Is Tone in Voluntary Disclosure Credible?

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January 11, 2024

Abstract

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JEL classification: G14, G18, G28, G41
Keywords: Disclosure tone, 8-K, Voluntary disclosure, Restatement

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Abstract

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1. Introduction

This paper examines managers' use of tone in voluntary disclosures in their 8-K filings. The literature has established that managers use voluntary disclosures to favorably influence market perceptions (Aboody and Kasznik 2000; Nagar et al. 2003; Graham et al. 2005; Hermalin and Weisbach 2007; Verrecchia 2001; Langberg and Sivaramakrishnan 2010). A consensus is emerging in the literature is that tone also plays a significant role in shaping market expectations (Loughran and McDonald 2011; Feldman et al. 2010). However, it is not clear whether the *tone* of voluntary disclosures would contribute to price discovery because it is difficult for market participants to ascertain credibility of tonal nuances, especially in textual voluntary disclosures. Yet, even a casual parsing of voluntary disclosures in 8-K filings reveals that firms often punctuate their narratives with tonal slants. Thus, whether tone does influence price discovery, and whether firms indeed benefit from the strategic use of tone, is an open empirical question.[1]

As voluntary disclosures are not subject to external statutory audits, their credibility is ostensibly a concern. Therefore, firms have a natural incentive to assure outsiders of the credibility of their disclosures to achieve desired price effects. *Quantitative* voluntary disclosures (i.e., earning forecasts, sales guidance, projections of R&D spending) are ex post verifiable to a degree, which limits the extent to which firms can be strategic (e.g., bias or be misleading) with these disclosures. Firms arguably have a greater leeway to be strategic in communicating *qualitative* information (i.e., expectations about future trends, likely corporate response to such trends, planned future initiatives) because of lack of ex post verifiability. Therefore, disclosing qualitative information arguably lends itself to the strategic use of tone to influence outside perceptions. But it is unclear why market participants would react to such tonal nuances—which raises an important question. Does tone influence price discovery despite its credibility being arguably suspect? In other words, do firms benefit from

[1] We use the term "strategic use of tone" throughout the paper to refer to a firm's incentive to favorably influence (i.e., by exaggerating good news or softening bad news) outsiders' perceptions.

using tone strategically in their voluntary disclosures?

Conceptually, tonal exaggerations are akin to bias in disclosures. Consider the following excerpt from an 8-K disclosure.

> *"...these issues were definitely undervalued by the market and we are seeing meaningful price appreciation."*

In this excerpt, the word *definitely* is clearly intended to accentuate the positive tone of the statement—such textual accentuation is similar in spirit to a positive bias. Early disclosure models assume that managers can choose between disclosing and staying silent, but rely on ex post verifiablity to assume disclosures are credible when made (Grossman 1981; Verrecchia 1983; Dye 1985). These models leave no room for studying biased tonal nuances in voluntary disclosures.

However, recent theoretical models provide some insight into whether and when biased disclosures might emerge in equilibrium. Stein (1989) characterizes an equilibrium in which managers take costly myopic actions to bias disclosures despite realizing that efficient markets can fully unravel their strategic intent. Fischer and Verrecchia (2000) shows that some firms stand to benefit from biasing disclosures provided the markets—though rational and efficient—are uncertain about managerial motives. Shin (1994) employs a "persuasion" framework to make the point that highlighting good news but suppressing bad news (telling the truth but not telling the *whole* truth) can help sway market beliefs. More salient in our context is the result in Einhorn and Ziv (2012) that even if the credible disclosure assumption of Grossman (1981), Verrecchia (1983), and Dye (1985) were relaxed, the equilibrium bias level can be monotonically increasing in the true information content underlying the disclosure, implying bias does convey information.

A key assumption underlying (most of) these models is that biasing is personally costly to managers for a variety of reasons including personal distaste for misreporting, reputation losses, and litigation costs. As Einhorn and Ziv (2012) observes, such costs distinguish them from cheap talk models. Under the reasonable premise that textual biases such as tonal exaggerations also impose similar costs on managers, these papers provide a theoretical backdrop for why tone might contribute to price discovery.

We have three specific empirical objectives. First, we use a state-of-the-art text parsing technology to capture tonal exaggerations/understatements and characterize cross-sectional and time-series variations in tone. Second, we examine whether tone is informative to markets in price discovery. Third, we examine whether managers use tone strategically in voluntary disclosures made before or after financial restatements.

Existing studies measure tone using simple counts of negative and positive words or dictionaries proposed by Loughran and McDonald (2011) (hereafter LM) (Purda and Skillicorn 2015; Drake et al. 2016; Glendening et al. 2019). While the use of positive and negative words contribute to tone, the use of adjectives, adverbs, and conjunctions (hereafter valence shifters) represent tonal exaggerations/understatements of the words they modify (Anand et al. 2021). The literature on the use of valence shifters is developing but sparse. We use a valence shifter-based methodology (hereafter VSM) to better understand the tone of voluntary disclosures in 8-Ks.

We focus on voluntary disclosures in items 7.01 and 8.01 of 8-K filings as they are an important source of information to the market (He and Plumlee 2020).[2] In related research, Allee and DeAngelis (2015) shows that tone dispersion (the degree to which tone words are spread evenly within a narrative) of conference calls (i) varies in the cross-section with firm performance and reporting choices, and (ii) is associated with the *tone* of financial analysts' questions, which in turn is associated with the market's response. Burks et al. (2018) use disclosure tone (based on positive and negative words) to study the interaction between competition and voluntary disclosure in press releases from the banking industry. However, these studies do not examine whether firms benefit (in terms of desired price effects) from the strategic use of tone in qualitative voluntary disclosures.

[2] See Section 2 for a detailed discussion.

We quantify the tone of voluntary disclosures in items 7.01 and 8.01 of 8-K filings using the LM dictionary along with valence shifters and sentence level analysis. Valence shifters are classified into four categories: amplifiers ("absolutely", "very", "acutely"), de-amplifiers ("few", "faintly", "barely"), negators ("not", "cannot"), and adversative conjunctions ("although", "despite", "but"). These valence shifters are given a certain weight: positive for an amplifier, negative for a de-amplifier, negative for the words before an adversative conjunction, and positive for the words after an adversative conjunction. (See Section 3 for details).[3] To see how this approach differs from LM, consider the following statement form the 8-K of Alexander and Baldwin, Inc. in 2004:

> *"...as described in the company's most recently filed Form 10-Q, 2004 earnings have been very favorable, surpassing 2003 in just the first nine months of the year."*

The score of this sentence using the bag-of words approach in the LM dictionary is 0.25. However, the sentence has one valence shifter "very," which is an tonal amplifier for the word "favorable." The altered score using the VSM is 0.31, representing a 24% change in tonality. Such valence-shifters constitute a mechanism by which firms can strategically introduce textual biases in their qualitative disclosures. The question we are interested in is whether such valence shifters can lead to significant difference in capturing how tone is interpreted in the markets and in the predictive ability of tone.

In examining cross-sectional variations in tone by industry, we find that the median tone is consistently negative for both the LM and VSM measures indicating that, on average, firms show a propensity to understate and not exaggerate news conveyed by qualitative voluntary disclosures. One plausible explanation is that in the face of uncertainty, an *average* firm would rather "low-ball" future expectations. However, the question is whether tactical considerations would drive a firm to strategically exaggerate/understate qualitative

[3]This is because adversative conjunctions such as "but" will amplify tone of the ensuing text and weight down the tone of the preceding text.

disclosures. We find that the VSM methodology is remarkably successful at detecting such exaggerations and understatements relative to the LM method.

On the question of whether tone contributes to price discovery, we find that tone in the 8-K filings is positively, and incrementally associated with cumulative abnormal returns after controlling for other information and news that could drive abnormal returns. We also find that tone is positively related to stock liquidity after accounting the quantity of disclosure. These positive associations indicate that market participants ascribe a degree of credibility to the tone of voluntary disclosures, consistent with the theoretical insight provided by Einhorn and Ziv (2012). Moreover, our results are stronger when we use the VSM method (relative to the LM method) to measure tone.

We use financial restatements as a setting to investigate managers' strategic use of tone when they are likely have private information. The literature posits that market participants may have limited resources and high information processing costs when reacting to news. For example, Hirshleifer et al. (2009) shows that when firms announce their earnings and other information on the same day, investors' attention to one firm's earnings can be distracted by irrelevant information. Driskill et al. (2020) demonstrates that financial analysts are similarly distracted although they are viewed as sophisticated market participants and arguably have the ability to filter out noise. Therefore, we hypothesize that managers, when privy to impending bad news, might seek to distract market participants by using tone to strategically exaggerate *other* positive news. To test this hypothesis, we examine the tone of voluntary disclosures in 8-K filings before and after financial restatements, and find evidence that managers modulate tone strategically. Specifically, the tone of voluntary disclosures is more *positive* in the period *prior* to a restatement, and is more *negative* in the period *after* the restatement.

In additional analysis, we use FinBERT—a methodology based on BERT NLP—to construct an alternate measure of tone. Huang et al. (2023) shows that FinBERT outperforms a slew of other machine learning algorithms in capturing the tone of financial texts. FinBERT classifies words as positive, neutral, or negative based on its computation of probability of words belonging to each category. It uses a discretization technique to quantify tone, but does not take into account the effect of valence shifters. We re-examine all our tests using FinBERT and again find that VSM is relatively more sensitive to tonal nuances than FinBERT. Specifically, we find positive significant associations between FinBERT and abnormal returns, however we fail to find any significant association with liquidity or likelihood of restatement.

Our paper contributes to the empirical literature on voluntary disclosure in 8-K filings by demonstrating management's strategic use of tone consistent with incentives they face when making voluntary disclosures. We examine the implications of tone using three measures, LM, FinBERT, and a measure that accounts for the role of valence shifters (Adjectives, Adverbs and Adversative Conjunctions) in determining the tone of a disclosure. Using these measures, we show that market attaches a degree of credibility to tone as it aids price discovery, and that managers strategically use tone to sway market expectations. Finally, we extend the prior research on the appeal of valence shifter methodology in capturing tonal nuances in textual disclosures.

