Imprecise and Informative: Lessons from Market Reactions to Imprecise Disclosure

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ABSTRACT

Imprecise language in corporate disclosures can convey valuable information on firms' fundamentals during uncertain times. To evaluate this idea, we develop a novel measure of linguistic imprecision based on sentences marked with the "weasel tag" on Wikipedia. Using our imprecision measure, we find that the percentage of imprecise language in 10-Ks 1) predicts positive abnormal returns, 2) reduces future information asymmetry, and 3) predicts positive earnings surprises. Our findings imply that the imprecise language in 10-Ks contains new information on positive but yet immature prospects of future cash flow, and that market participants initially under-react to it possibly due to its embedded immaturity but eventually digest it.

1 Introduction

The clarity of writing is an important consideration in financial disclosures. Indeed, concerns about unclear financial disclosures have led to the mandate that disclosures be as simple as possible (e.g., the Plain Writing Act). Despite the compelling motivation to keep disclosures simple, the academic literature disagrees regarding whether complex language contains more or less information. On one hand, the "obfuscation view" suggests that managers strategically increase the complexity of their disclosures, which increases information asymmetry (Li 2008) and decreases valuations (Hwang and Kim 2017). On the other hand, complex language can convey important information that cannot be disclosed in simple terms (e.g., Bushee, Gow, and Taylor (2018)). To help resolve this tension, we develop a novel measure of the clarity of financial disclosures — linguistic imprecision extracted from firms' 10-K filings — and use it to understand how imprecise disclosure relates to information asymmetry and shareholder valuations. Our core finding is that greater imprecision predicts permanent and positive abnormal returns, which supports the counterintuitive view that linguistic imprecision reflects valuable firm activities.

It is empirically challenging to measure linguistic imprecision in financial disclosures for at least two reasons. First, the selection of a list of imprecision words is likely to be fraught with subjectivity, leading to concerns about researcher degrees of freedom (Simmons, Nelson, and Simonsohn 2011). Second, despite there being related concepts in the literature (e.g., uncertainty, weak modality, vagueness), there is not a pre-existing list of imprecision keywords. We address these dual challenges by constructing a new dictionary of imprecise words and phrases (henceforth "imprecision keywords") that draws on Wikipedia's crowdsourced solution to identify imprecision — "weasel tags." Specifically, we analyze the text of Wikipedia articles and, more importantly, the weasel tags embedded into these articles. Wikipedia advises its users to attach weasel tags when they encounter sentences or phrases in Wikipedia articles that have vague phrasing that accompanies unverifiable information. By appealing to Wikipedia's crowdsourced solution, we simultaneously provide an externally-reliable basis for identifying words associated with imprecision and "tie our hands" by eliminating the subjective choices typically involved in building a dictionary of keywords.[1]

Using our dictionary of imprecision keywords, we generate a measure of linguistic imprecision at the firm-year level (and at the paragraph-year level for some tests) by computing the fraction of imprecision keywords in each firm's annual 10-K filing.[2] Consistent with the idea that our measure captures the linguistic imprecision in 10-Ks, we find that 10-Ks with greater linguistic imprecision tend to exhibit greater uncertainty and to contain more modal words that convey differing shades of meaning. Yet, we uncover that the information contained in our linguistic imprecision measure has distinctive and unique aspects compared to other existing textual measures proposed in earlier studies. We also find that 10-K disclosures with higher linguistic imprecision tend to have higher positive sentiment.

Our two core findings are that (i) linguistic imprecision is associated with positive market reactions that do not eventually revert and (ii) linguistic imprecision is associated with less information asymmetry (i.e., lower bid-ask spreads and fewer zero-volume days). Together, these core results provide compelling evidence that the use of imprecise language in 10-K disclosures reflects the value-relevant information on firms' fundamentals, which contrasts to the dominant obfuscation view. Moreover, when we evaluate the textual content of the disclosures that drive these results, our linguistic imprecision measure appears to reflect immature information on upcoming positive but yet uncertain prospects of earnings.

First, we find that firms whose 10-K disclosures contain greater linguistic imprecision earn higher buy and hold abnormal returns (BHARs) or cumulative abnormal returns (CARs) in subsequent weeks. We further note that this positive linguistic imprecision effect

[1]Our approach of appealing to an external source to ground our textual analysis of imprecision is similar to the approach taken in Bellstam, Bhagat, and Cookson (2020) who use an innovation textbook as a benchmark to evaluate which topics discussed by analysts reflect the innovation activities of the firms they cover.

[2]In the context of legally-required corporate disclosures, e.g., 10-Ks, we expect the incentives to use the imprecise language to be distinct from other source texts such as political statements and informal conference calls. As we discuss later at length, this distinction is important for how to interpret the use of the linguistic imprecision in 10-K disclosures.

emerges from the 3rd week after 10-K filing, monotonically increases until the 9th week, and remains at a similar level afterward. This implies that the information content that comes with linguistic imprecision in 10-Ks is positive and that investors initially under-react to it but eventually digest it, thus reflecting it into stock prices. We also show that our finding is not driven by the changes in systematic risks captured by Fama-French three-factor model.

Next, to ensure that our linguistic imprecision effect is driven by information, we investigate the relation between the use of imprecise language in 10-Ks and firms' information asymmetry. We find that the use of imprecise language reduces the information asymmetry in the subsequent weeks after 10-K filing using two proxies of information asymmetry. This is in particular surprising and novel evidence that the linguistic imprecision in 10-Ks is indeed associated with managers' providing additional value-relevant information on firms' fundamentals and that this information is digested by investors in financial markets, leading to the reduction in information asymmetry.

Last, to understand what value-relevant information comes with the imprecise language in 10-K disclosures on a deeper level, we perform tests that examine whether our linguistic imprecision measure can predict a subsequent earnings surprise, which is a proxy for news on future cash flows, after 10-K filing. We find that our linguistic imprecision measure can predict future standardized unexpected earnings (SUE) positively. We also find that the magnitude of the SUE predictability by the linguistic imprecision attenuates as the time gap between 10-K filing and future SUE increases. These findings suggest that security analysts initially under-react to the information that comes together with linguistic imprecision and provide eventual but delayed correction, which is consistent with our finding regarding stock price reactions. Collectively, our findings on market reaction, information asymmetry, and earning surprises suggest that the imprecise language used in 10-K disclosures reflects fundamentally valuable, but yet immature earnings opportunities.

Our paper makes several contributions to the literature. First, our evidence on the use of imprecise language in disclosure relates to the work on discretionary disclosure and persuasion through information revelation (e.g., Bloomfield (2002)). Discretionary disclosure leads to full disclosure in a perfect information environment, but not in the presence of proprietary costs or other market frictions (Ross 1979, Verrecchia 1983, Kamenica and Gentzkow 2011, Ely 2017). Following this line of research, recent empirical applications have focused on how the disclosure of bad news can signal quality (Gormley, Kim, and Martin 2012, Gao, Liang, Merkley, and Pacelli 2017). Our results on the informational value of imprecise language provide a new perspective on this question. We show that our explicit measure of linguistic imprecision is more related to information than obfuscation. Our results suggest that managers act in their decisions to provide more voluntary information on immature but positive earnings opportunities.

Second, our identification and analysis of linguistic imprecision in 10-K disclosures provide a useful perspective on the SEC regulatory mandate (the Plain Writing Act) to use plain English in firm disclosures, studied in Hwang and Kim (2017). The linguistic imprecision is not especially discouraged in this SEC mandate that regulates the readability of firm disclosure documents for the general public because our imprecision words and phrases accord with plain English. Our finding that imprecise language can reflect the informational content of disclosures that affects firm value, calls for more attention to the use of plain English and more careful conclusion in drawing a link between imprecise language and intentional obfuscation. At least in the average case, linguistic imprecision in corporate disclosures should be separately interpreted in the context of upcoming positive but immature prospects of earnings, rather than being used to discount the validity of the information in the disclosures.

Finally, our work is a part of a growing literature within finance and accounting that makes use of text descriptions to study important aspects of financial market reactions (Tetlock 2007, Hoberg and Phillips 2016, Hoberg and Moon 2017, Hoberg and Lewis 2017, Bellstam, Bhagat, and Cookson 2020). Within the broader literature on textual analysis in finance, our work is most closely related to applying textual analysis tools to analyze the tone of financial information (Hanley and Hoberg 2010, Dougal, Engelberg, Garcia, and Parsons 2012, Loughran and McDonald 2013, Garcia 2013, Jegadeesh and Wu 2017).

As we will show in our regression analyses later, our measure is sensibly related to, but distinct from the existing lexicon of measures — many of which are available at the master dictionary by Loughran and McDonald (2011). Relative to these other textual measures, our linguistic imprecision measure provides a useful description of imprecise language in financial disclosures, which is distinctive unto itself. In this respect, we anticipate fruitful applications of our linguistic imprecision measure to understand better the information environment into which linguistic imprecision can be injected.

The remainder of the paper proceeds as follows. Section 2 provides a description of Wikipedia's weasel tags, the construction of our list of imprecision keywords, and the development of our linguistic imprecision measure. Section 3 describes our sample and presents the test results relating our linguistic imprecision measure to other variables. Section 4 provides the main results from the tests that investigate the relations between linguistic imprecision in 10-Ks and subsequent abnormal returns, information asymmetry, and earnings surprises after 10-K filing. Section 5 concludes with directions for future research.

2 Data and Variable Construction

2.1 Wikipedia andWeaselWords

To construct our measure of linguistic imprecision, we take the entire Wikipedia articles as our text corpus to detect sentences of imprecise language and compile a list of imprecision keywords. A study by Wikipedia Ganter and Strube (2009) suggests three categories of weasel words: 1) numerically vague expressions (e.g., many), 2) the passive voice (e.g., it is said), and 3) adverbs that weaken (e.g., probably). Examples of these weasel words directly given by Wikipedia as style guidelines include "People are saying...", "There is evidence that...", and "It has been mentioned that."[3] Wikipedia users are then advised to avoid using weasel words and at the same time to detect and mark excessive uses of such words by others using a special weasel tag, {{Weasel-inline—{{subst:DATE}}}} for improvement.

[3]See Wikipedia's own article about weasel words for more details at `https://en.wikipedia.org/wiki/Weasel\_word`.

The examples below illustrate how the weasel tag is used in a sentence of each article:

- "The Tic Tok Men"

  Many{{weasel inline—date=March 2009}} consider this album to be the quintessential Tic Tok sound.

- "Manu Parrotlet"

  It has been said{{weasel inline—date=January 2014}} that the Manu parrotlet can be seen along the Man on top of trees across from the Altamira beach about 25 minutes from the Manu Resort.

