

The Primacy of Numbers in Financial and Accounting Disclosures: Implications for Textual Analysis Research

Federico Siano

*Boston University - Questrom School of Business
fsiano@bu.edu*

Peter Wysocki*

*Boston University - Questrom School of Business
wysockip@bu.edu*

June 2018 - Preliminary

Abstract:

Numbers are central to financial and accounting disclosures, yet current textual analysis research dissociates words and numbers, or ignores numbers altogether, within disclosures. We hypothesize and show that the prevalence of numbers within a corporate disclosure is highly correlated with the readability of the disclosure. More importantly, we show that prior findings on the links between disclosure readability and various economic outcomes are explained by the prevalence of numbers within the disclosures. We discuss implications for past and future research that attempts to analyze the determinants, attributes and outcomes of financial and accounting disclosures.

Key Words: *Accounting Quality, Analyst Following, Disclosure; Linguistics; Quantitative Information; Readability; Textual Analysis.*

Data Availability: From publicly-available data sets.

*We wish to thank George Papadakis and Taylor Wiesen for helpful discussions.

“It’s clearly a budget. It’s got a lot of numbers in it.”
---- *George W. Bush, May 5, 2000*

1. Introduction

The goal of this study is to provide evidence on the links between the often-ignored numbers *within* the text of corporate disclosures, the textual attributes of these disclosures, and associated economic outcomes. While prior textual analysis research in accounting and finance almost universally ignores numbers *within* the text of corporate disclosures¹, we present new evidence of a fundamental association between the prevalence of numbers within a business text and the readability of the text. First, we establish a foundational link between the prevalence of numbers and the readability of business articles published in the *Wall Street Journal*. We hypothesize and find that the prevalence of numbers within an article is associated with the use of less complex language (down to the sentence level), and thus more “readable” text. Second, we document a similarly strong association between the prevalence of numbers and the readability of the Management Discussion and Analysis (MD&A) section of firms’ financial reports. Finally, we hypothesize and show that the prevalence of numbers within MD&A disclosures subsumes and explains two key findings in the textual analysis literature that disclosure readability is directly associated with firm profitability (see Li, 2008) and analyst following (see Lehavy et al., 2011).

This study provides new insights into one of the more active research areas in accounting and finance that focuses on the determinants, attributes and outcomes of corporate disclosures (see, for example, Healy and Palepu, 2001, and Leuz and Wysocki, 2016). More recently, empirical researchers have applied new textual and linguistic analysis tools to characterize the textual

¹ See recent surveys of the textual analysis literature in accounting and finance by Li (2011), Das (2014), Kearney and Liu (2014), Loughran and McDonald (2016), and Dyer et al. (2017b).

attributes of corporate disclosures and then show that these attributes are associated with key outcomes such as reported profitability, trading behavior, analyst following, retail investor choices, cost of capital, earnings management, and firm valuation.² Notwithstanding these advances, the textual analysis literature almost universally ignores or deletes numbers *within* the text of accounting and financial documents.³ However, these numbers directly capture and summarize performance and financial position and are arguably the disclosures of primary interest for many stakeholders, while the surrounding disclosure text often plays a secondary role of describing or providing context for the disclosed numbers and quantitative information. Therefore, the current practice of ignoring numbers within disclosure texts leads to a correlated omitted variables problem for researchers that can affect inferences about the direct determinants and outcomes of the textual attributes of corporate disclosures.

We use two novel datasets to examine the association between numbers *within* and the readability of business texts. First, we analyze a large set of *Wall Street Journal* articles that are not primarily focused on companies' earnings reports. This dataset is used to establish the existence of structural association (for business/economic documents) between numbers and the readability of a document in a setting that is not confounded by managerial disclosure incentives. Then, we extend our analyses to corporate disclosures using a novel SEC dataset from 1987-1993 of corporate financial reports in the pre-EDGAR era.⁴ Specifically, we analyze machine-readable

² Key outcomes that have been correlated with the textual attributes of corporate disclosures include profitability (Li, 2008), trading behavior (Miller, 2010), analyst following (Lehavy et al., 2011), retail investor choices (Lawrence, 2013), cost of capital (Bonsall and Miller, 2017), earnings management (Lo et al., 2017), and firm valuation (Hwang and Kim, 2017).