The paper proceeds as follows. Section 2 motivates our paper and presents our hypothesis. Section 3 describes the data and methodology. Section 4 presents the results. Section 5 provides additional analyses and section 6 concludes.

2. Hypotheses and Context

2.1. Hypotheses

There is evidence in the literature that the tone of mandatory financial disclosures affects market prices. Anand et al. (2023) show that the valence shifters of 10-K filings, especially the tone in the MD&A section, explain subsequent return volatility. Furthermore, the tone of other regulatory communications such as the FED Board of Governors' speech moves markets (Anand et al. 2021). In the banking industry, Burks et al. (2018) provide evidence that press releases become increasingly negative in tone as barriers to entry decrease. In related research, Allee and DeAngelis (2015) show that tone dispersion (the degree to which tone words are spread evenly withing a narrative) of conference calls varies in the cross section with firm performance, and reporting choices.

To the best of our knowledge, prior research has not studied the tone in the voluntary disclosures captured in the 8-K. He and Plumlee (2020) explains the importance of 8-K filings in studying voluntary disclosures by noting that the SEC requirements for the 8-K filings cover a broader span of voluntary disclosure channels (See Section 2.2). While He and Plumlee (2020) characterizes the *amount* of voluntary disclosure in the 8-K, it does not speak to the tone of these disclosures. As noted previously, tonal nuances become especially salient with respect to disclosures that are inherently qualitative in nature and lack ex post verifiabiity. Consider the following excerpts form Exxon Corp's announcement on Dec 8, 2022:

> *"...Investments in 2023 are expected to be in the range of $23 billion to $25 billion to help increase supply to meet global demand. The company also remains on track to deliver a total of approximately $9 billion in structural cost reductions by year-end 2023 versus 2019."*

> *"...ExxonMobil Product Solutions expects to nearly triple earnings by 2027 versus 2019. These growth plans are focused on high-return projects that are anticipated..."*

The tone of these announcements is clearly positive (e.g., the use of words such as "nearly triple" and "high-returns"). While Exxon's corporate reputation and image arguably bring some credibility to this announcement, there no mechanism by which stakeholders can ascertain whether the company faithfully intends to deliver on its expectation of tripling earnings or whether its intent is more strategic in nature. Such lack of verifiability arguably handicaps markets and contracts from acting as disciplining mechanisms.[4]

It is well accepted in the literature that managers of publicly held firms have incentives to influence outside stakeholders' beliefs favorably via strategic disclosures. For example, Aboody and Kasznik (2000) document that CEO time their voluntary disclosure decisions to maximize stock option awards. Nagar et al. (2003) find that managers issue forecasts more frequently when their compensation is tied to the company's stock prices. Bao et al. (2019) provides evidence that managers tend to withhold bad news to prevent adverse impact on stock prices. Given these strategic incentives, a positive and proactive tone—if viewed as credible—could beneficially impact prices while a negative or defensive tone could erode confidence and trust. The question is whether, and to what extent, outsiders can decipher and discount the *strategic* use of tone in qualitative voluntary disclosures, or whether they still attach a measure of credibility to tone (despite being cognizant of its (potentially) strategic use by managers).

As previously noted, tonal exaggerations in textual disclosures are similar in spirit to biased quantitative disclosures. Recent theoretical literature provides some guidance on why, in equilibrium, managers might engage in biased disclosures to capital markets even given that these markets are rational and efficient. Fischer and Verrecchia (2000) shows that as long as market participants are uncertain about managerial motives, some managers can benefit from engaging in personally costly reporting biases to favorably influence market perceptions because the market is unable to fully adjust for the bias. However, the level of the equilibrium reporting bias is decreasing in the extent of this uncertainty. A direct implication for our analysis is that in the presence of such uncertainties, the market may partially but not fully discount tonal exaggerations, allowing managers some room to benefit from strategically using tone.

[4] This issue of ex post verifiability is less of a concern in the context of mandatory financial reports and filings which are subject to external audits.

In addition, Einhorn and Ziv (2012) shows that the "upper-tailed" disclosure results of Verrecchia (1983) and Dye (1985) are robust to relaxing the assumption that disclosures, when made, are credible and truthful.[5] More importantly, Einhorn and Ziv (2012) shows that relaxing the credible disclosure assumption also permits biased disclosure in equilibrium, and that the equilibrium bias level is *increasing* in the true information content underlying the disclosure. This result essentially implies that disclosure biases and tonal nuances possess information content in equilibrium and will be priced the market, and we should expect to see a relation between tone and abnormal returns. Even if the market is not certain about managerial incentives (Fischer and Verrecchia 2000), as long as it views some managers as using tone to convey information, we should once again expect to see a relation between tone and abnormal returns (perhaps muted).

Thus, under the premise that managers view disclosure tone to be helpful in altering outsiders' perceptions and contributes to price discovery, we examine the incremental association of tone in the 8-K filings with the abnormal returns around their release. Formally, we test the following hypothesis:

Hypothesis 1: *The cumulative abnormal returns surrounding 8-K filings is positively associated with the tone of voluntary disclosures in the filings.*

In prior work, Lerman and Livnat (2010) document significant return volatility and abnormal trading volume around 8-K filings, implying that these filings convey information to the market. In addition to the content of these filings, our premise is that the *way* managers convey information is useful to investors (i.e., tonal nuances are associated with price effects).

The literature suggests that voluntary disclosures reduce information asymmetry between managers and shareholders and improve stock liquidity. For example, He and Plumlee (2020) shows that quantitative 8-K based measures of voluntary disclosure affect stock liq-

[5]The "upper-tailed" disclosure result refers to the equilibrium result in which credible disclosure if news being disclosed is sufficiently good—i.e., beyond a certain disclosure threshold, and there is no disclosure otherwise.

uidity and bid-ask spreads. To the extent tone contributes to price discovery, we hypothesize that tone has an incremental effect on liquidity and bid-ask spreads.

Hypothesis 2: *Tone has a positive effect on stock liquidity. That is, a positive (negative) tone increases (decreases) stock liquidity.*

Hypothesis 3: *Tone has a negative effect on bid-ask spreads. That is, a positive (negative) tone decreases (increases) bid-ask spreads.*

While the above hypotheses speak to the impact of tone on price discovery per se, we are also interested in seeking evidence on whether managers use tone *strategically*. To this end, we appeal to prior research which suggests that limited attention on the part of investors provides an opportunity for managers to engage in strategic behavior. Hirshleifer et al. (2009) documents that when many different firms announce both earnings and other information on the same day, investor attention to firms' earnings can be distracted by irrelevant information. High disclosure processing costs and limited resources further constrain individual investors.

Does this limited attention theory apply to more sophisticated investors? There is some evidence suggesting that it does. Driskill et al. (2020) finds that financial analysts are less likely to issue timely forecasts/stock recommendations and ask questions during conference calls when another firm in their portfolio announces earnings on the same day. Accordingly, it is reasonable to posit that when faced with impending bad news, firms may perceive a benefit by distracting investor attention by voluntarily disclosing and exaggerating *other* positive news. We examine this conjecture in the context of accounting restatements.

Specifically, we test the hypothesis that when managers are privy to upcoming financial restatements, they may stand to benefit by distracting investors and presenting other news in 8-K filings with a more favorable tone (such as information about expected future returns from an investment or new acquisition opportunity). Formally, we test the following hypothesis on the strategic use of tone in this setting:

Hypothesis 4: *Tone is positively related to subsequent restatement. That is, a positive* *tone is associated with a higher likelihood of subsequent restatement.*

In a related paper, Dechow et al. (2011) examines economic and firm-specific factors that can predict future restatements. Support to Hypothesis 4 would indicate that 8-K disclosure tone also has predictive ability. To glean additional insight, we also examine whether disclosure tone changes from *before* to *after* the restatement.

2.2. The Context of 8-K Filings

In this subsection, we offer a motivation for why we choose voluntary disclosures in 8-K filings as our context. A primary reason is that 8-K filings are an important source of information to the market (He and Plumlee 2020). Drake et al. (2015) report that 8-K filings are one of the most accessed filings by investors from the SEC's EDGAR database. These filings serve as a way for companies to communicate qualitative information about significant developments such as mergers and acquisitions, executive changes, legal proceedings, and other important business events to stakeholders. When filing an 8-K, firms select from the 32 possible reporting items that identify the type of event being reported. Prior literature classifies items 7.01 and 8.01 in 8-Ks as containing disclosures that are voluntary in nature (Lerman and Livnat 2010; Segal and Segal 2016; He and Plumlee 2020). While the SEC mandates certain disclosures, companies often go beyond those requirements voluntarily to provide a greater understanding of their business activities in items 7.01 and 8.01 of their 8-K filings.

Therefore, it is not surprising that many papers use 8-K filings as a proxy for disclosure. For instance, Leuz and Schrand (2009) shows that 8-K filings increase around the Enron Scandal; Lerman and Livnat (2010) examines stock price reaction around 8-K filings; Guay et al. (2016) studies the relation between financial statement complexity and number of 8-K filings; Segal and Segal (2016) examines the relation between positive/negative tone in 8-K filings and the timing of disclosure.[6] Thus, disclosures in items 7.01 and 8.01 of 8-K filings provide us with a unique opportunity to examine the implications of tone in voluntary disclosures.

We quantify the tone of the 8-K voluntary disclosure sections using valence shifters, adverbs, adjectives, and adversative conjunctions, along with the existing Loughran and McDonald (2011) dictionary with sentence as the base unit of analysis. Such valence shifters are arguably used for a reason—to evoke a certain intended reaction from the recipients of information. As a first step, we examine whether our quantification of tone better captures the exaggerations and understatements that are attributable to the use of adjectives and adjectives relative to the simple bag-of-words LM approach.