- "Nathaniel Mather"

  He finished his studies in England probably{{weasel inline—date=January 2014}} returning with his brother [[Samuel Mather (Independent minister)—Samuel]] in 1650.

We process a recent Wikipedia dump completed on April 20, 2017 comprised of 17,483,910 articles and extract sentences that contain weasel tags.[4] To do so, we follow the methodology in Ganter and Strube (2009) with the following modifications. While Ganter and Strube (2009) examine the five words occurring right before each weasel tag, we consider all words in sentences that contain weasel tags. We also further consider the frequencies of all those words and their bigrams and trigrams as well to better identify potential weasel words and phrases. The bigrams and trigrams are particularly useful to capture weasel phrases that use passive voice and appeals to anonymous authority.

Because weasel tags are removed after the language is edited and improved, the tags are not frequently observed at any given snapshot of Wikipedia. Therefore, sentences containing weasel tags are not abundant, despite the large number of articles we process. We identify 433 sentences with weasel tags in 367 articles after removing corrupt or redundant sentences. Our number of weasel tags is slightly more than 328 weasel tags of Ganter and Strube (2009) who processed two Wikipedia dumps with different completion dates.

[4] Wikipedia dumps are available for downloading at `https://dumps.wikimedia.org/`.

The numbers of unique and total words in the extracted sentences containing weasel tags are approximately 6,000 and 16,000, respectively. We sort the roughly 6,000 unique words and their bigrams and trigrams by frequencies and assesses whether each word or phrase correctly qualifies for a weasel word. In this raw word frequency sort, commonly used words tend to show up as most frequent, despite not being weasel words themselves (e.g., words like “the”, “and”, and “that”). This is a larger issue with the unigrams than it is with the bigrams or trigrams. For example, Panel (a) of Table 1 displays the three separate lists of the top 10 most frequently mentioned unigrams, bigrams, and trigrams in our weasel-tagged sentences.

[Insert Table 1 Here]

To ensure we do not merely pick up common language in our keyword lists, we extract a control sample of sentences that occur three sentences later in the text of the same articles. Upon manually inspecting these sentences, these control sentences are free of weasel language, and have the virtue that they are on the same set of topics as the weasel text. Using these control sentences together with the weasel-tagged sentences, we compute the saliency of the words in the weasel-tagged sentences relative to control sentences based on Goldsmith-Pinkham, Hirtle, and Lucca (2016). The saliency measure captures the degree to which the words are overused relative to common language, and is thus, appropriate for screening our list of common language. Panel (b) of Table 1 shows how effective the saliency screen is in filtering out common language from the list of words.[5]

After filtering out common language using the saliency screen on unigrams, we compile our final list of imprecision keywords (unigrams, bigrams, trigrams). Further, we expand the list of imprecision keywords using variations on these words such as the singular and plural forms for nouns and the past, present, and future tenses for verbs. We also manually

[5]We also consider a re-weighted version of the measure using text frequency, inverse document frequency weights (tf-idf) that mirrors the intuition of the Goldsmith-Pinkham, Hirtle, and Lucca (2016) saliency filter. Results using the saliency filter and tf-idf weighting are nearly identical. Despite this robustness to a more sophisticated methodology, we prefer to use the main measure of imprecision because it is more transparent, and involves fewer researcher choices.

eliminate redundancy in bigrams and trigrams (especially) in cases where including both would count the same language twice.[6]

The dictionary of imprecision keywords is distinct from notable alternatives. Specifically, Panel (c) of Table 1 presents the top 10 most frequently used keywords in the 10-Ks using our dictionary of imprecision keywords, and for comparison, the same list for uncertainty words and weak and strong modal words taken from the Loughran and McDonald (2011) master dictionary. The most frequently used words in each of these dictionaries have minimal overlap with one another, indicating that our linguistic imprecision measure using the imprecision keywords provides unique information distinct from these related measures. For example, numerically vague expressions such as “other”, “number of”, and “various” are uniquely included in the top 10 most frequently used imprecision keywords.[7] Also, a number of passive expressions such as “said”, “considered”, and “found” are frequently used imprecision keywords in 10-Ks, although those are not included in the top 10 list. In robustness exercises, we construct our linguistic imprecision measure purged of uncertainty and weak modal words, and show that all the main conclusions of our analysis go through.

2.2 10-K Disclosure and Firm Linguistic Imprecision Measure

The final step in our text processing procedure is to download all 10-K filings with report dates from 1997 to 2015 and extract the raw counts of how many times a given firm mentions each of the imprecision keywords in a given year. This generates a full panel of imprecision keyword vectors with 219,491 firm-year observations. Our final sample is reduced to 46,157 firm-year observations after merging with Compustat data, CRSP data, and the product market threats and financial constraints data from Hoberg, Phillips, and Prabhala (2014)

[6] In addition, Wikipedia has published guidelines for weasel words, giving specific examples to help users identify weasel language. Our methodology captures the vast majority of the example phrases offered by Wikipedia, but several example phrases in the guidelines are not in the Wikipedia dump we analyze. To maintain the most comprehensive list of imprecision keywords, we also include these guideline weasel words in our final list. The complete list of imprecision keywords can be obtained by contacting the authors.

[7] The most frequently used unigram, “other”, can be simply mentioned in 10-Ks to refer to an accounting item that contains “other”, for example as in “Other Comprehensive Income”, “Assets - Other”, “Liabilities - Other - Total”. We note that our findings discussed later are robust to excluding “other” from our dictionary of imprecision keywords.

and Hoberg and Maksimovic (2015), respectively. We create our main linguistic imprecision measure, *Imprecision*, based on the vectors of our imprecision keywords. *Imprecision* is how many times the imprecision keywords are mentioned (i.e., the sum of all elements in the imprecision keyword vector) in a given firm's 10-K filing in a given year scaled by the total word count in the filing in the percentage term. Throughout the paper, we focus on *Imprecision* as our main variable of interest.

To provide a contextual understanding of our imprecision measure, we examine neighbor words that co-exist with imprecision keywords in 10-K disclosures. Neighbor words are those that occur in the same paragraph of any of the imprecision keywords. We only include words in the Loughran and McDonald (2011) master dictionary that are considered to add financial information content. We identify the part of speech for each of unique neighbor words and sort them by frequencies. Table 2 lists the top 30 most frequently mentioned neighbor words by parts of speech.

[Insert Table 2 Here]

The three columns of Table 2 list verbs, nouns, and adjectives or adverbs, respectively. In the list for verbs, the top 5 most frequently mentioned neighbor words are "hidden", "will", "required", "expected", and "estimated." These words appear to be associated with a firm's discussion on upcoming but uncertain situations. Besides, "anticipate(d)", "assumed", "intended", "achieve", "increasing", and "projected" in lower ranks of the verb list also suggest similar context around an imprecision keyword in a paragraph. The most frequently mentioned noun is "plan", and "future" follows it. These two words are also associated with forward-looking disclosures. The most frequently mentioned adjective or adverb was "approximately." It is worth noting that the adjective or adverb list includes neighbor words that imply positive attributes of circumstances, for example, "effective", "able", "greater", "beneficial", "successful", and "favorable."

Overall, the picture that emerges from examining neighbor words that co-exist with imprecision keywords is that firm disclosures containing imprecise language are more likely to express shades of possibility and convey forward-looking information that is by nature less specific and precise.

2.3 10-K Disclosures and Empirical Strategy

Before describing our empirical tests, it is important to comment on the meaning of imprecision within the context of 10-K disclosures relative to other potential source texts. We expect that the imprecision measure based on 10-K disclosures—which are required by Regulation S-K to include any information with material effects on the firm's financial condition or results of operations, are carefully curated by the firm's legal team, and also should be audited—is likely different from a similar measure on other source texts that do not have the same degrees of difficulty of censoring and ex ante scrutiny (e.g., the question and answer portion of the earnings conference call). Because of this high degree of care in preparing the 10-Ks, imprecise language in the 10-Ks is more deliberate than other source texts. With this background in mind, we expect our imprecision measure based on 10-K disclosures to contain genuine information that is not possible to make precise at the time of the disclosure because of market conditions or timing. This information is distinctively useful from the standpoint of investors in evaluating the likely consequences of conditions that the firm faces.

3 Preliminary Empirical Results

3.1 Summary Statistics

Table 3 presents the basic summary statistics of various textual tonal variables (in Panel A) and non-tonal firm-specific characteristics (in Panel B), respectively, which will be used in our subsequent analyses. Each variable is winsorized at the top and bottom 1% of its distribution. As for the textual tonal variables, we include our linguistic imprecision measure ($Imprecision$), existing textual tonal variables based on the master dictionary by Loughran and McDonald (2011) (Sentiment, Uncertain, Modal, Constraining, Litigious, Superfluous, and Interesting), and Fog index initially proposed by Robert Gunning in 1952 and used extensively in the literature to quantify the lack of plain English (e.g., Li (2008)). All textual tonal variables are expressed in percentage and their detailed definitions are provided in Appendix. In Panel A of Table (3), the mean and median of $Imprecision$ are 1.417 and 1.485, respectively. The average of Sentiment that is the difference in counts between positive words and percent negative words (out of total words) is -0.729, indicating that negative sentiment dominates positive one in our sample of 10-K disclosures. On average, according to Fog index, 30% of words are considered as complex words in our sample of 10-K disclosures. Uncertain or litigious words are mentioned as many times as our imprecise keywords on average.

[Insert Table 3 Here]

As for non-tonal firm characteristics, the average of market value of total assets is approximately $771 million (Size is in logarithm) and the average of firm age (Age) in our sample is roughly 11 years. We include two growth opportunities proxies: Tobin's Q and Sales growth, whose means are 2.077 and 0.102%, respectively, and two measures for the economic conditions that firms face: Product market fluidity by Hoberg, Phillips, and Prabhala (2014) and Financing constraints by Hoberg and Maksimovic (2015). For investigating how stock prices react to our linguistic imprecision measure (Section 4.1), we also have share turnover (Turnover), book-to-market ratio (Book-to-market), percentage of institutional investors' holdings (Institutional ownership), and risk-adjusted return before 10-K filing (Pre-filing Fama-French alpha). For our tests based on earnings surprise (Section 4.3), we additionally include two analysts' forecast related variables: Analyst dispersion and Analyst revision. More detailed definitions of these non-tonal firm-specific variables are provided in Appendix.

