covariates	Yes	Yes	Yes	Yes
Firm FE & YQ FE	Yes	Yes	Yes	Yes
Observations	92,726	92,726	92,727	92,727
Adjusted R-squared	0.172	0.173	0.337	0.338

Table 9: Robustness to Ex-Ante Information Asymmetry

This table includes interaction terms of unexpected earnings and ex-ante information asymmetry measures, namely, $IdioVol$ and $AnaDispersion$. Standard errors are double-clustered at the industry and year levels, and t-statistics are reported in parentheses. ***, **, and * stand for statistical significance at the 1%, 5%, and 10% level, respectively.

	(1) $CAR(0,1)$	(2) $CAR(2,61)$	(3) $CAR(0,1)$	(4) $CAR(2,61)$
SUE	0.779***	−0.063	0.751***	−0.111
	(8.75)	(−0.81)	(8.08)	(−1.09)
$SUE \times ATD\_High$	0.147***	−0.080		
	(4.02)	(−1.02)		
ATD_High	−1.306***	0.815		
	(−4.66)	(1.36)		
$SUE \times ETD\_High$	0.103**	0.058		
	(2.30)	(0.71)		
ETD_High	−1.302***	−0.678		
	(−4.26)	(−1.03)		
$SUE \times ATD\_Info\_High$			0.160***	0.076*
			(3.63)	(1.88)
ATD_Info_High			−1.387***	−0.216
			(−4.44)	(−0.66)
$SUE \times ATD\_Res\_High$			0.061***	−0.020
			(3.01)	(−0.28)
ATD_Res_High			−0.657***	0.162
			(−4.43)	(0.37)
$SUE \times ETD\_Info\_High$			0.095***	−0.025
			(3.43)	(−0.39)
ETD_Info_High			−0.918***	−0.008
			(−4.80)	(−0.01)
$SUE \times ETD\_Res\_High$			−0.002	0.032
			(−0.06)	(0.31)
ETD_Res_High			−0.430*	−0.646
			(−1.86)	(−0.95)
$SUE \times IdioVol$	−1.045	1.660	−1.004	2.053
	(−0.46)	(0.49)	(−0.45)	(0.61)
$IdioVol$	24.300	10.156	24.122	7.490
	(1.42)	(0.25)	(1.43)	(0.19)
$SUE \times AnaDispersion$	−0.445***	0.092	−0.438***	0.104
	(−5.09)	(0.57)	(−5.07)	(0.65)
$AnaDispersion$	3.334***	−2.192*	3.298***	−2.270*
	(4.19)	(−1.79)	(4.18)	(−1.81)
Covariates	Yes	Yes	Yes	Yes
Firm FE & YQ FE	Yes	Yes	Yes	Yes
Observations	92,726	90,663	92,726	90,663
Adjusted R-squared	0.175	0.044	0.175	0.044

Online Appendix for
"The Information Content of Tone Dispersion: Evidence from Earnings Conference Call Q&As"

IA.1 Details of NMF

First, we create a large word bag from all the Q&A transcripts of these calls (D scripts in total) for a given industry by removing stop words like 'the' and 'is', and transforming words to their root forms—for instance, converting 'profits' to 'profit'. Based on this word bag[1], we can give a numeric index for every word in this word bag from the first word(1) to the last one(N). Secondly, we use this word bag to construct a Term-Count matrix, where a row represents a Q&A script and a column counts how many times a word in the word bag appears in the given Q&A script. Mathematically, its row vector can be defined as the follows: $\overrightarrow{row}_{scriptk} = [tf(w_1, script_k), tf(w_2, script_k), \cdots, tf(w_N, script_k)]$, where $tf(w_t, script_k)$ is the count of word (w_t) appearing in the *script k*. Now, we can represent all scripts as Figure IA.1.

[1] The word bag also contains the two-word phrase and three-word phrase according to standard Natural Language Process.