3. Data and Methodology

3.1. Data

We begin by downloading all 8-K filings with two voluntary 8-K items (items 7.01 and 8.01) from the SEC EDGAR. Our sample period spans from January 2004 to December 2021. The SEC changed 8-Ks and its filing requirements to include items 7.01 and 8.01 in 2005. However, even in 2004 a substantial number of firms were filing 8-Ks with items 7.01 and 8.01. We obtain accounting data from the quarterly Compustat and stock-related data from CRSP. We then merge 8-K filings to Compustat and CRSP to calculate liquidity measures and firm-level characteristics. Finally, we obtain analyst data from IBES and financial restatements data from Audit Analytics. We winsorize all continuous variables at 1% and 99% to mitigate outlier effects. Our final sample consists of 200,788 firm-quarter observations.

[6] In other studies, Bourveau et al. (2018) reports that firms issue more 8-K filing the adoption of Universal Demand (UD) laws. Bao et al. (2019) reports that managers withhold negative private information using number of voluntary items in 8-K filings as the proxy for voluntary news. Ellahie et al. (2019) uses the same measure and report that more disclosure increases firms risk premium when long-term growth rate exceeds the threshold.

3.2. Tone Quantification

We quantify the tone of the text using the Loughran and McDonald dictionary (Loughran and McDonald 2011) along with valence shifters (adverbs and adjectives) and sentence level analysis (Anand et al. 2021). We classify valence shifters into four categories: amplifiers ("absolutely", "very", "acutely"), de-amplifiers ("few", "faintly", "barely"), negators ("not", "cannot") and adversative conjunctions ("although", "despite", "but"). The amplifiers, de-amplifiers, and adversative conjunctions are given a weight of 0.8: positive for an amplifier and for the words after adversative conjunction, negative for a de-amplifier and for the words before adversative conjunction. This is because adversative conjunction such as "but" will amplify the tone after it and weigh down the tone before it. The default weight of 0.8 is as per the existing literature (Kennedy and Inkpen 2006; Polanyi and Zaenen 2006; Schulder et al. 2018) which is the weight as agreed upon by the individual and independent annotators. Schulder et al. (2018) gave varied texts with and without the valence shifters, annotators agreed that the weight of 0.8 seems to be the most suitable with respect to the impact of valence shifters on tonal words. However, we verify our results by varying the weight of valence shifters from 0.5 to 0.9 and confirm that our findings continue to hold.

We use the following sentence taken from the item 8.01 of the 8-K of Alexander and Baldwin, Inc. in 2004 to illustrate the process of tone quantification.

> *"as described in the company's most recently filed form 10-q, 2004 earnings have been very favorable, surpassing 2003 in just the first nine months of the year."*

The score of this sentence using the bag-of-words approach and LM dictionary is:

$$\frac{(+1)[=\text{favorable}] + (+1)[=\text{surpassing}]}{8} = +0.25$$

However, the sentence has one valence shifter, "very," which is an amplifier for the tonal word "favorable." Thus, the altered score using VSM is:

$$\frac{(+1.8)[=\text{very favorable}] + (+1)[=\text{surpassing}]}{9} = +0.31$$

That is a change in tonality of 24% for a single sentence.

Figure 1 presents the median tone calculated using both LM and VSM for the 8-K text for section 7.01 and 8.01 from 2004 to 2021. The median tone is negative for overall text as well as for items 7.01 and 8.01 of 8-Ks. We also observe that the tone become more negative post-2019. We find that the median tone calculated using the VSM is more negative as compared to the tone calculated using the LM methodology. This is due to the usage of valence shifters and is further examined in the sub-section 4.1.

[Figure 1 about here.]

Figure 2 presents the median tone calculated using both LM and VSM for years between 2004 and 2021 for each Fama French 12 industries. We observe that the median tone is mostly negatively except for healthcare, manufacturing, chemicals and utilities industries.

[Figure 2 about here.]

3.3. Summary Statistics

Panel A of Table 1 provides summary statistics of the variables we use in this paper. Mean *Tone VSM* and *Tone LM* measures are negative, suggesting that on average firms are cautious in the language they use in their disclosures. We also find that about 17% of sentences include valence shifters. The average firm in our sample is mature with mean firm age of about 20 years, has a mean analyst following of 6.7 and operates in roughly 4 segments.

Panel B of Table 1 reports average values of tone measures, percentage of valence shifters and forward-looking statements for each of the Fama-French 12 industries. Chemicals and allied products, business equipment, and telephone industries have the most negative *Tone VSM*. Note that the same three industries also have the most negative tone as measured by *Tone LM* as well. We find that the utilities and energy industries have the highest percentages of the usage of valence shifters and forward-looking statements.

Panel C of Table 1 reports average values of tone measures, percentage of valence shifters and forward-looking statements for each year in our sample. This panel reveals a couple of interesting facts. First, it appears that over time *Tone VSM* is becoming less negative, while this trend is less manifested in *Tone LM*. Second, the percentage of valence shifters has been steadily increasing between 2004 and 2021 while the percentage of forward-looking statements is about the same during this period. Less negative *Tone VSM* and higher percentage of valence shifter usage provides initial evidence suggesting that firms are increasingly using valence shifters to make the tone of their disclosures less negative.

[Insert Table 1 Here.]

4. Results

4.1. Do Firms Over/Under Exaggerate News

We begin by characterizing how firms use valence shifters to shape the tone of voluntary disclosures in 8-K filings. Do firms over-exaggerate news or moderate them? Does this over-exaggeration/moderation depend on the *nature* of the news? We interpret news as good or bad news based on the *sign* of *Tone LM*. Under the premise that managers have incentive to convey any news in favorable terms, we expect they would increase the positive tone of good news and decrease the negative tone of bad news using valence shifters (adverbs and adjectives). That is, we expect that *Tone VSM* would be more positive when *Tone LM* tone is positive, and that *Tone VSM* would be less negative when *Tone LM* tone is negative.

Table 2 presents our findings. Referring to the first row, when both *Tone VSM* and *Tone LM* measures are positive, the magnitude of *Tone VSM* is significantly greater than the *Tone LM* tone. In particular, *both* tone measures are positive in 5% of the cases, and for approximately 84% of these 5% cases, *Tone VSM* is more positive than *Tone LM*. The mean value of *Tone VSM* also significantly higher than *Tone VSM*. Thus, firms appear to exaggerate positive news using valence shifters. Similarly, the second row presents the cases when both *Tone VSM* and *Tone LM* measures are negative, which happens for 28% of the sample. Interestingly, for 75% of these 28% cases, *Tone VSM* is less negative than *Tone LM*. Thus, as per our expectations, firms appear to exaggerate positive news and soften negative news using valence shifters.

[Table 2 about here.]

Similar to He and Plumlee (2020), we next examine whether tone varies systematically across quintiles of key firm characteristics—Total Assets, Market Value of Equity, Number of Analysts, Number of Business Segments, Firm Age, Return on Asset, Book to Market, R&D expenses, Competition.

Referring to Figure 3, some interesting patterns emerge. Both small and large firms appear to have a less negative tone (on average) relative to medium-sized firms. However, tone appears to become less negative on average with respect to the market value of equity (MVE), although this relation is not fully monotonic. A similar trend holds with respect to analyst following as well. Mature firms (firm age) and value firms (higher BTM firms) appear to adopt a more negative tone in their 8-K voluntary disclosures.

[Figure 3 about here.]

4.2. Tone and price discovery

Hypothesis 1 predicts that tone of the voluntary disclosure content in 8-Ks will bear a positive association with cumulative abnormal returns triggered by their filing. Following Lerman and Livnat (2010), we calculate the cumulative abnormal returns (CARs) during three days centered on the filing date using a Fama-French three-factor model. We use the following specifications to test this hypothesis:

$$CAR_{i,t} = \alpha_0 + \alpha_1 Tone_{i,t} + \alpha_2 Controls_{i,t} + FE + \epsilon_{i,t}, \tag{1}$$

where i and t are firm and time (quarter) subscripts. Following Lerman and Livnat (2010), we control for the market value of equity (MVE), book to market ratio (BTM), Size, ROA, R&D, and Competition. Panel A of Table 3 presents the impact of tone calculated using both *Tone LM* and *Tone VSM* measures. We find that the *Tone VSM* measure, which is calculated using valence shifters, loads positively, implying an increase in positive tone (decrease in negative tone) is associated with an increase in cumulative abnormal return around 8-K filing. On the other hand, the *Tone LM* measure does not seem to have any explanatory power. Panel B of Table 3 presents results for item 7.01 and 8.01 8-K filings separately. The results with respect to *Tone VSM* are consistent with those reported in Panel A. While the association between *Tone LM* and CAR remains insignificant for item 7.01 8-Ks, it is positive and significant for item 8.01 8-Ks.

[Table 3 about here.]

Hypothesis 2 predicts that disclosure tone, and in particular the use of valence shifting to shape tone, has a positive impact on stock liquidity by attracting greater investor attention. We test this association using the Amihud measure of illiquidity calculated using daily return and volume (Amihud 2002). We use the following regression specification.

$$Amihud\_Illiquidity_{i,t+1} = \alpha_0 + \alpha_1 Tone_{i,t} + \alpha_2 LPrice_{i,t} + \alpha_3 LVolume_{i,t} + \alpha_4 BTM_{i,t} + \alpha_5 TA_{i,t} + FE + \epsilon_{i,t}, \tag{2}$$

where i and t are firm and time (quarter) subscripts. We calculate the Amihud measure using the average value of daily returns over the quarter following the 8-K filings (i.e., quarter $t+1$). Panels A and B of Table 4 presents the results. Odd columns reports the results with levels (changes) of Amihud Illiquidity measure. We calculate changes as the average Amihud Illiquidity from quarter $t-1$ to quarter $t+1$. Consistent with hypothesis 2, we find that the *Tone VSM* measure, calculated using valence shifters, is negatively associated with the Amihud illiquidity measure for both item 7.01 and 8.01 8-K filings combined as well as for item 8.01. In contrast, *Tone LM* measure does not exhibit any such association with the Amihud measure.