3.2 Relations to Other Textual Tonal Variables

In this section, we examine the relations of our linguistic imprecision measure ($Imprecision$) to existing textual tonal measures proposed in earlier studies, which can deepen our understanding of the use of imprecise language in 10-K disclosures. Specifically, although the imprecise language is distinct from uncertainty and weak modal language, we expect it to be positively related to uncertainty and weak modal language to a certain extent. It is because, intuitively, we expect firms to use more imprecise language in 10-Ks at times and in situations where they face greater uncertainty, captured by uncertainty and weak modal words.

We validate this intuition of linguistic imprecision using uncertainty words, and weak and strong modal words from the master dictionary by Loughran and McDonald (2011). Portraying a series of univariate comparisons to the use of imprecise language in 10-K disclosures, Figure 1 presents sets of side-by-side box plots for the usage of linguistic imprecision by whether uncertainty, weak modality, and strong modality are above versus below the median.

[Insert Figure 1 Here]

These box plots in Figure 1 indicate that the imprecise language in 10-Ks is more commonly used with high uncertainty words and high modality words. In addition, they show that there are substantial overlaps in the distributions of the linguistic imprecision for high and low uncertainty, weak modality, and strong modality, implying that there is useful residual variation in our linguistic imprecision measure when holding the other textual tonal measures constant.

To examine the associations between our linguistic imprecision measure and other textual tonal measures more systematically, we regress $Imprecision$ on a set of existing textual tonal measures, where all variables are contemporaneous. In Panel A of Table 4, we report the test results of this regression model which also controls for firm and year fixed effects. To account for potential serial correlation in the linguistic imprecision measure, the standard errors are clustered by firm.

[Insert Table 4 Here]

In Column (1) of Panel A, we include Fog index to quantify the readability or complexity of 10-K disclosures, Uncertain, and Modal constructed based on the master dictionary by Loughran and McDonald (2011) as independent variables. Column (1) show that readability, uncertainty, and modality are all positively associated with our linguistic imprecision measure, even when controlling for unobserved firm characteristics by including firm fixed effect. In Column (2), we additionally examine the relations of linguistic imprecision with Sentiment (the difference in counts between positive words and negative words) and two other textual tonal variables: Constraining and Litigious, which capture firm's constraining and litigious situations, respectively. We find evidence that our measure of linguistic imprecision is positively associated with Sentiment, Constraining, and Litigious, suggesting an interpretation that firm uses less precise language when it discusses its positive prospects that likely have not been realized in those negative situations. In Column (3), we also control for the percentages of superfluous words and interesting words (out of total words), which are captured by Superfluous and Interesting, respectively, and find that the test results in Columns (1) and (2) remain intact. Although we do not report the results to conserve space, when controlling for Size, Age, Tobin's Q, and Sales growth additionally, we find that our results are robust in terms of the magnitudes and statistical significance of slope coefficients.[8]

Taken together, these evidence suggests that the imprecise language used in the 10-Ks captures relatively positive tone with high uncertainty and high modality. Because uncertainty and modality aspects of the text are to a large degree parts of the content of linguistic imprecision, we do not control for Uncertain and Modal in our subsequent tests in Section 4. We do, however, find robustness to controlling for Uncertain and Modal.

[8]We conduct two additional tests for robustness. First, we repeat the same analyses at the paragraph level, reaching the same conclusions about how the linguistic imprecision relates to uncertainty and modality. In the paragraph-level analyses, we can control for firm-year (i.e., report level) fixed effects, identifying only on the variation within 10-K disclosure. Second, beyond the normalization by calculating the percentage of imprecision keywords in our linguistic imprecision measure, we rerun all tests by additionally controlling for the log of the total number of words in 10-K, which is related to readability (e.g., Loughran and McDonald (2014)), and find that our test results are robust.

3.3 Relations to Non-tonal Firm Characteristics

The language choices in firms' disclosures are likely to be affected by situations that those firms face, which can be captured at least partially by various non-tonal firm-specific characteristics. For example, imprecise language ought to be more frequently used by firms when they face greater growth opportunities that are difficult to quantify at the moment of disclosure. Based on this intuition, we try to relate lagged non-tonal firm characteristics to our linguistic imprecision measure constructed from 10-K disclosures.

[Insert Figure 2 Here]

We first illustrate graphically which non-tonal firm characteristics (among notable ones) are related to the use of imprecise language in 10-Ks. Figure 2 presents the 95% confidence intervals for the means of Size, Age, and two proxies for growth opportunities (Tobin's Q and Sales growth) by each quartile of the distribution of our linguistic imprecision measure. From Figure 2, we find strong patterns that smaller (Panel (a)) and younger (Panel (b)) firms which are likely to have more growth opportunities (Panels (c) and (d)) tend to use more imprecise language in their 10-Ks.

We then examine the strong associations with those firm characteristics more systematically with the regression models in Panel B of Table 4. All regression models in Table 4 include firm and year fixed effects, and standard errors are clustered by firm to account for potential serial correlation in the linguistic imprecision measure. All non-tonal firm-specific characteristics are lagged by one year. In Column (1) of Panel B, we consider the first set of non-tonal firm-specific characteristics employed in Figure 2, that is, Size, Age, Tobin's Q, and Sales growth. The test results in Column (1) of Panel B present evidence that the strong associations between the linguistic imprecision measure in 10-Ks and Size, Age, and Tobin's Q, as indicated in Figure 2, are also present in the regression analysis.

The next set of non-tonal firm characteristics include proxies for product market threats and financial constraints. An important strand of the corporate finance literature has paid particular attention to how corporate policies relate to product markets and financial constraints. In this context, we investigate how firms' use of imprecise language in their disclosures changes upon facing greater product market threats (captured by Product market fluidity) and financial constraints (captured by Financial constraints). Column (2) of Panel B in Table 4 provides the test results. We find significant positive associations between our measure of linguistic imprecision and both Product market fluidity and Financial constraints. This supports strongly that product market threats or financial constraints place pressure on firms to disclose some information using imprecise language in their 10-K disclosures.

As the last set of non-tonal firm characteristics, in Column (3), we consider a list of variables that have been known to affect firms' returns on the event days of 10-K release. Those variables include Turnover, Institutional ownership, and Pre-filing Fama-French alpha, which captures the risk-adjusted return before 10-K filing.[9] The test results in Column (3) show that these firm characteristics are not significantly related to the use of imprecise language in 10-K disclosures.

Overall, the test results in this section are particularly informative in designing our main empirical analyses and interpreting the associated results in the next section with respect to market reactions to imprecise language in 10-K disclosures.[10]

4 Main Empirical Results

4.1 Market Reactions to Imprecise Language in Disclosure

This section examines the relation between imprecise language in 10-Ks and subsequent stock returns after 10-K filing. Specifically, for each 10-K release, we compute the buy and hold abnormal returns (BHARs) over subsequent weekly windows after its filing and test whether our linguistic imprecision measure predicts abnormal returns using the following

[9] We do not include Market value and Book-to-market in Column (3) since their inclusion can be redundant due to Size and Tobin's Q.

[10] For robustness, we additionally include Fog index and Sentiment to control for readability and sentiment of 10-K disclosures. The test results are robust to controlling for these additional variables.

regression specification. For stock i, over the nth week after its 10-K filing in year t,

$$BHAR_{itn} = \alpha_n + \beta_n Imprecision_{it} + \eta_n^{'} \mathbf{X}_{it} + \epsilon_{itn}, \quad (1)$$

where $BHAR_{itn}$ is defined as the return difference between stock i and the CRSP value-weighted index over the nth week window (the 1st week window starts from the fourth day after the 10-K release date), $Imprecision_{it}$ is the percentage of imprecision keywords (out of the total words) in the 10-K disclosure, and $\mathbf{X}_{it}$ is a column vector that has control variables used in prior studies (e.g., Loughran and McDonald (2011)), including Sentiment, Market value, Book-to-market, Turnover, Institutional ownership, and Pre-filing Fama-French alpha. All independent variables in Model (1) are standardized and their detailed definitions are provided in Appendix. We estimate Model (1) for each week separately over the subsequent 10-week period after the 10-K release date (thus $n = 1, \ldots, 10$), where we employ clustered standard errors by filing year-month to account for cross-sectional correlation of returns across stocks. The coefficient of interest in Model (1) is β_n, which captures how each stock's week n price reacts to the imprecise language used in its 10-K disclosure. We hypothesize that the linguistic imprecision in 10-K disclosures contains positive but immature value-relevant information about firms and market participants need some time to digest it. Thus we expect positive price reactions to the linguistic imprecision in 10-Ks, that is, $\beta_n > 0$ for some $n > 0$.

[Insert Table 5 Here]

The test results of Model (1) are presented in Table 5. The evidence in Panel (a) of Table 5 supports our hypothesis. We find positive and significant slope coefficients for $Imprecision_{it}$ from the 3rd through 7th weeks after 10-K filing date. The slope coefficients for $Imprecision_{it}$ in weeks 8 to 10 are also positive but statistically insignificant, indicating that the positive market reaction to the linguistic imprecision in 10-Ks does not revert over time. To investigate whether systematic risks drive our results, we add the exposure to the Fama-French three-factor model to Model (1) as additional control variables, where the factor loadings are estimated over the preceding one year before 10-K release date. We find that our test results on β_n remains almost intact even after controlling for those factor loadings.

Panel (b) of Table 5 reports analogous test results over multiple-week post-filing windows to capture longer-term market reactions and we call them cumulative BHARs. The positive and significant return effect of imprecise language in 10-K disclosures cumulatively emerges from the 3rd week, monotonically increases afterward until the 9th week, and remains at the same level in the 10th week. This monotonic pattern again indicates that the positive return effect of imprecise language does not experience a reversal. The economic magnitude of the positive linguistic imprecision effect can be gauged as follows. Based on Column (10), one standard deviation increase in the use of imprecise language in 10-K disclosure (=0.45%) is associated with about 1% higher BHAR over the ten-week period after its release.

As an alternative presentation of our positive linguistic imprecision effect, Figure 3 plots cumulative BHARs over the subsequent ten-week period after 10-K releases by high-imprecision (above median) versus low-imprecision (below median) disclosures.

[Insert Figure 3 Here]

In Figure 3, the line with black circles shows that on average the cumulative BHAR increases about 5% over the ten-week period for 10-Ks with high linguistic imprecision, compared to about 3% increase for 10-Ks with low linguistic imprecision. The difference in cumulative BHARs between high and low imprecision disclosures is 1.8% over ten weeks after the 10-K release dates. This graphical illustration also confirms that the positive linguistic imprecision effect does not lead to a reversal, which is consistent with Table 5. The positive market reaction to imprecise language discussed above suggests that the linguistic imprecision in 10-Ks can provide positive but immature value-relevant information about firms.