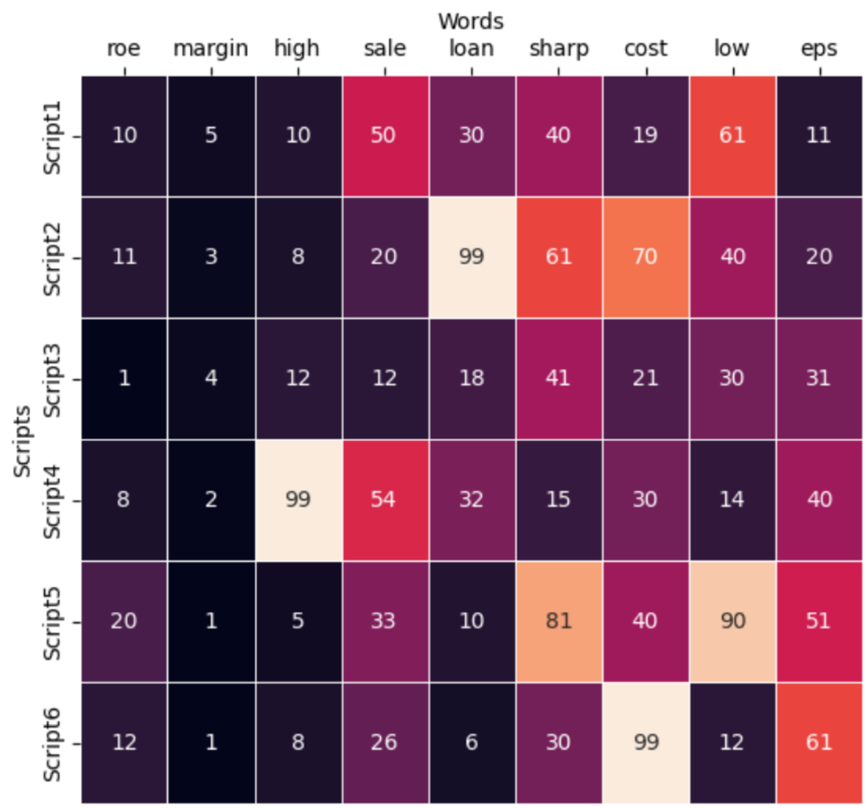

Figure IA.1: Word-Count Matrix

Next, we convert Word-Count matrix into TF-IDF(Term Frequency Inverse Document Frequency) matrix by calculating TF-IDF weight of every word in the Term-Count matrix. The TF-IDF weight is defined as:

$idf\,(w_i) = log\left[\frac{|D|}{1+|\{d:w_i \in D\}|}\right]$, where $|D|$ is the total number of scripts, $|\{d : w_i \in D\}|$ is the number of scripts where the word w_i appears. We add 1 into the formula to avoid zero-division. Then, we calculate TF-IDF weight as:

$TF - IDF(w_i, script_k) = tf(w_i, script_k) \times idf(w_i)$.

This formula has an importance consequence that a high weight of the tf-idf calculation is reached when we have a high word frequency(tf) in the given script(local parameter) and a low document frequency of the word in the whole collection of scripts(global parameter).

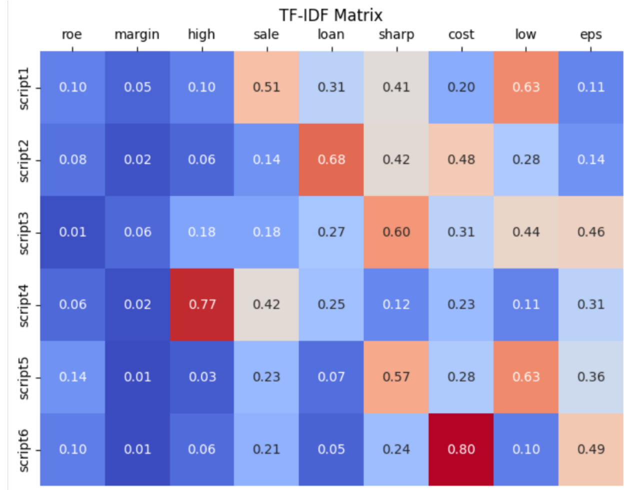

Figure IA.2: Term Frequency Inverse Document Frequency Matrix

Finally, we apply Non-Negative Matrix Factorization to decompose TF-IDF matrix into two non-negative matrices of the original n-words by K topics and those same K topics by the D original documents(See Figure IA.3).