[Table 4 about here.]

Hypothesis 3 predicts that disclosure tone has a negative impact on bid-ask spreads. We test this association the following regression specification.

$$BidAsk\_Spread_{i,t+1} = \alpha_0 + \alpha_1 Tone_{i,t} + \alpha_2 LPrice_{i,t} + \alpha_3 LVolume_{i,t} + \alpha_4 BTM_{i,t} + \alpha_5 TA_{i,t} + FE + \epsilon_{i,t}, \tag{3}$$

where i and t are firm and time (quarter) subscripts. We measure bid-ask spread as the average value of daily quoted bid-ask spread over the quarter following the quarter of the 8-K filing (i.e., quarter $t+1$). Panels C and D of Table 4 presents the results. Odd columns reports the results with levels (changes) of bid-ask spread. We calculate changes as the average bid-ask spread from quarter $t-1$ to quarter $t+1$. Consistent with hypothesis 3, we find that the tone is negatively associated with the bid-ask spread in the following quarter. This result is largely consistent across different specifications using the *Tone VSM* measure, but not using the *Tone LM* measure.

Taken together, the results in this subsection indicate that tone is indeed priced by the market, which is consistent with the theoretical predictions of Fischer and Verrecchia (2000) and Stein (1989) that reporting/disclosures can be associated with price effects in equilibrium. More importantly, valence shifting—as reflected in the *Tone VSM* measure—appears to have the desired price effect from the firm's perspective. Without considering such valence shifting, we are not able to detect the effect of tone on price discovery.

4.3. Restatements

Hypothesis 4 predicts that when faced with an impending negative event, managers have incentives to exaggerate other positive news such as voluntary disclosures in items 7.01 and 8.01 of 8-K filings to divert the attention of investors and induce them to place less emphasis on the negative event. We test this hypothesis in the context of accounting restatements by examining the tone of items 7.01 and 8.01 of 8-K filings ahead of the restatement. We ask (i) whether there is a difference in tone with respect to the occurrence of restatement (presence/absence of restatement) and (ii) given a restatement, whether there is a difference between the tone of voluntary disclosure of before, during, and after the restatement.

Table 5 presents the mean tone ahead of the restatement using the *Tone LM* and *Tone VSM* measures. We find that there is a difference in average tone for firms with and without restatement, but it is only statistically significant when we measure tone with VSM. This result indicates that that the companies with impending restatements are making changes in tone using adverbs and adjective, and this behavior is captured more precisely by *Tone VSM*.

[Table 5 about here.]

Table 5 also presents the mean difference in tone using both methodologies for different types of restatements. The restatements are classified into eight broad categories as defined below. It should also be noted that each restatement can be classified into more than one of the below eight categories.

- Accounting - Accounting-related restatements which constitute a major proportion of the restatements.
- Fraud - Restatements pertaining to items such as non-reliance on previously issued financial statements or related audit reports.
- Clerical Error - Restatements issued in response to clerical errors.
- Adverse - Restatements issued to correct the previously specified financial items that are worse than previously reported, such as liabilities that were understated before and now have to be restated.
- Improves - Opposite of the adverse restatements.
- SEC Investigation - Restatements pertaining to SEC investigation. For example, in cases where the company has not considered all relevant information while dealing with certain disputed receivables.
- Audit Letter - Restatements in response to communication received from the auditor.
- Board Approval - Restatements in accordance with items pertaining to board approval.

The difference in tone is evident for accounting restatements, but only in the *Tone VSM* measure.

Panel A of Table 6 presents statistics on disclosure tone ahead of a restatement and after the restatement. As we can see, the tone is markedly less negative (more positive) ahead of the restatement relative to the tone after the restatement. Both the tone measures reflect this difference, providing compelling evidence that managers use voluntary disclosure tone to assuage investors ahead of a restatement. Panel B of table 6 presents similar statistics but in the specific context of 8-K related disclosures. The inferences are qualitatively the same as from Panel A.

[Table 6 about here.]

Panel C of Table 6 presents the impact of tone (using both methodologies) on the probability of restatement using Logit regression (Dechow et al. 2011). We find that *Tone VSM* measure is significant and positive, implying that an increase in positivity/decrease in negativity of the tone is indicative of a higher probability of restatement, which is consistent with our earlier results in Section 4.1 in that firms exaggerate positive news and understate negative news (Table 2). Considering that an increase in positive tone/decrease in negative tone is significantly associated with an increase in the probability of restatement, it could be the case that the exaggeration of positive news/understatement of negative news, which is based on financial items, could lead to restatement in the next quarter. However, the coefficient of the tone calculated using *Tone LM* is negative but not statistically significant.

[Table 7 about here.]

In addition, we also examine if 8-Ks that are proceeded by restatements have different market reactions as compared to 8-Ks that are not proceeded by restatements. Table 7 presents the impact for both cases. Panel A presents the impact of 8-K voluntary disclosure tone calculated using both methodologies for 8-Ks which are not proceeded by restatements. We find that the association between cumulative abnormal return and Tone VSM is positive and significant. However, for 8-Ks proceeded by restatements, the impact is not significant for either measure of tone, as presented in Panel B. Note that these results should be interpreted with caution since there is a significant difference in the sample size of panels A and B.

5. Additional Analysis

5.1. FinBERT Tone

We examine the disclosure tone of items 7.01 and 8.01 of 8-K filings calculated using the FinBERT methodology (Araci 2019; Huang et al. 2023). FinBERT is trained on a large corpus of pre-trained financial data to first tokenize and then classify the words of the supplied text into three groups—positive, negative, and neutral. The algorithm specifies the probability of a particular statement to be in each of these groups (positive, negative, and neutral), and then classifies the sentence in a particular category based on which group has the highest probability. Each sentence is provided a discrete score of +1, 0, or -1 if it is classified as positive, neutral, or negative. Thus, the classification value is discrete rather than a continuous number between -1 and +1 which is the case with dictionary-based techniques (such as LM and VSM in this study). A pitfall with this method is highlighted by the following example. Consider the sentence:

> *"the slowing or stopping of the development or acceptance of cryptocurrency systems may adversely affect an investment in us."*

The above sentence receives the probabilities of being negative, neutral, and positive—0.4935, 0.4959, and 0.0104 respectively. The probabilities of being negative and neutral are higher than being positive. However, since the probability of being neutral is marginally higher than being negative, the sentence is classified as neutral. However, as indicated by both *Tone LM* and *Tone VSM* measures, the sentence has a negative tone. Such issues can also arise in cases where the probabilities are high for neutral and positive and can lead to incorrect classification. This point is also highlighted in Arslan et al. (2021) and Kim et al. (2023), who specify how domain-specific models such as FinBERT do not necessarily lead to improvements as compared to generic models such as BERT (Devlin et al. 2018).

We calculate the tone of the voluntary disclosure part of 8-K using FinBERT at a sentence level to ensure the methodology and results are comparable to existing results. Thus, we define voluntary disclosure as a collection of sentences and then for each sentence calculate the FinBERT tone. Thus, each sentence is classified as positive (+1), negative (-1) or neutral (0). Finally, the FinBERT tone of the voluntary disclosure text of 8-K is defined as the average of tone of sentences i.e.

$$\frac{\text{Number of Positive Sentences} - \text{Number of Negative Sentences}}{\text{Total Number of Sentences}}$$

This gives a measure of FinBERT's tone for each voluntary disclosure text which is continuous in nature even though the sentences are classified as discrete (positive/negative/neutral).

Table 8 presents the impact of FinBERT tone on cumulative abnormal return, liquidity, and restatements. Overall, we find that FinBERT tone does not exhibit explanatory power, except in explaining market reaction to 8-K filings.

[Table 8 about here]

5.2. Additional text-based measures

It could be the case that the results observed in Section 4 would be due to other text based variables in the voluntary discussion of the 8-K. Hence, the results could be due to the complexity of language (readability variables such as percentage of complex words and average word per sentence) as well as the forward looking statements and not the tone as expected. Thus, to ensure the robustness of our results we include additional text-based measures such as the percentage of forward-looking sentences (Per FL) among others for both CAR as well as liquidity results. The results are robust to the inclusion of these results as presented in Tables 9 and 10 respectively.

[Tables 9 and 10 about here]

Further, we also ensure the robustness of the impact of the tone of voluntary disclosures on restatement by using propensity score matching. We use the "nearest" sample matching methodology. The matched sample is based on the propensity score of all independent variables. The results are presented in Table 11 are consistent with those in Table 6.[7]

[Table 11 about here]

[7] In untabulated analyses we ensure the robustness of restatement results excluding year 2004 due to new 8-K reporting requirements. All results are consistent with our inferences presented in the paper.

6. Conclusion

Our purpose in this paper is to quantify the tone firms adopt in their voluntary disclosures in items 7.01 and 8.01 of 8-K filings, and to investigate its effect on price discovery. With the remarkable advances in textual analysis techniques in recent years, it (textual analysis) has assumed significant importance in helping us better understand what qualitative disclosures and the narrative content of financial reports convey to outsiders and the market. The question is really whether manager and firms can shape outsiders' beliefs by strategical wording these narratives and using appropriate tonal nuances.

To the extent firms use tone to exaggerate or play down real news to achieve some strategic ends—and the markets are able to discern such motives—we should not expect tone to have any effect on price discovery. On the other hand, firms will have an incentive to strategically use tone only if it has the desired effect on outsiders' beliefs. To address this issue, we use a technique developed in Anand et al. (2021) specifically designed to capture tonal nuances by factoring in the effects of valence shifters such as adjectives and adverbs (which is a natural way of slanting what is being conveyed).