We conduct multiple robustness checks. First, to ensure that the positive market reaction to the linguistic imprecision in 10-Ks are not mechanically related to the future earnings announcements, we estimate Model (1) and repeat tests with a refined sample that excludes all 10-K filings that have new earnings announcements over the next three to seven weeks after 10-K release dates. The associated test results are presented in Appendix Table A.1 in the same format as in Table 5, indicating that the positive linguistic imprecision effect is not mechanically driven by upcoming future earnings announcements over the next three to seven weeks. Second, to ensure that our test results are not sensitive to how to compute abnormal returns, we estimate Model (5) with cumulative abnormal return (CAR), i.e., CAR_{itn}, as the dependent variable instead of $BHAR_{itn}$.[11] The associated test results are presented in Appendix Table A.2, which are similar to those in Table 5. This evidence indicates that the positive market reactions to imprecise language in 10-Ks are robust to how to measure firms' abnormal returns. Third, we include the following additional control variables in Model (5): Sales growth, Product market fluidity, and Financial constraints and repeat the tests. With this extended model, we find qualitatively similar test results for the positive linguistic imprecision effect to Table 5.

4.2 Subsequent Information Asymmetry

In this section, we examine how the use of imprecise language in 10-Ks affects the information asymmetry over subsequent weekly windows after 10-K release dates. If the positive price reaction to the linguistic imprecision in 10-Ks is primarily driven by value-relevant information and investors digest it over the subsequent periods, we expect a negative relation between our linguistic imprecision measure and firms' information asymmetry after 10-K filing. To test this potential link between linguistic imprecision and the level of a proxy for information asymmetry, we employ the following specification:

$$Information\ asymmetry_{itn} = \alpha_n + \beta_n Imprecision_{it} + \eta_n^{'} \mathbf{X}_{it} + \epsilon_{itn}, \tag{2}$$

[11]Fama (1998) advocates CAR and argues that BHAR exacerbates the "bad-model problems" by compounding an expected-return model's problem in explaining short-term returns. In contrast, Barber and Lyon (1997) advocates BHAR.

where $Information\ asymmetry_{itn}$ is the post-filing level of an information asymmetry proxy in logarithm over the nth week window (the 1st week window starts from the fourth day after the 10-K release date). We employ two proxies for information asymmetry that have been widely used in the literature. These proxies are the quoted relative bid-ask spread and zero-volume days by Lesmond, Ogden, and Trzcinka (1999). $Imprecision_{it}$ is the percentage of imprecision keywords (out of total words) used in firm i's 10-K disclosure in year t, and $\mathbf{X}_{it}$ is a column vector that has control variables, including Sentiment, Market value, and Book-to-market. All independent variables in Model (2) are standardized and their detailed definitions are provided in Appendix. To model unobserved heterogeneity across firms and a secular reduction in market illiquidity over time, respectively, we also control for firm and filing year-month fixed effects in Model (2). To account for serial and cross-sectional correlations of information asymmetry proxies in our tests, we employ the clustered standard errors by firm and filing year-month (see Amihud (2002) and Chordia, Roll, and Subrahmanyam (1997), respectively).

The coefficient of main interest in Model (2) is β_n, which captures how the imprecise language in 10-Ks affects firms' information asymmetry in the nth week window after 10K filing. We expect either that $\beta_n < 0$ if higher linguistic imprecision in 10-Ks comes with more value-related information, which is digested by investors or that $\beta_n > 0$ if more imprecise language in 10-Ks is associated with greater obfuscation, producing higher asymmetry between the informed and the uninformed. Table 6 reports the test results of Model (2).

[Insert Table 6 Here]

In Panel (a) of Table 6, we examine information asymmetry as measured by the quoted relative bid-ask spread. We find that the slope coefficients for our linguistic imprecision measure are negative and significant at the 5% level from the 1st through 10th weeks after 10-K filing dates. This indicates that information asymmetry decreases as the use of imprecise language increases in 10-Ks. In Panel (b) of Table 6, we examine zero-volume days by Lesmond, Ogden, and Trzcinka (1999) as an alternative measure of information asymmetry.

We continue to find that the slope coefficients for our linguistic imprecision measure are negative and significant throughout all columns. We further note that the negative effect of linguistic imprecision on information asymmetry is the strongest in the 3rd and 4th weeks after 10-K filing and coincides with the time that the market valuation improves the most as in Table 5. These results are consistent with the interpretation that more use of imprecise language in 10-Ks is indeed associated with more value-relevant information about firms and that the information is digested by investors in financial markets, thus leading to a decrease in information asymmetry after 10-K filing.

As for the control variables in Model (2), their effects on information asymmetry are consistent with existing studies in the literature. We find evidence that the slope coefficients for Sentiment are negative in almost all weeks and significant from the 4th through 9th weeks in Panel (a). This indicates that the percentages of positive and negative words in 10-Ks also contain value-related information, consistent with the pricing evidence of textual tones in Tetlock, Saar-Tsechansky, and Macskassy (2008), Loughran and McDonald (2011), and Jegadeesh and Wu (2013). The negative and significant coefficient for Market value and the positive and significant coefficient for Book-to-market are respectively consistent with Amihud (2002) and Fang, Noe, and Tice (2009).

As a robustness check, we add a pre-fling level of each information asymmetry proxy into $\mathbf{X}_{it}$ in Model (2) and examine whether the significant negative effect of our linguistic imprecision measure on the two information asymmetry proxies survives. In this extended model, we find that the slope coefficients for $Imprecision_{it}$ remain negative and significant for the two proxies of information asymmetry.

Based on the test results so far, we conclude that the linguistic imprecision in 10-K disclosures contains the information on firms' fundamentals rather than obfuscation. Our earlier findings that stock prices eventually respond positively to the use of imprecise language in 10-K disclosure and that these positive reactions do not lead to reversal are consistent with this conclusion on the post-fling information asymmetry.

4.3 Subsequent Earnings Surprise

To understand what value-relevant information comes with the imprecise language in 10-K disclosures on a deeper level, we now test whether our linguistic imprecision measure can predict subsequent earnings surprise, a proxy for news on future cash flow, after 10-K release dates.

For each firm and each quarterly earnings announcement, we first compute standardized unexpected earnings (SUE) as actual earnings minus the mean of analysts' forecasts divided by price which is available as of one day before the earnings announcement day. We then estimate the following regression model with either a SUE indicator or a SUE rank as the dependent variable:

$$\textit{Earnings surprise}_{itq} = \alpha_q + \beta_q \textit{Imprecision}_{it} + \eta_q^{'} \mathbf{X}_{it} + \epsilon_{itq}, \tag{3}$$

where $\textit{Earnings surprise}_{itq}$ is based on the nearest future SUE in qth quarter to stock i's 10-K release date in year t. For the SUE indicator, $\textit{Earnings surprise}_{itq}$ is 1, 0, or -1 when the nearest future SUE in the qth quarter is above zero, equal to zero, or below zero, respectively. For the SUE rank, $\textit{Earnings surprise}_{itq}$, is +2, +1, 0, -1, or -2 when the nearest future SUE in the qth quarter is above 80%, between 80% (inclusive) and 60%, between 60% (inclusive) and 40%, between 40% (inclusive) and 20%, or below 20% (inclusive), respectively, where the percentiles are computed based on all available SUEs of other firms within the three-week period before each of the nearest future SUE. $q = 0$ means that the nearest future earnings announcement and 10-K filing are made in the same quarter, and $q = 1$ means that the nearest future earnings is announced in the next quarter to 10-K filing. In addition, $q = 0\&1$ means that the nearest future earnings is announced either in the same quarter or in the next quarter of 10-K filing (whichever comes earlier is selected).

In Model (3), the variable of interest is $\textit{Imprecision}_{it}$, the percentage of imprecision keywords (out of total words) used in firm i's 10-K disclosure in year t. $\mathbf{X}_{it}$ is a column vector that contains control variables, including Sentiment, Market value, Book-to-market, Turnover, Institutional ownership, Pre-filing Fama-French alpha, Analyst dispersion, and Analyst revision. All these independent variables in Model (3) are standardized and their detailed definitions are provided in Appendix. To account for potential serial and cross-sectional correlations of SUEs, we cluster the standard errors by firm and quarter.

[Insert Table 7 Here]

The test results of SUE predictability in Model (3) are presented in Table 7. In Columns (1) and (2), when the nearest future SUE and 10-K filing are required to be in the same quarter ($q = 0$), the number of observations is significantly smaller than our earlier tests, which can potentially lead to lower power in statistical tests. Despite of this disadvantage, we find that our linguistic imprecision measure can predict future SUE positively and significantly in the 5 % level both for the SUE indicator and rank variables. In Columns (3) and (4), when the nearest future SUE is in the next quarter to the corresponding 10-K filing ($q = 1$), the number of observations substantially increases relative to Columns (1) and (2) and we continue to find evidence that the imprecise language in 10-Ks leads to positive future SUE.

We also find that the slope coefficient for $Imprecision_{it}$ is much larger for $q = 0$ (e.g., 0.086 in Column (2)) than for $q = 1$ (e.g., 0.028 in Column (4)). This indicates that the magnitude of SUE predictability by linguistic imprecision attenuates quickly as longer time horizon is allowed for security analysts to digest the value-relevant information contained in the imprecise language used in 10-Ks.[12] In Columns (5) and (6), we allow the nearest future SUE to be either in the same quarter or in the next quarter of each 10-K filing and find again the significant and positive SUE predictability by our linguistic imprecision measure although its magnitude reduces compared to Columns (1) and (2).

In sum, we conclude that the test results in Table 7 show that the imprecise language employed in 10-K disclosures contains the novel information on firms' cash flow in the near future and security analysts initially under-react to it possibly due to its embedded

[12] We also estimate Model (3) for $q = 2$ when the nearest future SUE is required to be in the second next quarter to each 10-K filing, yielding positive but insignificant slope coefficients for $Imprecision_{it}$.

immaturity although they eventually digest and reflect its implication related to future cash flow into their earnings forecasts. These evidence and interpretation are also consistent with the initial under-reaction and eventual but delayed correction by stock prices to the linguistic imprecision in 10-Ks as discussed above in our earlier tests.