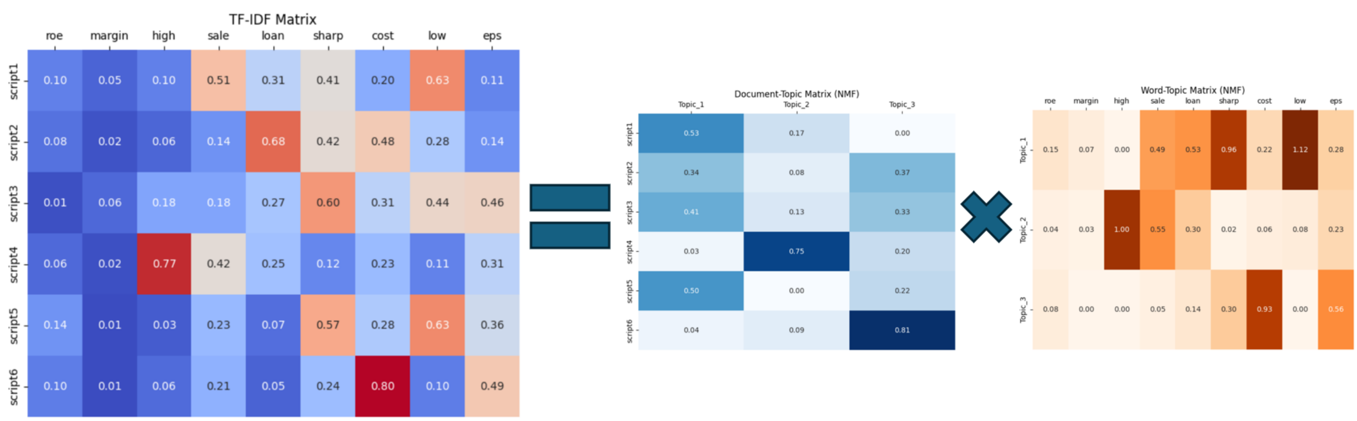

Figure IA.3: Non-Negative Matrix Factorization

In the result, the first matrix shows how possible a topic is included in a given script, and the second matrix represents how possible a word is in a given topic. The second matrix represents the topic model as it shows the loading of every words in a topic.

IA.2 Summary Statistics and Correlation Matrix

This table presents the summary statistics and the correlation matrix for the dependent variables, key independent variables, and covariates in empirical analyses. The sample period spans 2006Q1 - 2023Q4. $CAR(t_1, t_2)$ is the cumulative DGTW-adjusted return in percentage points over day t_1 to day t_2. Following Hershleifer, Lim and Teoh (2009), daily abnormal trading volume is constructed as the difference between the natural log of daily trading volume and the 30-day average of log daily trading volume from day -40 to day -11. $AbVol(0,1)$ is the two-day average of daily trading volume on the earnings announcement date and the very next day. Standardized unexpected earnings (SUE) are calculated as the difference between actually announced earnings per share and analyst forecast consensus, and then scaled by share price at the previous quarter end. Following Dellavigna and Pollet (2009), we sort all $SUEs$ into 11 quantiles where quantile 6 is for zero earnings surprises, quantiles 1-5 for negative earnings surprises, and quantiles 7-11 for positive earnings surprises. ATD (ETD) is analyst (executive) tone dispersion calculated using the dispersion measure in Bachmann et al. (2013) over what the analysts (executives) say during the Q&A session of an earnings conference call. Analyst tone level (A_Tone) and executive tone level (E_Tone) are calculated separately for analysts and executives as the differential between the numbers of positive and negative sentences scaled by the number of total sentences. $Friday$ is an indicator variable that equals one if a firm announces its quarterly earnings on a Friday. $Sameday\_EAs$ is the natural log of the total number of all other firms announcing their quarterly earnings on the same day. $MarketCap$ is the natural log of a firm's market capitalization. BM is the book-to-market ratio; $Leverage$ is the ratio of total liabilities over total assets; $Turnover$ is the ratio of trading volume over number of shares outstanding at the previous quarter end. Ret_l3m is a stock's holding period return for the previous quarter, and $Momentum$ is a firm's nine-month holding period return before Ret_l3m. $IdioVol$ is the standard deviation of a firm's daily stock returns in the past quarter. $InstOwn$ measures a firm's percentage ownership by 13f institutional investors. $FollowingAnalysts$ is the natural log of total number of estimates to form a firm's analyst consensus for its to-be-announced quarterly earnings. $AnaDispersion$ is the standard deviation of analyst earnings forecasts. All variables are winsorized at 1% each tail.