Our analysis offers three main insights. First, the tone of voluntary disclosures in items 7.01 and 8.01 of 8-K filings is positively associated with the market reaction to these filings. This result suggests that the market reaction to 8-K filings previously documented in (Lerman and Livnat 2010) is attributable at least partially to voluntary disclosures in these filings—in particular to the tone of these voluntary disclosures. Second, tone also affects stock liquidity and bid-ask spreads further confirming that traders and the market pay attention. Finally, we provide evidence that firms use tone strategically, as reflected in the predictive ability of tone with respect to future events such as restatements. We have only taken a first step in how firms might use tone in shaping the market's expectations. Examining the nature of disclosure tone firms adopt ahead of (or subsequent to) various corporate events and the consequent implications for price discovery is a promising avenue for future research.

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Appendix A: Variable Definitions

Variable	Definition
Text measures:	
Tone VSM	The positive and negative tone of the text calculated using positive/negative words (Loughran and McDonald 2011), adverbs and adjectives, and sentence level.
Tone LM	The positive and negative tone of the text calculated using positive/negative words from Loughran and McDonald (2011) using the "bag-of-words" approach.
Per Valence Shifter (VS)	% of sentences containing atleast one adverbs and adjectives (Anand et al. 2021).
AWPS	Average Words Per sentence — defined as the total number of words divided by the total number of sentences (Gunning 1952).
Per CW	Percentage of complex words — defined as the percentage of words (with respect to the total number of words) with more than 2 syllabi (Gunning 1952).
FL	Percentage of forward-looking sentences — defined as the percentage of sentences (with respect to the total number of sentences) with more than the mean level of forward-looking words (Li 2010).
Dependent variables:	
Amihud Illiquidity Measure	Average value of daily return/volume during quarter t+1 post the 8-K filing (Amihud 2002).
Bid Ask Spread	Average value of daily quoted bid-ask spread over quarter t+1 post the 8-K filing.
Control variables:	
BTM	Book-to-Market ratio—book value of equity divided by market value of equity at the end of quarter t (Compustat item CEQQ/(PRCCQ x CSHOQ)
Total Assets	Log of total assets at the end of quarter t—Compustat item ATQ
MVE	The market value of equity at the end of the quarter t (Compustat item PRCCQ x CSHOQ). LMVE is the natural log of this value.
Analyst	The number of analysts who follow the firm during quarter t from I/B/E/S. If the data is missing from I/B/E/S, it is set to zero.
Segment	The number of business segments plus geographic segments during quarter t.
Firm Age	The number of years that a firm appears on Compustat.
ROA	Return on assets for quarter t – net income divided by total assets (Compustat item NIQ/- ATQ).
RD	Research and development expense at quarter t (Compustat item XRDQ), scaled by total assets. If the variable is missing from Compustat, RD is set to zero.

Variable	Definition
Competition	Competition, measured using the Herfindahl index. Calculated as the sum of the squares of the market shares of the firms within an industry. An industry is defined as all firms reported on Compustat sharing the same four-digit SIC code.
Price	The natural log of the average of the daily firm price, split-adjusted price over quarter t.
Volume	The natural log of the average of the daily firm trading volume over quarter t.

Table 1: Descriptive Statistics

Panel A of this table presents summary statistics for the sample variables. 'SD' and 'IQR' refers to standard deviation and interquartile range, respectively. Panel B (C) presents summary statistics for tone measures by Fama French 12 industries (Year). Variable definitions are reported in Appendix A.

Panel A: Summary Statistics

	N	Mean	P25	Median	P75	SD
Tone VSM	200,788	-0.018	-0.026	0.001	0.001	1.401
Tone LM	200,788	-0.029	-0.055	-0.025	0.001	0.250
% of Valence Shifters	200,788	17.759	0.000	16.667	33.333	18.502
Amihud Illiquidity	167,170	1.015	0.001	0.004	0.049	5.125
Bid-Ask Spread	167,161	0.006	0.001	0.002	0.006	0.012
Price	170,136	2.737	2.009	2.902	3.608	1.245
Volume	170,132	12.473	11.244	12.675	13.859	2.008
BTM	191,173	0.509	0.212	0.467	0.811	0.891
Size	200,788	6.530	4.971	6.800	8.275	2.573
MVE	191,476	4321.818	96.045	494.921	2352.540	12982.415
Number of Analysts	179,028	6.669	1.000	4.000	9.000	6.515
Segments	181,032	3.581	2.000	3.000	5.000	2.380
Age	194,652	19.627	7.000	15.000	26.000	16.302
ROA	200,245	-0.051	-0.014	0.003	0.014	0.244
R&D	200,788	0.015	0.000	0.000	0.005	0.042
Competition	199,072	0.059	0.024	0.044	0.068	0.056

Panel B: Mean Values by Industry					
FF 12	# of Obs.	Mean Tone VSM	Mean Tone LM	% Mean VS	% Mean FLW
1	6378	-0.046	-0.033	23.010	6.901
2	3332	-0.051	-0.034	24.194	7.385
3	11844	-0.044	-0.032	23.872	7.167
4	6969	-0.045	-0.032	25.552	5.096
5	3344	-0.058	-0.038	22.603	6.159
6	17454	-0.052	-0.035	22.790	7.436
7	3708	-0.053	-0.035	24.536	5.846
8	5734	-0.038	-0.027	25.861	8.438
9	13837	-0.047	-0.033	23.516	6.648
10	17649	-0.047	-0.036	23.025	5.359
11	44072	-0.040	-0.030	24.573	5.692
12	23906	-0.047	-0.032	24.979	6.372

Panel C: Mean Values by Year					
Year	# of Obs.	Mean Tone VSM	Mean Tone LM	% Mean VS	% Mean FLW
2004	3741	-0.037	-0.022	14.528	3.984
2005	9659	-0.035	-0.022	14.779	3.880
2006	10003	-0.034	-0.020	15.118	3.974
2007	9908	-0.033	-0.020	15.188	4.209
2008	9673	-0.032	-0.019	16.313	4.014
2009	8877	-0.030	-0.020	17.159	4.022
2010	8724	-0.030	-0.019	16.969	3.809
2011	8798	-0.029	-0.018	16.985	4.054
2012	8880	-0.029	-0.017	17.337	3.718
2013	9066	-0.027	-0.016	17.702	3.527
2014	9563	-0.029	-0.017	17.869	3.316
2015	9730	-0.028	-0.016	18.718	3.220
2016	9604	-0.026	-0.016	19.504	3.173
2017	9553	-0.026	-0.015	19.527	3.103
2018	9663	-0.025	-0.014	20.156	3.164
2019	9376	-0.025	-0.016	20.110	3.445
2020	9463	-0.026	-0.026	22.345	3.573
2021	3946	-0.024	-0.016	21.512	3.329

Table 2: Understatement versus overstatement in voluntary financial disclosures (Tone)

This table presents tone quantified using valence shifters and sentence level analysis (VSM) along with the one using bag of words approach (LM) and its relation to whether firms overstate or understate information in the items 7.01 and 8.01 of 8-K filings. "Prop." denotes the proportion of the "% of Sample" column. The *p*-value is that for the t-test for equality of means.

Case	VSM	LM	% of Sample	Prop.	*p*-value
VSM $>$ LM	$+$	$+$	5.010%	84.270%	0.001
$\lvert VSM \rvert < \lvert LM \rvert$	$-$	$-$	28.750%	75.720%	0.001

Table 3: Impact on Cumulative Abnormal Return (CAR)

This table reports the results from the regression of CAR calculated during three day window around the 8-K filing dates on tone measures and control variables. The regression includes year and Fama and French 12-Industry fixed effects. The standard errors (reported in parentheses) are clustered by firm and year (column 1 and 3) and industry and year (column 2 and 4). ***, ** and * indicate that the coefficient estimate are significantly different from zero at the 1 percent, 5 percent and 10 percent levels respectively. Variable definitions are reported in Appendix A.

Panel A: Items 7.01 and 8.01 Combined

Dependent Variable =	CAR			
	(1)	(2)	(3)	(4)
Tone VSM	0.038***	0.038***		
	(0.000)	(0.000)		
Tone LM			0.007	0.007
			(0.334)	(0.344)
MVE	0.000	0.000	0.000	0.000
	(0.316)	(0.275)	(0.344)	(0.396)
BTM	-0.000	-0.000	-0.000	-0.000
	(0.123)	(0.317)	(0.111)	(0.201)
Size	-0.001***	-0.001***	-0.001***	-0.001***
	(0.000)	(0.001)	(0.000)	(0.001)
ROA	0.001	0.001	0.001	0.001
	(0.416)	(0.398)	(0.409)	(0.388)
R&D	-0.031**	-0.031	-0.031**	-0.031
	(0.040)	(0.156)	(0.040)	(0.156)
Competition	-0.006***	-0.006**	-0.006***	-0.006*
	(0.003)	(0.043)	(0.004)	(0.052)
Year FE	Y	Y	Y	Y
Industry FE	Y	Y	Y	Y
Adjusted R^2	0.002	0.002	0.001	0.001
Observations	162,786	162,786	162,786	162,786