5 Conclusions

In this paper, we introduce a novel textual measure to the finance and accounting literature, which quantifies the degree of linguistic imprecision in firms' disclosures. Our imprecision measure is distinct from existing textual measures such as sentiment and uncertainty, and has ability to identify the unique qualitative information in firm disclosures beyond quantitative information. In contrast to a dominant view in the literature, we find that firms tend to use more imprecise language in 10-Ks during uncertain times, which inevitably make their language relatively more imprecise, to deliver new information on positive but yet immature prospects of future cash flow. We also find that market participants, e.g., investors and security analysts, initially under-react to the information contained in linguistic imprecision possibly due to its embedded immaturity but eventually understand and digest it. Collectively, our findings and approach suggest that there is much more to learn from the qualitative content of firm disclosures.

Appendix. Variable Definitions

This appendix provides the detailed definitions of the variables used in the paper.

Imprecision	is the number of imprecision keywords scaled by the total word count in the 10-K filing (in percentage).
Positive	is the number of positive words from the master dictionary by Loughran and McDonald (2011) scaled by the total word count in the 10-K filings (in percentage).
Negative	is the number of negative words from the master dictionary by Loughran and McDonald (2011) scaled by the total word count in the 10-K filings (in percentage).
Sentiment	is Pct Positive minus Pct Negative.
Uncertain	is the number of uncertain words from the master dictionary by Loughran and McDonald (2011) scaled by the total word count in the 10-K filings (in percentage).
Modal	is the number of (weak and strong) modal words from the master dictionary by Loughran and McDonald (2011) scaled by the total word count in the 10-K filings (in percentage).
Constraining	is the number of constraining words from the master dictionary by Loughran and McDonald (2011) scaled by the total word count in the 10-K filings (in percentage).
Litigious	is the number of litigious words from the master dictionary by Loughran and McDonald (2011) scaled by the total word count in the 10-K filings (in percentage).
Superfluous	is the number of superfluous words from the master dictionary by Loughran and McDonald (2011) scaled by the total word count in the 10-K filings (in percentage).
Interesting	is the number of interesting words from the master dictionary by Loughran and McDonald (2011) scaled by the total word count in the 10-K filings (in percentage).
Fog index	is the number of words of three or more syllables that are not hyphenated words or two-syllable verbs made into three with -es and -ed endings, scaled by the total word count in the 10-K filing (in percentage).
Product market fluidity	is a 10-K based textual measure for the competitive threats faced by a firm in its product markets that captures the changes in rival firms' products relative to the firm, from Hoberg, Phillips and Prabhala (2014).
Financial constraints	is a 10-K based textual measure for financial constraints from Hoberg and Maksimovic (2015) with higher values indicating that firms are more at the risk of delaying their investments due to issues with liquidity.
Size	is the log of market value of total assets (market value of common equity plus book value of preferred stock, long-term and short-term debt, and minority interest) in a given year.
Age	is the log of one plus firm age in a given year based on its first appearance in Compustat.
Tobin's Q	is the market value of assets divided by book value of assets in a given year.

Sales growth	is the percentage growth in sales in a given year.
Market value	is the log of market value of equity, which is the number of shares outstanding times the price of the stock on the day before 10-K filing date.
Book-to-market	is the log of the book-to-market ratio using the book value from firm's annual report known as of the end of the previous fiscal year and the market value known as of December of the year before the year of analysis.
Turnover	is the log of the volume of shares traded over the period from the beginning of the prior month to six days (inclusive) before 10-K filing, divided by the number of shares outstanding at the end of the period.
Pre-filing Fama-French alpha	is the intercept estimated by regressing daily excess returns on daily Fama-French's three factors over one year before 10-K filing date. For each stock, at least 60 observations of daily returns are required to be included in the sample.
Institutional ownership	is the percentage of institutional investors' holdings available from the CDA/Spectrum database for the most recent quarter before 10-K filing date. The variable is treated as missing for negative values and winsorized to 100% for values above 100%.
Bid-ask spread	is the average of daily ratio of quoted bid-ask spread to the bid-ask midpoint over a given period in logarithm.
Zero-volume days	is the ratio of the number of days with zero return or zero volume to the total number of days in a given period, which is proposed by Lesmond, Ogden, and Trzcinka (1999), in logarithm.
SUE	is the standardized unexpected earnings defined as actual earnings minus the consensus (mean) of analysts' forecasts divided by the stock price on the day before each earnings announcement day.
Analyst dispersion	is the standard deviation of analysts' forecasts for the most recent quarter prior to the earnings announcement to compute SUE, divided by the stock price at the end of the quarter.
Analyst revision	is the change in the consensus (mean) of analysts' forecasts, divided by the stock price in the prior month before the earnings announcement day.

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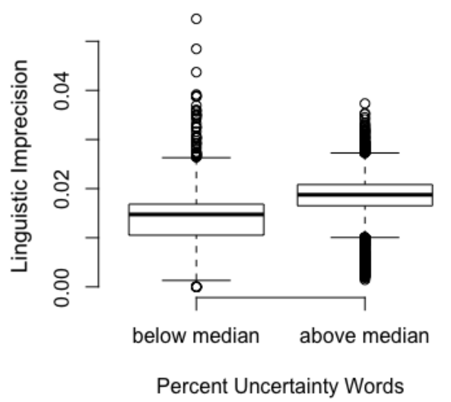
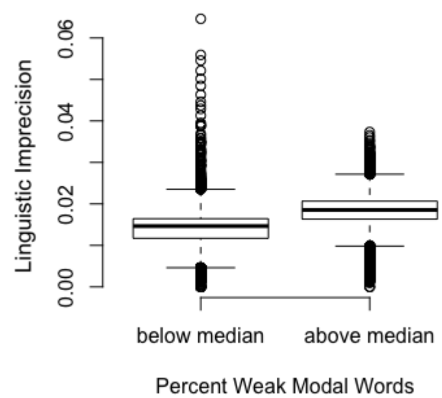
Figure 1: Linguistic Imprecision versus Uncertainty and Modality

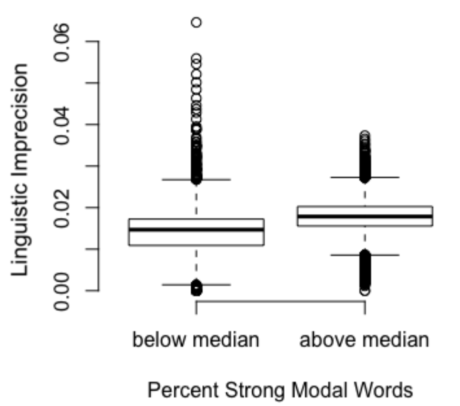
This figure shows the relation between each of notable textual tonal measures: (a) uncertainty words, (b) weak modal words, and (c) strong modal words (from the master dictionary by Loughran and McDonald (2011)) and the propensity of a firm to use imprecise language in its 10-K disclosure. Each panel presents two side-by-side box plots for the distribution of our linguistic imprecision measure by above and below the median of each textual tonal measure. Each box displays the interquartile range between the 25th to 75th percentiles of the distribution of the linguistic imprecision measure, where the thick solid line inside the box displays the median. The top and bottom solid lines outside the box display the maximum and minimum, respectively, where the maximum and minimum are defined as the 75th percentile + 1.5*the interquartile range and 25th percentile - 1.5*the interquartile range. Circles above and below those two solid lines represent outliers. The difference in medians for each panel is statistically significant at the 1% level.



(a) Percentage of Uncertainty Words



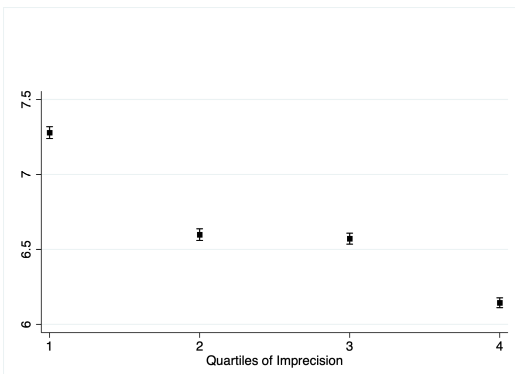
(b) Percentage of Weak Modal Words



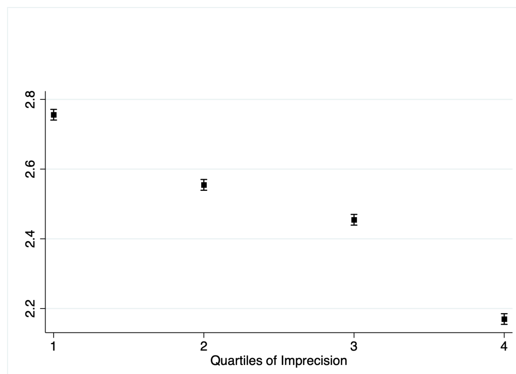
(c) Percentage of Strong Modal Words

Figure 2: Linguistic Imprecision and Non-tonal Firm Characteristics

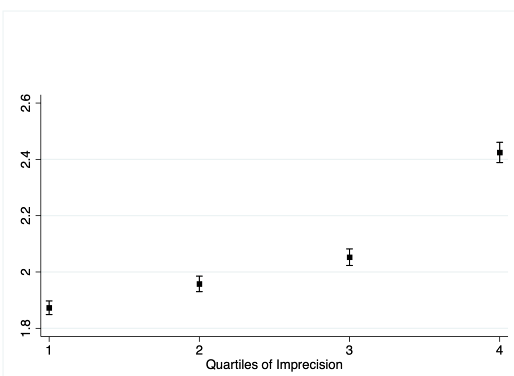
This figure shows the relation between each of notable non-tonal firm characteristics and the propensity of a firm to use imprecise language in its 10-K disclosure. Each panel presents the 95% confidence interval for the mean of each of four characteristics for the first, second, third, and fourth quartile of the distribution of the linguistic imprecision measure. The four firm characteristics are Size, Age, Tobin's Q, and Sales growth.



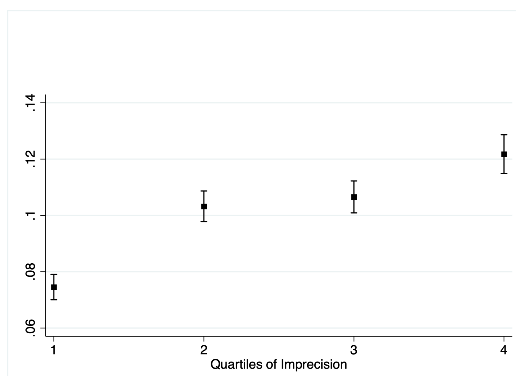
(a) Size



(b) Age



(c) Tobin's Q



(d) Sales growth

Figure 3: Linguistic Imprecision and Subsequent Cumulative BHARs

This figure presents the plots of average cumulative buy and hold abnormal returns (BHARs) over various multiple-week post-filing windows after 10-K filing for high (> median) imprecision disclosures and low (< median) imprecision disclosures. First, each cumulative BHAR is computed over the period from the fourth day after 10-K filing until the end of nth week ($n = 1, \ldots, 10$). Then the average of cumulative BHARs is taken across firms for each imprecision group.