Panel A: Summary Statistics

Variable	N Obs	Mean	SD	P10	P25	Median	P75	P90
$CAR(0,1)$	116,668	0.148	7.282	-9.471	-4.082	0.040	4.277	9.518
$CAR(2,61)$	114,234	-0.288	17.972	-19.736	-9.454	-0.724	7.854	18.431
$AbVol(0,1)$	116,670	64.199	53.052	0.509	27.476	61.229	96.439	131.450
SUE	116,670	7.000	2.941	2.000	5.000	7.000	9.000	11.000
ATD	116,670	0.366	0.095	0.258	0.319	0.377	0.428	0.472
ETD	116,670	0.490	0.080	0.399	0.451	0.498	0.540	0.577
A_Tone	116,670	0.048	0.066	-0.032	0.000	0.045	0.088	0.131
E_Tone	116,670	0.173	0.091	0.059	0.110	0.169	0.233	0.294
$Friday$	116,670	0.052	0.223	0.000	0.000	0.000	0.000	0.000
$Sameday\_EAs$	116,670	4.490	1.007	2.944	4.060	4.796	5.220	5.447
$MarketCap$	116,670	14.509	1.693	12.385	13.296	14.424	15.594	16.841
BM	94,423	1.522	2.737	0.213	0.379	0.698	1.277	3.264
$Leverage$	94,670	0.241	0.198	0.000	0.067	0.219	0.369	0.508
$Turnover$	116,670	2.251	1.743	0.769	1.129	1.721	2.747	4.419
Ret_l3m	116,670	0.027	0.227	-0.240	-0.091	0.031	0.146	0.280
$Momentum$	116,670	0.092	0.398	-0.379	-0.119	0.093	0.292	0.538
$IdioVol$	116,670	0.021	0.013	0.009	0.012	0.017	0.026	0.036
$InstOwn$	115,122	0.760	0.230	0.434	0.667	0.825	0.928	1.000
$FollowingAnalysts$	116,670	2.129	0.631	1.386	1.609	2.079	2.639	2.996
$AnaDispersion$	116,670	0.084	0.199	0.010	0.010	0.030	0.070	0.160

Panel B: Correlation Matrix

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)
(1) $CAR(0,1)$	1.00																			
(2) $CAR(2,61)$	0.01	1.00																		
(3) $AbVol(0,1)$	-0.03	0.02	1.00																	
(4) SUE	0.32	0.02	0.01	1.00																
(5) ATD_High	0.03	0.01	0.10	0.09	1.00															
(6) ETD_High	0.00	0.01	0.12	0.07	0.48	1.00														
(7) A_Tone	0.22	0.03	-0.03	0.16	0.20	0.02	1.00													
(8) E_Tone	0.13	0.03	0.07	0.15	0.19	0.40	0.34	1.00												
(9) $Friday$	-0.01	0.00	-0.01	0.00	0.01	0.01	-0.03	-0.01	1.00											
(10) $Sameday\_EAs$	0.01	0.00	-0.19	0.01	-0.07	-0.07	0.03	-0.01	-0.35	1.00										
(11) $MarketCap$	-0.01	-0.01	-0.10	0.07	0.17	0.13	0.01	0.15	0.06	-0.05	1.00									
(12) BM	0.01	0.00	-0.16	-0.03	-0.07	-0.07	-0.07	-0.16	0.03	-0.02	-0.08	1.00								
(13) $Leverage$	-0.01	0.00	-0.01	-0.03	0.05	0.06	-0.01	0.05	0.03	0.03	0.15	-0.15	1.00							
(14) $Turnover$	-0.02	0.00	-0.02	-0.01	-0.05	-0.05	-0.02	-0.01	-0.02	-0.02	-0.03	-0.04	0.08	1.00						
(15) Ret_l3m	0.03	0.00	0.03	0.10	0.02	0.01	0.13	0.10	0.00	0.00	0.08	-0.08	-0.01	-0.03	1.00					
(16) $Momentum$	-0.01	-0.01	0.03	0.05	0.00	-0.02	0.11	0.09	-0.01	0.00	0.13	-0.12	-0.05	0.00	-0.03	1.00				
(17) $IdioVol$	0.01	0.00	-0.05	-0.07	-0.18	-0.16	0.00	-0.07	-0.05	0.06	-0.49	0.00	0.02	0.44	-0.06	-0.15	1.00			
(18) $InstOwn$	0.02	0.00	0.12	0.07	0.13	0.15	0.01	0.08	0.00	0.02	0.24	-0.10	0.08	0.13	0.01	0.04	-0.22	1.00		
(19) $FollowingAnalysts$	-0.01	0.00	0.00	0.06	0.14	0.12	-0.02	0.13	0.02	-0.06	0.69	-0.06	0.10	0.21	0.00	0.01	-0.23	0.24	1.00	
(20) $AnaDispersion$	-0.02	-0.03	-0.07	-0.11	-0.13	-0.13	-0.02	-0.08	0.01	0.02	-0.05	0.07	0.07	0.16	-0.03	-0.04	0.21	-0.11	-0.03	1.00

IA.3 Using Continuous Measures of Tone Dispersion

This table replicates the results in Table 4 but using the continuous raw measures of analyst and executive tone dispersion. All variables are defined in Appendix A1. Standard errors are double-clustered at the industry and year levels, and t-statistics are reported with coefficients. ***, **, and * stand for statistical significance at the 1%, 5%, and 10% level, respectively.