Panel B: Items 7.01 and 8.01 Separately								
Dependent Variable =	CAR							
	Item 7.01				Secton 8.01			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Tone VSM	0.034***	0.034***			0.040***	0.040***		
	(3.82)	(4.10)			(8.77)	(4.97)		
Tone LM			-0.008	-0.008			0.023**	0.023**
			(-0.90)	(-0.70)			(2.62)	(3.07)
MVE	0.000	0.000	0.000	0.000	0.000	0.000	-0.000	-0.000
	(1.43)	(1.39)	(1.52)	(1.53)	(0.01)	(0.01)	(-0.12)	(-0.13)
BTM	0.000*	0.000**	0.000*	0.000**	-0.000***	-0.000**	-0.000***	-0.000**
	(1.94)	(2.75)	(1.93)	(2.72)	(-2.93)	(-2.90)	(-3.04)	(-3.02)
Size	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***
	(-3.60)	(-3.27)	(-3.65)	(-3.34)	(-4.50)	(-5.01)	(-4.66)	(-5.24)
ROA	0.000	0.000	0.000	0.000	0.001	0.001	0.002	0.002
	(0.87)	(0.87)	(0.87)	(0.88)	(0.77)	(0.72)	(0.85)	(0.82)
R&D	-0.009	-0.009	-0.008	-0.008	-0.048***	-0.048***	-0.048***	-0.048***
	(-0.73)	(-0.67)	(-0.72)	(-0.67)	(-5.10)	(-3.33)	(-5.03)	(-3.35)
Competition	-0.003	-0.003	-0.003	-0.003	-0.008***	-0.008*	-0.008***	-0.008*
	(-0.62)	(-0.74)	(-0.60)	(-0.73)	(-4.40)	(-2.14)	(-4.28)	(-2.03)
Year FE	Y	Y	Y	Y	Y	Y	Y	Y
Industry FE	Y	Y	Y	Y	Y	Y	Y	Y
Adjusted R^2	0.001	0.001	0.001	0.001	0.002	0.002	0.002	0.002
Observations	73,850	73,850	73,850	73,850	94,694	94,694	94,694	94,694

Table 4: Impact on Liquidity

This table reports the results from the regression of Amihud Illiquidty (Panels A and B) and Bid-Ask Spread (Panels C and D) on tone measures. The dependent variables in odd (even) columns are in levels (changes) specification. The regression includes year and Fama and French 12 industry fixed effects. The standard errors (reported in parentheses) are clustered by firm. ***, ** and * indicate that the coefficient estimate are significantly different from zero at the 1 percent, 5 percent and 10 percent levels respectively. Variable definitions are reported in Appendix A.

Panel A

Dependent Variable =	Amihud Illiquidity					
	Items 7.01 and 8.01		Item 7.01		Item 8.01	
	(1)	(2)	(3)	(4)	(5)	(6)
Tone VSM	-0.107***	-0.036*	0.003	-0.009	-0.093***	-0.044*
	(0.001)	(0.097)	(0.947)	(0.786)	(0.008)	(0.078)
Year FE	Y	Y	Y	Y	Y	Y
Industry FE	Y	Y	Y	Y	Y	Y
Controls	Y	Y	Y	Y	Y	Y
Adjusted R^2	0.314	0.016	0.279	0.013	0.332	0.019
Observations	158,234	150,285	72,047	69,127	91,680	86,458

Panel B

Dependent Variable =	Amihud Illiquidity					
	Items 7.01 and 8.01		Item 7.01		Item 8.01	
	(1)	(2)	(3)	(4)	(5)	(6)
Tone LM	-0.249***	-0.035	-0.157	-0.025	0.040	-0.034
	(0.001)	(0.231)	(0.225)	(0.531)	(0.654)	(0.437)
Year FE	Y	Y	Y	Y	Y	Y
Industry FE	Y	Y	Y	Y	Y	Y
Controls	Y	Y	Y	Y	Y	Y
Adjusted R^2	0.314	0.016	0.279	0.013	0.332	0.019
Observations	158,234	150,285	72,047	69,127	91,680	86,458

Panel C

Dependent Variable =	Bid-Ask Spread					
	Items 7.01 and 8.01		Item 7.01		Item 8.01	
	(1)	(2)	(3)	(4)	(5)	(6)
Tone VSM	-0.002***	-0.001	0.001	-0.000	-0.002***	-0.001
	(0.003)	(0.192)	(0.372)	(0.712)	(0.010)	(0.124)
Year FE	Y	Y	Y	Y	Y	Y
Industry FE	Y	Y	Y	Y	Y	Y
Controls	Y	Y	Y	Y	Y	Y
Adjusted R^2	0.357	0.031	0.360	0.027	0.357	0.034
Observations	158,227	150,276	72,047	69,127	91,673	86,449

Panel D

Dependent Variable =	Bid-Ask Spread					
	Items 7.01 and 8.01		Item 7.01		Item 8.01	
	(1)	(2)	(3)	(4)	(5)	(6)
Tone LM	-0.005***	-0.001	-0.004	-0.001	0.001	-0.001
	(0.002)	(0.192)	(0.211)	(0.348)	(0.652)	(0.256)
Year FE	Y	Y	Y	Y	Y	Y
Industry FE	Y	Y	Y	Y	Y	Y
Controls	Y	Y	Y	Y	Y	Y
Adjusted R^2	0.357	0.031	0.361	0.027	0.357	0.034
Observations	158,227	150,276	72,047	69,127	91,673	86,449

Table 5: Tone Statistics (With and Without Restatement)

This table presents the mean value of tone (and respective p-value for t-test of difference in mean with and without restatement) calculated using the VSM specified in this study as well as the "bag-of-words" approach (LM) for various types of restatements. Variable definitions are reported in Appendix A.

Differences in means for different types of restatements						
	Tone LM			Tone VSM		
	Without Res	With Res	P-value	Without Res	With Res	P-value
All	-0.031	-0.034	0.880	-0.042	-0.035	0.020
Accounting	-0.031	-0.031	0.690	-0.042	-0.035	0.006
Fraud	-0.031	-0.034	0.720	-0.042	-0.031	0.410
Clerical Error	-0.031	-0.038	0.330	-0.042	-0.062	0.290
Adverse	-0.031	-0.031	0.560	-0.042	-0.035	0.010
Improves	-0.031	-0.033	0.470	-0.042	-0.038	0.430
SEC Investigation	-0.031	-0.037	0.360	-0.042	-0.032	0.460
Aud Letter	-0.031	-0.032	0.840	-0.042	-0.038	0.240
Board Approval	-0.031	-0.033	0.480	-0.042	-0.036	0.250

Table 6: Disclosure Tone and Restatements

Panels A and B present summary statistics of tone measures band after the restatement. Panel C reports the results from the logit regression of event of restatement on measures of tone and control variables (Dechow et al. 2011). The controls include change in receivables, change in inventory, percentage of soft assets, change in cash sales, change in ROA, and lagged market-adjusted return. The regression includes year and Fama and French 12-Industry fixed effects. The standard errors (reported in parentheses) are clustered by firm. ***, ** and * indicate that the coefficient estimate are significantly different from zero at the 1 percent, 5 percent, and 10 percent levels respectively. Variable definitions are reported in Appendix A.

Panel A: Tone (All Restatements)

Variable	Mean	SD	IQR	P-Value for Diff in Mean
Tone LM				
Before Restatement	-0.031	0.042	0.057	
After Restatement	-0.033	0.045	0.060	0.014
Tone VSM				
Before Restatement	-0.018	0.074	0.034	
After Restatement	-0.025	0.091	0.039	0.001

Panel B: Tone (8-K Related Restatements)

Variable	Mean	SD	IQR	P-Value for Diff in Mean
Tone LM				
Before Restatement	-0.033	0.042	0.060	
After Restatement	-0.036	0.048	0.066	0.117
Tone VSM				
Before Restatement	-0.018	0.075	0.033	
After Restatement	-0.030	0.094	0.047	0.001

Panel C: Multivariate Analysis								
Dependent Variable =	Restatement							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Tone VSM	0.713**	0.784**	0.781**	0.784**				
	(0.042)	(0.026)	(0.027)	(0.026)				
Tone LM					-0.897	-0.560	-0.529	-0.564
					(0.259)	(0.486)	(0.516)	(0.490)
AWPS		0.000**	0.000**	0.000**		0.000*	0.000*	0.000*
		(0.048)	(0.046)	(0.049)		(0.053)	(0.051)	(0.054)
Per CW		-2.501***	-2.476***	-2.385***		-2.380***	-2.362***	-2.270***
		(0.000)	(0.000)	(0.000)		(0.000)	(0.000)	(0.001)
Per VC			-0.000	-0.001			-0.000	-0.001
			(0.803)	(0.694)			(0.821)	(0.718)
Per FL				0.003				0.003
				(0.140)				(0.138)
Year FE	Y	Y	Y	Y	Y	Y	Y	Y
Industry FE	Y	Y	Y	Y	Y	Y	Y	Y
Controls	Y	Y	Y	Y	Y	Y	Y	Y
Pseudo R^2	0.056	0.058	0.058	0.058	0.056	0.058	0.058	0.058
Observations	22,064	22,064	22,064	22,064	22,064	22,064	22,064	22,064

Table 7: Impact on CAR with Respect to Restatements

This table reports the results from the regression of CAR calculated during three day window around the 8-K filing dates on tone measures and control variables. The regression includes year and Fama and French 12-Industry fixed effects. The standard errors (reported in parentheses) are clustered by firm and year (column 1 and 3) and industry and year (column 2 and 4). ***, ** and * indicate that the coefficient estimate are significantly different from zero at the 1 percent, 5 percent and 10 percent levels respectively. Variable definitions are reported in Appendix A.