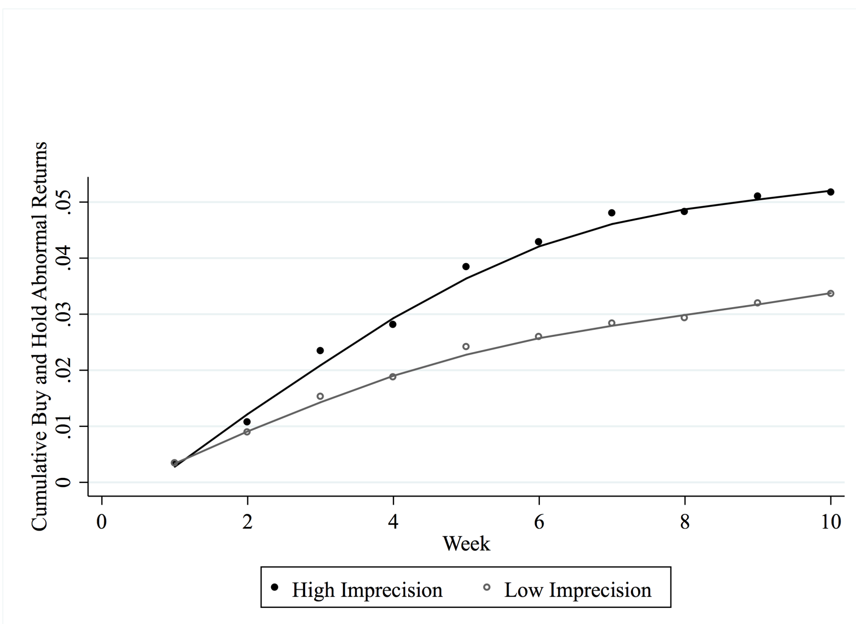


Table 1: Frequently Used Words and Salient Words in Sentences with Weasel Tags

Panel (a) of this table presents the lists of the top 10 most frequently mentioned unigrams, bigrams, and trigrams in the 433 sentences that have weasel tags ({{Weasel-inline—{{subst:DATE}}}}) from an Wikipedia dump completed on April 20, 2017. This Wikipedia dump contains 17,483,910 articles and is available at `https://dumps.wikimedia.org/`. To illustrate the influence of our saliency screen, Panel (b) of the table presents the top 10 unigrams and the bottom 10 unigrams sorted on the saliency score of Goldsmith-Pinkham, Hirtle, and Lucca (2016). Panel (c) provides the lists of the top 10 most frequently mentioned imprecision keywords, uncertainty words, and weak and strong modal words. The keyword lists of uncertainty, weak modality, and strong modality words come from the master dictionary by Loughran and McDonald (2011).

(a) Top 10 Unigrams, Bigrams, and Trigrams

Rank	Unigrams	Bigrams	Trigrams
1	the	of the	one of the
2	and	in the	it has been
3	some	it is	considered by many
4	that	to be	is considered by
5	was	has been	of the most
6	many	to the	is one of
7	for	for the	it can be
8	with	one of	may have been
9	has	and the	according to some
10	have	that the	be one of

(b) Top and Bottom 10 Unigrams, Sorted on Saliency

Rank	Top 10 Unigrams	Bottom 10 Unigrams
1	some	the
2	many	and
3	although	for
4	considered	was
5	may	from
6	said	their
7	have	new
8	argued	united
9	believed	also
10	often	first

(c) Top 10 Imprecision, Uncertainty, and Modal Words

Rank	Imprecision Words	Uncertainty Words	Weak Modal Words	Strong Modal Words
1	other	hidden	may	will
2	may	may	could	must
3	clear	could	possible	best
4	could	approximately	might	highest
5	would	risk	depend	never
6	number of	intangible	uncertain	lowest
7	can	believe	depending	always
8	well	assumptions	depends	clearly
9	however	risks	appears	strongly
10	various	believes	appearing	undisputed

Table 2: Frequently Used Words Neighboring Imprecision Keywords in 10-Ks

The table presents the lists of the top 30 most frequently mentioned nouns, verbs, and adjectives/adverbs from the paragraphs of 10-K disclosures that contain our keywords of linguistic imprecision.

Rank	Verb	Noun	Adjective/Adverb
1	hidden	plan	approximately
2	will	future	effective
3	required	loss	generally
4	expected	losses	regulatory
5	estimated	obligations	adverse
6	require	risk	legal
7	restricted	benefit	adversely
8	amended	requirements	able
9	requires	estimates	greater
10	permitted	impairment	unable
11	expect	plans	contractual
12	comply	contracts	beneficial
13	terminated	termination	notwithstanding
14	disclosed	laws	pending
15	terminate	claims	successful
16	differ	law	unpaid
17	anticipated	regulations	favorable
18	impaired	contract	statutory
19	assumed	assumptions	difficult
20	restructuring	risks	successfully
21	intended	default	duly
22	discontinued	decrease	critical
23	intend	obligation	uncertain
24	restated	collapse	strong
25	anticipate	court	hazardous
26	prevent	closing	doubtful
27	achieve	intangible	negatively
28	increasing	amendment	satisfactory
29	projected	failure	furthermore
30	depend	gains	beneficially

Table 3: Summary Statistics

This table presents the summary statistics for various variables used in our empirical analyses. The sample period is from 1997 to 2015. Panel A presents the summary statistics for our linguistic imprecision measure (*Imprecision*), existing textual tonal variables based on the master dictionary by Loughran and McDonald (2011), and Fog index initially proposed by Robert Gunning in 1952 and used extensively in the literature to quantify the lack of plain English (e.g., Li (2008)). Panel B presents the summary statistics for non-tonal firm characteristics. The detailed definitions of all variables are provided in Appendix. Each variable is winsorized at the top and bottom 1% of its distribution.

Panel A: Textual Tonal Variables

	Mean	Std.Dev	Min	Median	Max	Num.ofObs.
Imprecision	1.417	0.450	0.000	1.485	5.231	46157
Sentiment	-0.729	0.451	-4.362	-0.681	1.670	46157
Uncertain	1.022	0.354	0.000	1.042	3.230	46157
Modal	0.820	0.371	0.000	0.849	2.607	46157
Constraining	0.566	0.233	0.000	0.582	2.116	46157
Litigious	1.255	0.885	0.042	1.018	6.819	46157
Superfluous	0.009	0.012	0.000	0.006	0.233	46157
Interesting	0.124	0.080	0.000	0.116	1.666	46157
Fog index	30.210	4.316	14.066	29.882	51.590	46157

Panel B: Non-tonal Firm Characteristics

	Mean	Std.Dev	Min	Median	Max	Num.ofObs.
Size	6.648	2.062	0.515	6.570	13.989	46157
Age	2.484	0.867	0.000	2.565	3.970	46157
Tobin's Q	2.077	1.640	0.646	1.527	11.159	46157
Sales growth	0.102	0.312	-0.944	0.079	1.360	46157
Product market fluidity	6.640	3.292	1.482	6.051	17.363	45546
Financial constraints	-0.014	0.091	-0.193	-0.020	0.237	35378
Turnover	-1.943	1.122	-9.556	-1.849	2.939	46092
Book-to-market	-0.745	0.912	-8.864	-0.680	4.324	44462
Institution ownership	57.079	28.222	0.622	62.284	100.000	37415
Pre-filing Fama-French alpha	0.001	0.002	-0.005	0.000	0.010	46157
Analyst dispersion	0.003	0.005	0.000	0.001	0.039	21437
Analyst revision	-0.000	0.016	-0.073	0.000	0.061	26076

Table 4: Relations between Linguistic Imprecision and Various Variables

This table presents the test results of regressing our linguistic imprecision measure (*Imprecision*) in 10-K disclosures on various textual tonal measures (Panel A) and non-tonal firm characteristics (Panel B). In Panel A, the fog index is based on Robert Gunning in 1952 and the other tonal measures: Uncertainty, Modal, Positive and Negative (for Sentiment), Constraining, Litigious, Superfluous, and Interesting are based on the master dictionary by Loughran and McDonald (2011). Panel B includes non-tonal firm characteristics that have been used in existing studies. The detailed definitions of all variables are provided in Appendix. Each variable is winsorized at the top and bottom 1% of its distribution. (Z) indicates that the variable is standardized to have mean 0 and standard deviation 1 for ease of interpretation. Firm and year fixed effects are also included in the model. Standard errors that are clustered by firm are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

Panel A: Textual Tonal Variables

	Dependent variable = Imprecision		
	(1)	(2)	(3)
Fog index(Z)	0.0589***	0.0615***	0.0614***
	(0.003)	(0.003)	(0.003)
Uncertain(Z)	0.102***	0.129***	0.127***
	(0.005)	(0.005)	(0.005)
Modal(Z)	0.292***	0.247***	0.241***
	(0.005)	(0.005)	(0.005)
Sentiment(Z)		0.00984***	0.0112***
		(0.002)	(0.002)
Constraining(Z)		0.0556***	0.0551***
		(0.002)	(0.002)
Litigious(Z)		0.0662***	0.0677***
		(0.002)	(0.002)
Superfluous(Z)			0.00969***
			(0.002)
Interesting(Z)			0.0129***
			(0.002)
Fixed effect		Firm / Year	
Observations	44971	44971	44971
Adjusted R^2	0.862	0.881	0.882

Panel B: Non-tonal Firm Characteristics

	Dependent variable = Imprecision		
	(1)	(2)	(3)
Size(Z)	-0.0456***	-0.0594***	-0.0607***
	(0.009)	(0.010)	(0.013)
Age(Z)	-0.0624***	-0.0608***	-0.0668***
	(0.008)	(0.009)	(0.012)
Tobin's Q(Z)	0.0165***	0.0189***	0.0168***
	(0.003)	(0.003)	(0.004)
Sales growth(Z)	-0.000704	0.000182	-0.00148
	(0.001)	(0.002)	(0.002)
Product market fluidity(Z)		0.0223***	0.0210***
		(0.005)	(0.006)
Financial constraints(Z)		0.0186***	0.0199***
		(0.003)	(0.004)
Turnover(Z)			0.0000188
			(0.003)
Institution ownership (Z)			-0.00404
			(0.006)
Pre-filing Fama-French alpha(Z)			-0.000469
			(0.002)
Fixed effect		Firm / Year	
Observations	44971	33898	27090
Adjusted R^2	0.645	0.657	0.663

Table 5: Imprecise Language in Disclosure and Subsequent BHARs

This table presents the test results of Model (1) regressing buy and hold abnormal returns (BHARs) over various estimation windows after 10-K filing on our linguistic imprecision measure as follows:

$$BHAR_{itn} \quad = \quad \alpha_n + \beta_n Imprecision_{it} + \eta_n^{'} \mathbf{X}_{it} + \epsilon_{itn},$$

where $BHAR_{itn}$ is the return difference between stock i and the CRSP value-weighted index over the nth week window (the 1st week window starts from the fourth day after the 10-K release date), $Imprecision_{it}$ is the percentage of imprecision keywords (out of the total words), and $\mathbf{X}_{it}$ is a column vector that contains various control variables used in prior studies: Sentiment, Market value, Book-to-market, Turnover, Institutional ownership, and Pre-filing Fama-French alpha. The detailed definitions of these independent variables are given in Appendix. (Z) indicates that the variable is standardized to have mean 0 and standard deviation 1. Standard errors that are clustered by filing year-month to account for cross-sectional correlation of BHARs are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively. In Panel (a), we estimate Model (1) for each week separately over the subsequent 10-week period after 10-K filing ($n = 1, \ldots, 10$). In Panel (b), we repeat to estimate Model (1) with cumulative BHARs over multiple-week post-filing windows.