	(1) $CAR(0,1)$	(2) $CAR(2,61)$	(3) $CAR(0,1)$	(4) $CAR(2,61)$	(5) $CAR(0,1)$	(6) $CAR(2,61)$
SUE	0.828***	-0.020	0.821***	-0.017	0.829***	-0.018
	(17.08)	(-0.40)	(16.72)	(-0.34)	(18.46)	(-0.37)
$SUE \times ATD$	0.119***	0.004			0.088***	-0.015
	(5.48)	(0.08)			(5.50)	(-0.42)
ATD	-1.111***	-0.019			-0.811***	0.126
	(-6.89)	(-0.06)			(-6.41)	(0.45)
$SUE \times ETD$			0.111***	0.039	0.071***	0.045
			(3.91)	(0.95)	(3.38)	(1.34)
ETD			-1.245***	-0.320	-0.912***	-0.374
			(-4.70)	(-0.99)	(-4.15)	(-1.26)
A_Tone	19.154***	4.481***	17.983***	4.360***	18.351***	4.341**
	(10.29)	(2.99)	(10.43)	(2.91)	(10.40)	(2.85)
E_Tone	7.754***	5.280***	9.127***	5.400***	8.958***	5.417***
	(9.61)	(3.41)	(9.57)	(3.44)	(9.44)	(3.44)
$Friday$	0.077	-0.498	0.081	-0.497	0.090	-0.498
	(0.56)	(-1.26)	(0.59)	(-1.25)	(0.65)	(-1.25)
$Sameday\_EAs$	-0.028	-0.099	-0.029	-0.099	-0.025	-0.100
	(-0.74)	(-0.65)	(-0.81)	(-0.64)	(-0.68)	(-0.63)
$MarketCap$	-0.788***	-4.208***	-0.811***	-4.211***	-0.805***	-4.211***
	(-5.19)	(-8.29)	(-5.26)	(-8.30)	(-5.29)	(-8.27)
BM	0.141***	0.211	0.141***	0.210	0.138**	0.210
	(3.00)	(1.09)	(2.99)	(1.09)	(2.88)	(1.09)
$Leverage$	-0.293	-1.207	-0.246	-1.205	-0.268	-1.200
	(-1.02)	(-0.94)	(-0.81)	(-0.93)	(-0.90)	(-0.92)
$Turnover$	-0.028	0.012	-0.026	0.012	-0.029	0.012
	(-0.76)	(0.07)	(-0.74)	(0.07)	(-0.80)	(0.07)
Ret_l3m	-0.451	-0.924	-0.472	-0.940	-0.495	-0.937
	(-1.19)	(-0.80)	(-1.24)	(-0.82)	(-1.31)	(-0.82)
$Momentum$	-0.762***	-0.991	-0.778***	-1.001	-0.793***	-0.998
	(-4.44)	(-1.47)	(-4.33)	(-1.51)	(-4.46)	(-1.49)
$IdioVol$	18.015**	20.799	17.878**	20.541	17.360**	20.604
	(2.28)	(0.64)	(2.30)	(0.63)	(2.23)	(0.63)
$InstOwn$	0.374	-2.722*	0.418	-2.719*	0.409	-2.718*
	(0.79)	(-2.09)	(0.88)	(-2.05)	(0.86)	(-2.05)
$FollowingAnalysts$	-0.053	-1.098*	-0.056	-1.093*	-0.040	-1.095*
	(-0.38)	(-2.02)	(-0.40)	(-2.00)	(-0.29)	(-2.01)
$AnaDispersion$	0.683*	-1.679	0.712*	-1.685	0.674*	-1.679
	(1.80)	(-1.20)	(1.90)	(-1.20)	(1.78)	(-1.20)
Firm FE & YQ FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	92,726	90,663	92,726	90,663	92,726	90,663
Adjusted R-squared	0.173	0.044	0.174	0.044	0.175	0.044