Panel A: 8-Ks not proceeded by restatements				
Dependent Variable =	CAR			
	(1)	(2)	(3)	(4)
Tone VSM	0.039***	0.039***		
	(0.000)	(0.001)		
Tone LM			0.011	0.011
			(0.394)	(0.420)
MVE	0.000	0.000	0.000	0.000
	(0.701)	(0.767)	(0.716)	(0.780)
BTM	-0.000**	-0.000	-0.000**	-0.000*
	(0.043)	(0.114)	(0.035)	(0.057)
Size	-0.001***	-0.001***	-0.001***	-0.001***
	(0.001)	(0.002)	(0.001)	(0.002)
ROA	-0.000	-0.000	-0.000	-0.000
	(0.920)	(0.960)	(0.993)	(0.995)
R&D	-0.055***	-0.055***	-0.055***	-0.055***
	(0.000)	(0.005)	(0.000)	(0.005)
Competition	-0.007***	-0.007	-0.007**	-0.007
	(0.007)	(0.115)	(0.010)	(0.131)
Year FE	Y	Y	Y	Y
Industry FE	Y	Y	Y	Y
Adjusted R^2	0.002	0.002	0.001	0.001
Observations	63,484	63,484	63,484	63,484

Panel B: 8-Ks proceeded by restatements				
Dependent Variable =	CAR			
	(1)	(2)	(3)	(4)
Tone VSM	0.027	0.027		
	(0.406)	(0.410)		
Tone LM			0.008	0.008
			(0.856)	(0.915)
MVE	0.000	0.000	0.000	0.000
	(0.552)	(0.612)	(0.574)	(0.637)
BTM	-0.005	-0.005	-0.005	-0.005
	(0.136)	(0.175)	(0.138)	(0.186)
Size	-0.002	-0.002	-0.002	-0.002
	(0.307)	(0.327)	(0.288)	(0.305)
ROA	0.023	0.023	0.023	0.023
	(0.302)	(0.383)	(0.296)	(0.382)
R&D	0.050	0.050	0.051	0.051
	(0.599)	(0.165)	(0.593)	(0.162)
Competition	-0.011	-0.011	-0.011	-0.011
	(0.499)	(0.538)	(0.527)	(0.560)
Year FE	Y	Y	Y	Y
Industry FE	Y	Y	Y	Y
Adjusted R^2	0.010	0.010	0.009	0.009
Observations	2,304	2,304	2,304	2,304

Table 8: Results using FinBert Tone Measure

Panel A of this Table reports the results from the regression of CAR (cumulative abnormal return) calculated around the 8-K dates on finbert tone and control variables. Panel B of this table reports the results from the regression of Amihud Illiquidty measure and Bid-Ask spread, respectively, on finbert tone and control variables. Panel C reports the results from the logit regression of event of restatement on measure on finbert tone in voluntary disclosure of 8-K and control variables (Dechow et al. 2011). All regressions includes year and Fama and French 12-Industry fixed effects. The standard errors (reported in parentheses) are clustered by firm. ***, ** and * indicate that the coefficient estimate are significantly different from zero at the 1 percent, 5 percent and 10 percent levels respectively. Variable definitions are reported in Appendix A.

Panel A

Dependent Variable =	CAR	
	(1)	(2)
Finbert Tone	0.038***	0.038***
	(0.000)	(0.009)
Year FE	Y	Y
Industry FE	Y	Y
Controls	Y	Y
Adjusted R^2	0.002	0.002
Observations	162,786	162,786

Panel B

Dependent Variable =	Amihud Illiquidity		Bid-Ask Spread	
	(1)	(2)	(3)	(4)
Finbert Tone	-0.034	0.019	-0.001	0.000
	(0.209)	(0.335)	(0.335)	(0.650)
Year FE	Y	Y	Y	Y
Industry FE	Y	Y	Y	Y
Controls	Y	Y	Y	Y
Adjusted R^2	0.314	0.016	0.357	0.031
Observations	158,234	150,285	158,227	150,276

Panel C				
Dependent Variable =	Restatement			
	(1)	(2)	(3)	(4)
Finbert Tone	0.045	0.117	0.104	0.109
	(0.897)	(0.737)	(0.766)	(0.756)
AWPS		0.000*	0.000*	0.000*
		(0.054)	(0.051)	(0.054)
Per CW		-2.447***	-2.417***	-2.329***
		(0.000)	(0.000)	(0.000)
Per VC			-0.001	-0.001
			(0.764)	(0.661)
Per FL				0.003
				(0.143)
Year FE	Y	Y	Y	Y
Industry FE	Y	Y	Y	Y
Controls	Y	Y	Y	Y
Pseudo R^2	0.055	0.058	0.058	0.058
Observations	22,064	22,064	22,064	22,064

Table 9: Impact on CAR (Additional Controls)

This table reports the results from the regression of CAR calculated during three day window around the 8-K filing dates on tone measures and control variables. The regression includes year and Fama and French 12-Industry fixed effects. The standard errors (reported in parentheses) are clustered by firm and year (column 1 and 3) and industry and year (column 2 and 4). ***, ** and * indicate that the coefficient estimate are significantly different from zero at the 1 percent, 5 percent and 10 percent levels respectively. Variable definitions are reported in Appendix A.

Dependent Variable =	CAR			
	(1)	(2)	(3)	(4)
Tone VSM	0.038***	0.039***	0.038***	0.039***
	(0.000)	(0.000)	(0.000)	(0.000)
Per CW		-0.005	-0.004	-0.004
		(0.281)	(0.329)	(0.430)
AWPS		0.000*	0.000*	0.000**
		(0.059)	(0.077)	(0.032)
Per VC			-0.000	-0.000
			(0.217)	(0.138)
Per FL				0.000*
				(0.099)
MVE	0.000	0.000	0.000	0.000
	(0.316)	(0.289)	(0.338)	(0.390)
BTM	-0.000	-0.000	-0.000	-0.000
	(0.123)	(0.364)	(0.119)	(0.321)
Size	-0.001***	-0.001***	-0.001***	-0.001***
	(0.000)	(0.001)	(0.000)	(0.001)
ROA	0.001	0.001	0.001	0.001
	(0.416)	(0.397)	(0.415)	(0.396)
R&D	-0.031**	-0.031	-0.031**	-0.031
	(0.040)	(0.156)	(0.040)	(0.156)
Competition	-0.006***	-0.006*	-0.006***	-0.006*
	(0.003)	(0.052)	(0.003)	(0.054)
Year FE	Y	Y	Y	Y
Industry FE	Y	Y	Y	Y
Adjusted R^2	0.002	0.002	0.002	0.002
Observations	162,786	162,786	162,786	162,786

Table 10: Impact on Liquidity (Additional Controls)

This table reports the results from the regression of Amihud Illiquidty (Panel A) and Bid-Ask Spread (Panel B) on tone measures. The regression includes year and Fama and French 12 industry fixed effects. The standard errors (reported in parentheses) are clustered by firm. ***, ** and * indicate that the coefficient estimate are significantly different from zero at the 1 percent, 5 percent and 10 percent levels respectively. Variable definitions are reported in Appendix A.

Panel A

Dependent Variable =	Amihud Illiquidity			
	(1)	(2)	(3)	(4)
Tone VSM	-0.107***	-0.105***	-0.118***	-0.111***
	(0.001)	(0.001)	(0.000)	(0.000)
Per CW		-0.121**	-0.098*	-0.095*
		(0.024)	(0.066)	(0.077)
AWPS		0.000	0.000**	0.000*
		(0.236)	(0.046)	(0.071)
Per VC			-0.000***	-0.001***
			(0.002)	(0.001)
Per FL				0.001**
				(0.012)
Price	-0.170***	-0.170***	-0.170***	-0.170***
	(0.000)	(0.000)	(0.000)	(0.000)
Volume	-0.181***	-0.181***	-0.181***	-0.181***
	(0.000)	(0.000)	(0.000)	(0.000)
BTM	0.002	0.002	0.002	0.002
	(0.189)	(0.188)	(0.188)	(0.185)
Size	0.060***	0.061***	0.061***	0.061***
	(0.000)	(0.000)	(0.000)	(0.000)
Year FE	Y	Y	Y	Y
Industry FE	Y	Y	Y	Y
Adjusted R^2	0.314	0.314	0.314	0.314
Observations	158,234	158,234	158,234	158,234

Panel B				
Dependent Variable =	Bid-Ask Spread			
	(1)	(2)	(3)	(4)
Tone VSM	-0.002***	-0.002***	-0.002***	-0.002***
	(0.003)	(0.004)	(0.001)	(0.002)
Per CW		-0.003***	-0.003***	-0.003***
		(0.002)	(0.007)	(0.009)
AWPS		0.000*	0.000***	0.000***
		(0.061)	(0.006)	(0.009)
Per VC			-0.000***	-0.000***
			(0.000)	(0.000)
Per FL				0.000**
				(0.041)
Price	-0.004***	-0.004***	-0.004***	-0.004***
	(0.000)	(0.000)	(0.000)	(0.000)
Volume	-0.004***	-0.004***	-0.004***	-0.004***
	(0.000)	(0.000)	(0.000)	(0.000)
BTM	-0.000	-0.000	-0.000	-0.000
	(0.408)	(0.408)	(0.404)	(0.410)
Size	0.001***	0.001***	0.001***	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)
Year FE	Y	Y	Y	Y
Industry FE	Y	Y	Y	Y
Adjusted R^2	0.357	0.357	0.357	0.357
Observations	158,227	158,227	158,227	158,227

Table 11: Disclosure Tone and Restatements (Propensity Score Matching)

Table reports the results from the logit regression of event of restatement on measures of tone and control variables (Dechow et al. 2011) using propensity score matching. The controls include change in receivables, change in inventory, percentage of soft assets, change in cash sales, change in ROA, and lagged market-adjusted return. The regression includes year and Fama and French 12-Industry fixed effects. The standard errors (reported in parentheses) are clustered by firm. ***, ** and * indicate that the coefficient estimate are significantly different from zero at the 1 percent, 5 percent, and 10 percent levels respectively. Variable definitions are reported in Appendix A.

Dependent Variable =	Restatement							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Tone VSM	0.701*	0.778**	0.778**	0.780**				
	(0.052)	(0.031)	(0.032)	(0.031)				
Tone LM					-1.119	-0.773	-0.753	-0.799
					(0.170)	(0.348)	(0.368)	(0.341)
AWPS		0.000**	0.000**	0.000**		0.000**	0.000**	0.000**
		(0.036)	(0.036)	(0.038)		(0.028)	(0.028)	(0.030)
Per CW		-2.565***	-2.563***	-2.490***		-2.453***	-2.441***	-2.320***
		(0.000)	(0.000)	(0.000)		(0.000)	(0.000)	(0.001)
Per VC			-0.000	-0.000			-0.000	-0.001
			(0.983)	(0.897)			(0.890)	(0.758)
Per FL				0.003				0.004*
				(0.274)				(0.067)
Year FE	Y	Y	Y	Y	Y	Y	Y	Y
Industry FE	Y	Y	Y	Y	Y	Y	Y	Y
Controls	Y	Y	Y	Y	Y	Y	Y	Y
Pseudo R^2	0.054	0.056	0.056	0.056	0.056	0.058	0.058	0.058
Observations	20,990	20,990	20,990	20,990	20,558	20,558	20,558	20,558

Figure 1: Median Tone Over the Years

The figure presents the movement of median tone for combined items 7.01 and 8.01 of 8-Ks using Tone LM and Tone VSM (using valence shifters and sentence as a base unit of analysis) for each year.