(a) Weekly BHARs

	Week1 (1)	Week2 (2)	Week3 (3)	Week4 (4)	Week5 (5)	Week6 (6)	Week7 (7)	Week8 (8)	Week9 (9)	Week10 (10)
Imprecision(Z)	0.000	0.001	0.002***	0.002**	0.001**	0.001**	0.002**	0.001	0.001	-0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)
Sentiment(Z)	-0.000	0.000	0.000	0.000	-0.001	-0.000	0.000	-0.001*	-0.001	-0.001
	(0.001)	(0.000)	(0.001)	(0.000)	(0.001)	(0.001)	(0.000)	(0.000)	(0.001)	(0.001)
Market value(Z)	-0.002*	-0.003***	-0.003***	-0.002**	-0.002**	-0.002***	-0.002**	-0.002*	-0.001	-0.002**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Book-to-market(Z)	0.001*	0.000	0.001*	-0.000	0.000	0.000	0.000	0.001	0.000	-0.001**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)	(0.001)
Turnover(Z)	-0.001	-0.001	0.002**	-0.000	-0.000	-0.001	-0.001	-0.000	-0.000	0.001
	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Institutional ownership(Z)	0.002*	0.001	-0.000	0.001	0.000	0.001	0.003***	0.001	0.000	-0.001
	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Fama-French alpha(Z)	-0.001	-0.002	0.000	-0.000	0.001	-0.000	0.000	-0.002***	0.000	0.001
	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Observations	46454	46297	46148	46095	45994	45842	45723	45621	45589	45398
Adjusted R^2	0.002	0.003	0.003	0.002	0.002	0.001	0.001	0.002	0.001	0.001

(b) Cumulative BHARs

	Week1 (1)	Week1-2 (2)	Week1-3 (3)	Week1-4 (4)	Week1-5 (5)	Week1-6 (6)	Week1-7 (7)	Week1-8 (8)	Week1-9 (9)	Week1-10 (10)
Imprecision(Z)	0.000	0.001	0.003**	0.005***	0.006***	0.007***	0.008***	0.009***	0.010***	0.010***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)
Sentiment(Z)	-0.000	0.000	0.001	0.001	-0.000	-0.000	0.000	-0.001	-0.002	-0.002
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)
Market value(Z)	-0.002*	-0.005***	-0.008***	-0.011***	-0.013***	-0.016***	-0.018***	-0.021***	-0.024***	-0.025***
	(0.001)	(0.002)	(0.002)	(0.003)	(0.004)	(0.005)	(0.006)	(0.007)	(0.008)	(0.008)
Book-to-market(Z)	0.001*	0.001	0.003**	0.002	0.002	0.002	0.003	0.004	0.003	0.002
	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)
Turnover(Z)	-0.001	-0.002	0.000	-0.000	-0.000	-0.001	-0.002	-0.002	-0.002	-0.002
	(0.002)	(0.003)	(0.003)	(0.004)	(0.004)	(0.005)	(0.005)	(0.006)	(0.006)	(0.006)
Institutional ownership(Z)	0.002*	0.003	0.003	0.004	0.004	0.005	0.008*	0.009*	0.010*	0.008
	(0.001)	(0.002)	(0.003)	(0.003)	(0.003)	(0.004)	(0.004)	(0.005)	(0.006)	(0.006)
Fama-French alpha(Z)	-0.001	-0.002	-0.002	-0.002	-0.002	-0.002	-0.002	-0.004	-0.005	-0.004
	(0.001)	(0.003)	(0.003)	(0.004)	(0.004)	(0.005)	(0.005)	(0.006)	(0.006)	(0.006)
Observations	46454	46473	46480	46516	46644	46648	46649	46650	46687	46688
Adjusted R^2	0.002	0.004	0.006	0.007	0.008	0.010	0.010	0.012	0.012	0.012

Table 6: Imprecise Language in Disclosure and Subsequent Information Asymmetry

This table presents the test results of Model (2) regressing the post-filing level of an information asymmetry proxy on our linguistic imprecision measure as follows:

$$Information\ asymmetry_{itn} = \alpha_n + \beta_n Imprecision_{it} + \eta_n^{'} \mathbf{X}_{it} + \epsilon_{itn},$$

where $Information\ asymmetry_{itn}$ is an information asymmetry proxy in logarithm over the nth week window (the 1st week window starts from the fourth day after the 10-K release date). The following two proxies for information asymmetry are employed: the quoted relative bid-ask spread and the zero-volume days by Lesmond, Ogden, and Trzcinka (1999). $Imprecision_{it}$ is the percentage of imprecision keywords (out of total words) and $\mathbf{X}_{it}$ is a column vector that contains various control variables: Sentiment, Market value, and Book-to-market. The detailed definitions of these independent variables are given in Appendix. (Z) indicates that the variable is standardized to have mean 0 and standard deviation 1. We also control for firm and filing year-month fixed effect in Model (2). Standard errors that are clustered by firm and filing year-month are calculated and reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

(a) Weekly bid-ask spread

	Week1 (1)	Week2 (2)	Week3 (3)	Week4 (4)	Week5 (5)	Week6 (6)	Week7 (7)	Week8 (8)	Week9 (9)	Week10 (10)
Imprecision(Z)	-0.008***	-0.010***	-0.010***	-0.010***	-0.009***	-0.009***	-0.008**	-0.008***	-0.006**	-0.005*
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Sentiment(Z)	-0.002	-0.004	-0.004	-0.005**	-0.004	-0.005*	-0.005**	-0.005**	-0.005*	-0.004
	(0.003)	(0.003)	(0.003)	(0.002)	(0.003)	(0.003)	(0.002)	(0.003)	(0.003)	(0.002)
Market value(Z)	-0.426***	-0.421***	-0.412***	-0.406***	-0.401***	-0.401***	-0.399***	-0.391***	-0.389***	-0.382***
	(0.017)	(0.017)	(0.017)	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)
Book-to-market(Z)	0.014***	0.014***	0.013***	0.017***	0.016***	0.016***	0.014***	0.015***	0.012***	0.016***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)	(0.004)	(0.003)	(0.003)	(0.003)
Observations	52705	52587	52483	52474	52453	52354	52306	52269	52335	52232
Adjusted R^2	0.801	0.800	0.799	0.799	0.796	0.795	0.796	0.793	0.790	0.792

(b) Weekly zero-volume days

	Week1 (1)	Week2 (2)	Week3 (3)	Week4 (4)	Week5 (5)	Week6 (6)	Week7 (7)	Week8 (8)	Week9 (9)	Week10 (10)
Imprecision(Z)	-0.019**	-0.021**	-0.023***	-0.038***	-0.020**	-0.024**	-0.023**	-0.025**	-0.016*	-0.028***
	(0.009)	(0.010)	(0.009)	(0.009)	(0.010)	(0.010)	(0.009)	(0.010)	(0.009)	(0.009)
Sentiment(Z)	0.000	-0.007	-0.009	-0.014	-0.000	-0.017**	-0.008	-0.006	-0.007	-0.013
	(0.009)	(0.008)	(0.009)	(0.009)	(0.008)	(0.009)	(0.009)	(0.010)	(0.008)	(0.009)
Market value(Z)	-0.476***	-0.459***	-0.473***	-0.426***	-0.474***	-0.443***	-0.452***	-0.419***	-0.396***	-0.433***
	(0.034)	(0.047)	(0.032)	(0.031)	(0.030)	(0.032)	(0.027)	(0.029)	(0.029)	(0.033)
Book-to-market(Z)	0.015	0.026**	0.022**	0.032***	0.023**	0.012	0.009	0.002	0.014	0.024***
	(0.010)	(0.013)	(0.010)	(0.010)	(0.010)	(0.011)	(0.011)	(0.010)	(0.011)	(0.009)
Observations	52705	52587	52483	52474	52453	52354	52306	52269	52335	52232
Adjusted R^2	0.192	0.198	0.193	0.185	0.187	0.197	0.198	0.202	0.183	0.201

Table 7: Imprecise Language in Disclosure and Subsequent Earnings Surprise

This table presents the test results of Model (3) regressing either an indicator for future standardized unexpected earnings (SUE) or a rank for future SUE on our linguistic imprecision measure as follows:

$$Earnings\ surprise_{itq} = \alpha_q + \beta_q Imprecision_{it} + \eta_q^{'} \mathbf{X}_{it} + \epsilon_{itq},$$

where $Earnings\ surprise_{itq}$ is based on the nearest future SUE in qth quarter to stock i's 10-K release date in year t. For the SUE indicator, $Earnings\ surprise_{itq}$ is 1, 0, or -1 when the nearest future SUE in the qth quarter is above zero, equal to zero, or below zero, respectively. For the SUE rank, $Earnings\ surprise_{itq}$, is +2, +1, 0, -1, or -2 when the nearest future SUE in the qth quarter is above 80%, between 80% (inclusive) and 60%, between 60% (inclusive) and 40%, between 40% (inclusive) and 20%, or below 20% (inclusive), respectively, where the percentiles are computed based on all available SUEs of other firms within the three-week period before each of the nearest future SUE. $q = 0$ (Quarter 0) means that the nearest future earnings announcement and 10-K filing are made in the same quarter, and $q = 1$ (Quarter 1) means that the nearest future earnings is announced in the next quarter to 10-K filing. In addition, $q = 0\&1$ (Quarters 0&1) means that the nearest future earnings is announced either in the same quarter or in the next quarter of 10-K filing (whichever comes earlier is selected). $Imprecision_{it}$ is the percentage of imprecision keywords (out of total words) and $\mathbf{X}_{it}$ is a column vector that contains various control variables: Sentiment, Market value, Book-to-market, Turnover, Institutional ownership, Pre-filing Fama-French alpha, Analyst dispersion, and Analyst revision. The detailed definitions of these independent variables are given in Appendix. (Z) indicates that the variable is standardized to have mean 0 and standard deviation 1. Standard errors that are clustered by firm and quarter are calculated and reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

	Quarter 0 ($q = 0$)		Quarter 1 ($q = 1$)		Quarters 0&1 ($q = 0\&1$)	
	Indicator	Rank	Indicator	Rank	Indicator	Rank
	(1)	(2)	(3)	(4)	(5)	(6)
Imprecision(Z)	0.058**	0.086**	0.021**	0.028*	0.030***	0.034**
	(0.027)	(0.042)	(0.010)	(0.014)	(0.011)	(0.015)
Sentiment(Z)	0.028	-0.025	0.006	-0.028*	0.015	-0.029*
	(0.021)	(0.032)	(0.010)	(0.015)	(0.011)	(0.016)
Market value(Z)	0.164***	0.134**	0.134***	0.067***	0.141***	0.074***
	(0.033)	(0.057)	(0.010)	(0.019)	(0.012)	(0.021)
Book-to-market(Z)	0.015	0.131***	0.007	0.091***	0.002	0.100***
	(0.027)	(0.035)	(0.009)	(0.014)	(0.009)	(0.015)
Turnover(Z)	0.058**	0.092**	0.005	0.055***	0.010	0.064***
	(0.028)	(0.046)	(0.013)	(0.016)	(0.015)	(0.018)
Institutional ownership(Z)	0.026	-0.028	0.040***	0.021	0.046***	0.020
	(0.032)	(0.049)	(0.010)	(0.021)	(0.011)	(0.022)
Fama-French alpha(Z)	0.132***	0.092*	0.120***	0.106***	0.139***	0.117***
	(0.032)	(0.047)	(0.018)	(0.024)	(0.020)	(0.026)
Analyst dispersion(Z)	-0.025***	-0.041***	-0.046***	-0.040***	-0.046***	-0.043***
	(0.008)	(0.014)	(0.008)	(0.013)	(0.007)	(0.013)
Analyst revision(Z)	0.019***	0.036***	0.017***	0.031***	0.032***	0.054***
	(0.002)	(0.003)	(0.006)	(0.008)	(0.006)	(0.013)
Observations	1965	1965	20358	20358	20537	20537
Adjusted R^2	0.055	0.025	0.033	0.010	0.036	0.013

Appendix Tables to:
Imprecisely Informative: Lessons from Market Reactions to Imprecise Disclosure

Table A.1: Imprecise Language in Disclosure and Subsequent BHARs: Excluding Future Earnings Announcements

This table is similar to Table 5 except that we employ a refined subsample that excludes all 10-K filing that have new earnings announcements over the next three to seven weeks after 10-K release dates.

(a) Weekly BHARs

	Week1 (1)	Week2 (2)	Week3 (3)	Week4 (4)	Week5 (5)	Week6 (6)	Week7 (7)	Week8 (8)	Week9 (9)	Week10 (10)
Imprecision(Z)	0.000	0.001	0.002**	0.002***	0.001**	0.001**	0.001	0.000	-0.000	0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Sentiment(Z)	0.000	0.001	0.000	0.000	-0.000	0.000	-0.000	-0.001*	-0.002**	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Market value(Z)	-0.003**	-0.003**	-0.003**	-0.001	-0.002	-0.002	-0.002	-0.003*	-0.002	-0.001
	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Book-to-market(Z)	0.001	0.001	0.001	0.000	0.000	0.000	0.001	0.001*	0.001	-0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Turnover(Z)	0.000	-0.001	0.001	-0.001	0.000	-0.000	0.000	0.001	0.000	-0.001
	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Institutional ownership(Z)	0.001	0.001	-0.000	0.001	-0.000	-0.000	0.002	0.001	0.001	0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Fama-French alpha(Z)	-0.001	-0.001	-0.001	-0.001	0.000	-0.001	-0.000	-0.003**	-0.001	-0.001
	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Observations	22446	22361	22269	22234	22157	22087	22011	21955	21934	21853
Adjusted R^2	0.004	0.002	0.005	0.002	0.002	0.002	0.002	0.004	0.002	0.001

(b) Cumulative BHARs

	Week1 (1)	Week1-2 (2)	Week1-3 (3)	Week1-4 (4)	Week1-5 (5)	Week1-6 (6)	Week1-7 (7)	Week1-8 (8)	Week1-9 (9)	Week1-10 (10)
Imprecision(Z)	0.000	0.002	0.003**	0.005***	0.007***	0.008***	0.009***	0.009***	0.009***	0.010***
	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)
Sentiment(Z)	0.000	0.001	0.001	0.001	0.000	0.000	0.000	-0.001	-0.004	-0.005
	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)	(0.004)	(0.005)
Market value(Z)	-0.003**	-0.006***	-0.009***	-0.009***	-0.012***	-0.013**	-0.015**	-0.019**	-0.022**	-0.023**
	(0.002)	(0.002)	(0.003)	(0.003)	(0.004)	(0.005)	(0.007)	(0.008)	(0.010)	(0.010)
Book-to-market(Z)	0.001	0.001	0.002	0.002	0.002	0.002	0.003	0.004	0.005	0.005
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)	(0.004)
Turnover(Z)	0.000	-0.001	0.001	-0.000	0.000	0.000	0.001	0.002	0.002	0.001
	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)	(0.004)	(0.005)	(0.006)	(0.006)	(0.007)
Institutional ownership(Z)	0.001	0.002	0.002	0.003	0.003	0.002	0.004	0.006	0.007	0.007
	(0.001)	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)	(0.004)	(0.004)	(0.005)	(0.005)
Fama-French alpha(Z)	-0.001	-0.002	-0.004	-0.005	-0.005	-0.006	-0.007	-0.010	-0.011*	-0.012*
	(0.002)	(0.002)	(0.003)	(0.003)	(0.004)	(0.005)	(0.006)	(0.006)	(0.007)	(0.007)
Observations	22446	22459	22463	22478	22526	22530	22531	22532	22547	22548
Adjusted R^2	0.004	0.005	0.008	0.009	0.010	0.011	0.013	0.016	0.017	0.017

Table A.2: Imprecise Language in Disclosure and Subsequent CARs

This table is similar to Table 5 except that we employ cumulative abnormal returns (CARs) as the dependent variable for Model (1).

(a) Weekly CARs

	Week1 (1)	Week2 (2)	Week3 (3)	Week4 (4)	Week5 (5)	Week6 (6)	Week7 (7)	Week8 (8)	Week9 (9)	Week10 (10)
Imprecision(Z)	0.000	0.001	0.002***	0.002**	0.001**	0.001**	0.001**	0.000	0.000	-0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)
Sentiment(Z)	-0.000	0.000	0.000	0.000	-0.001	-0.000	0.000	-0.001*	-0.001	-0.001
	(0.001)	(0.000)	(0.001)	(0.000)	(0.001)	(0.001)	(0.000)	(0.000)	(0.001)	(0.001)
Market value(Z)	-0.003**	-0.003***	-0.003***	-0.003***	-0.003***	-0.002***	-0.003**	-0.002**	-0.002	-0.002***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Book-to-market(Z)	0.001	0.000	0.001	-0.000	0.000	-0.000	0.000	0.001	0.000	-0.001**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)	(0.001)
Turnover(Z)	-0.001	-0.001	0.002**	-0.000	-0.000	-0.001	-0.001	-0.000	-0.000	0.001
	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Institutional ownership(Z)	0.002	0.001	-0.000	0.001	0.000	0.000	0.003***	0.001	0.000	-0.001
	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Fama-French alpha(Z)	-0.000	-0.002	0.001	0.000	0.001	0.000	0.000	-0.002***	0.000	0.001
	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Observations	46454	46297	46148	46095	45994	45842	45723	45621	45589	45398
Adjusted R^2	0.002	0.003	0.004	0.002	0.002	0.002	0.001	0.002	0.001	0.001

(b) Cumulative CARs

	Week1 (1)	Week1-2 (2)	Week1-3 (3)	Week1-4 (4)	Week1-5 (5)	Week1-6 (6)	Week1-7 (7)	Week1-8 (8)	Week1-9 (9)	Week1-10 (10)
Imprecision(Z)	0.000	0.001	0.003**	0.005***	0.006***	0.007***	0.008***	0.008***	0.009***	0.009***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)
Sentiment(Z)	-0.000	0.000	0.001	0.001	0.000	0.000	0.000	-0.000	-0.001	-0.002
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)
Market value(Z)	-0.003**	-0.006***	-0.009***	-0.012***	-0.015***	-0.017***	-0.020***	-0.021***	-0.023***	-0.025***
	(0.001)	(0.002)	(0.002)	(0.003)	(0.004)	(0.004)	(0.005)	(0.006)	(0.006)	(0.007)
Book-to-market(Z)	0.001	0.001	0.002**	0.002	0.002	0.002	0.002	0.003	0.003	0.002
	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)
Turnover(Z)	-0.001	-0.002	-0.000	-0.000	-0.000	-0.001	-0.002	-0.002	-0.003	-0.002
	(0.001)	(0.003)	(0.003)	(0.004)	(0.004)	(0.004)	(0.005)	(0.005)	(0.006)	(0.005)
Institutional ownership(Z)	0.002	0.003	0.003	0.003	0.003	0.004	0.006	0.007	0.007	0.006
	(0.001)	(0.002)	(0.003)	(0.003)	(0.003)	(0.004)	(0.004)	(0.005)	(0.005)	(0.005)
Fama-French alpha(Z)	-0.000	-0.002	-0.001	-0.001	-0.001	-0.000	-0.000	-0.002	-0.002	-0.001
	(0.001)	(0.003)	(0.003)	(0.003)	(0.004)	(0.004)	(0.005)	(0.005)	(0.005)	(0.005)
Observations	46454	46473	46480	46516	46644	46648	46649	46650	46687	46688
Adjusted R^2	0.002	0.005	0.008	0.009	0.011	0.013	0.013	0.014	0.014	0.014