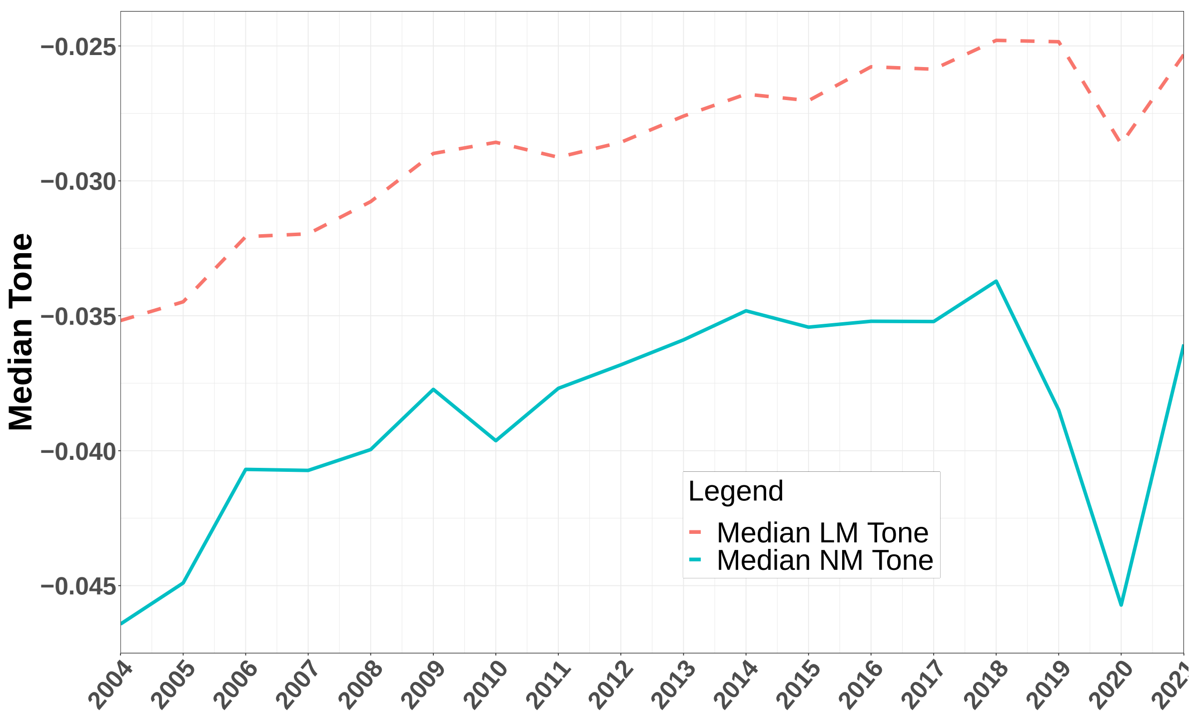


Figure 2: Median Tone by Industries

The figure presents the movement of median tone for item 7.01 and 8.01 of 8-Ks using Tone LM and Tone VSM (using valence shifters and sentence as a base unit of analysis) for years between 2004 and 2021 for each Fama French 12 industries.

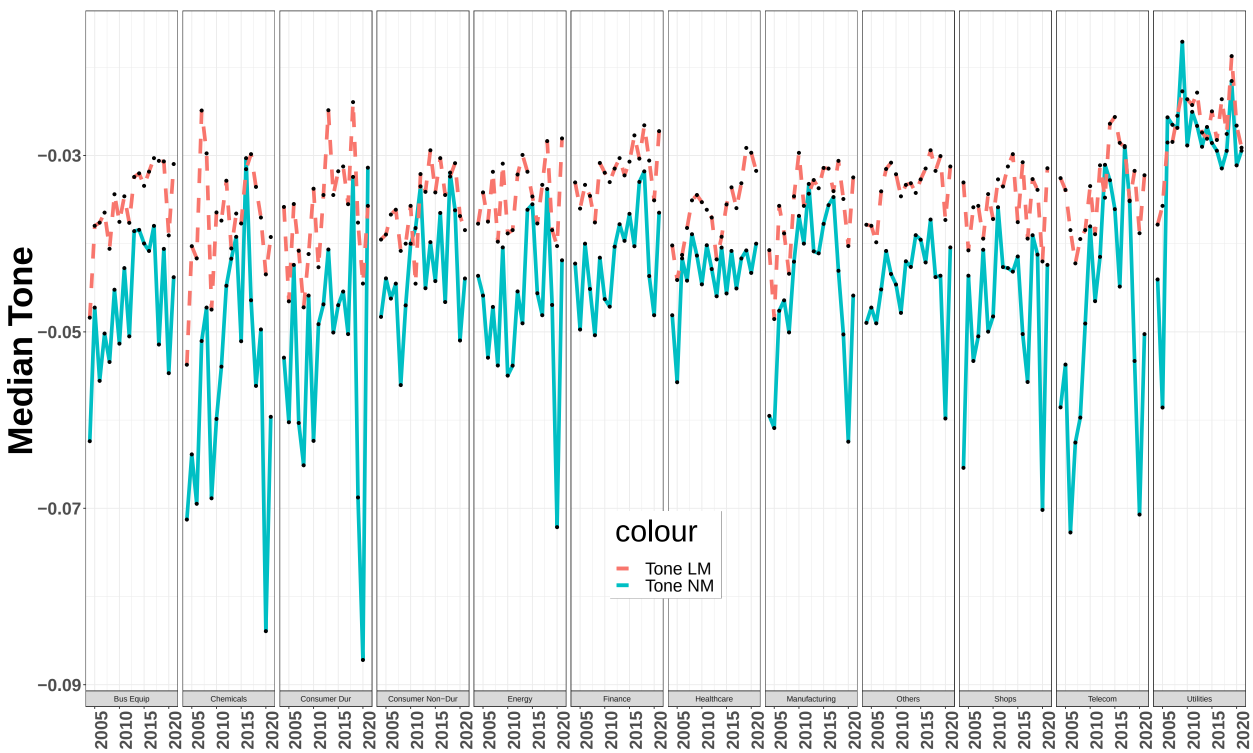
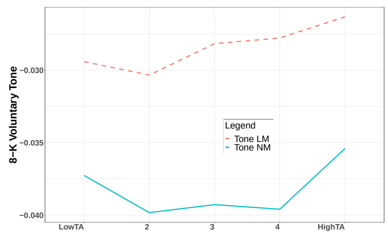
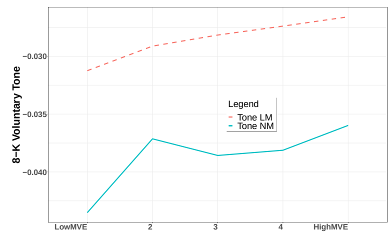


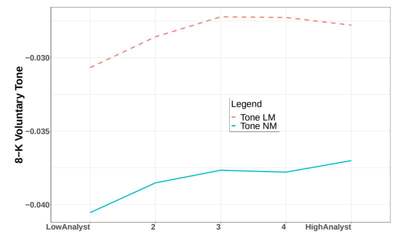
Figure 3: Figure presents the movement of tone with respect to firm and industry variables.



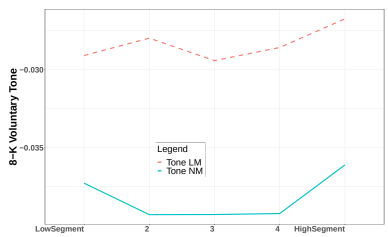
(a) Total Assets



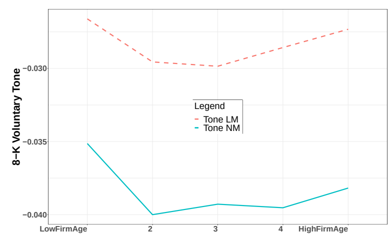
(b) MVE



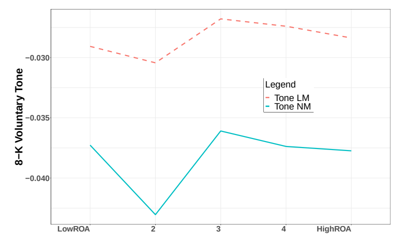
(c) No. of Analyst



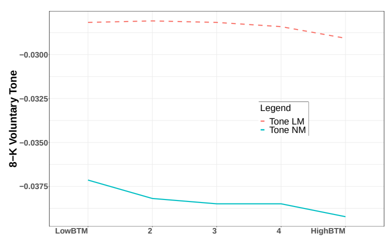
(d) Segments



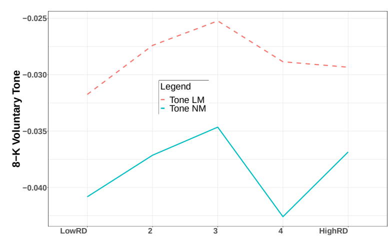
(e) Firm Age



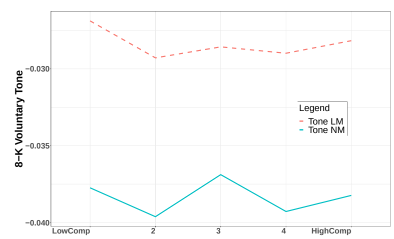
(f) ROA



(g) BTM



(h) R&D



(i) Competition