³ The notable exception is found in Lundholm et al. (2014) who examine the relative readability and “number of numbers” in annual reports of foreign firms compared to domestic U.S. firms. While Lundholm et al. (2014) do not correlate disclosure readability with the “number of numbers” within a disclosure, they do find that foreign firms’ disclosures have both higher average readability and greater average “number of numbers” compared to U.S. firms.

⁴ We chose to first analyze a sample of pre-EDGAR disclosures for a number of reasons including: (i) introducing new and potentially useful data to other researchers, (ii) undertaking “out of sample” tests of prior empirical findings, (iii) using data that is less subject to recent corporate disclosure trends that can introduce noise into the textual analysis

10-Q reports for a large sample of U.S. companies and calculate the readability (as captured by the *Fog* index - Gunning, 1952) of the MD&A section of each report as well as the prevalence of numbers within the MD&A.

Overall, our initial findings show a strong association between the prevalence of numbers within business documents (both *Wall Street Journal* articles and the MD&A section of 10-Q reports) and the complexity of words within and readability of the documents. We are currently extending our analyses to other samples (i.e., 10-K EDGAR filings from 1994-2017) and testing the associations with other textual attributes of corporate disclosures such as tone, ambiguity, etc. More importantly, we show that the prevalence of numbers within the text of corporate disclosures subsumes two key findings from the early textual analysis literature that disclosure readability is directly associated with firm profitability (see Li, 2008) and analyst following (see Lehavy et al., 2011). Our initial findings suggest that ignoring numbers within corporate disclosure texts is likely to impact researchers' inferences about the links between textual attributes of the disclosures and numerous accounting, financial and economic outcomes. Like prior textual analysis research, our current findings primarily document associations, so there remain open questions about the mechanisms underlying the associations. For example, does the disclosure of numbers fundamentally *cause* other textual attributes, or are both the prevalence of numbers and other textual attributes the joint outcomes of managers' unobserved latent disclosure objectives?⁵

Our findings on the prevalence of numbers within the text of corporate disclosures also contributes the literature on accounting quality which proposes a number of competing measures

of disclosures including the use of boiler-plate disclosures, the profusion of imbedded tables and images in recent EDGAR filings, and corporate disclosure "bloat" to comply with new reporting regulations (see, for example, Cazier and Pfeiffer, 2016; and Dyer et al., 2017a).

⁵ It should be noted that our findings for the sample of *WSJ* news articles (not focused on corporate earnings reports) suggests that the existence of sentence-level quantitative information structurally *leads to* the use of less complex language in the sentence.

of disclosure quality, complexity and comparability based on the *quantity* of numbers presented in accounting reports (see, for example, Chen et al., 2015, Hoitash et al., 2017, and Hoitash and Hoitash, 2018). Our evidence suggests that more quantitative information disclosed *within* the text of corporate disclosures is associated with higher quality disclosures. This aligns with the empirical evidence for a financial statement disaggregation measure proposed by Chen et al. (2016) and contrasts with the “number of recognized numbers” evidence for XBRL-coded financial statement data presented in Hoitash and Hoitash (2018). Related research by Siano and Wysocki (2018b) further explores the links between numbers *disclosed* within the text of a financial report and the numbers *recognized* in the financial statements (i.e., income statement, balance sheet and cash flow statement).

The structure of remainder of the paper is as follows: In section 2, we discuss the related literature. In section 3, we present our hypotheses. Section 4 presents the data sample, describes the variables, and discusses the empirical tests. In section 5, we summarize our results, outline conclusions and discuss future work.

2. Related literature

Our research is related to and has implications for two main streams of existing accounting research: (1) research on the textual attributes of disclosures and their connections with various financial, accounting, disclosure and economic outcomes, and (2) empirical research that attempts to characterize the quality, complexity and comparability of firms’ reported numbers and disclosures.

First, our paper contributes to the emerging empirical literature in accounting and finance that develops and uses textual analysis tools to better understand the content and characteristics of the text of accounting and financial disclosures (see, for example, Li, 2011; Das, 2014; Kearney

and Liu, 2014; Loughran and McDonald, 2016; and, Dyer et al., 2017b). A large part of this literature focuses on quantifying the readability (or language complexity) of accounting and financial disclosures and then correlating disclosure readability with various outcomes.

Many disclosure readability studies focus on a company's annual report readability (often highlighting the MD&A section of the report) and correlate this text attribute with a wide array of issues and outcomes. For example, Ertugrul et al. (2017) investigate the links between annual report readability and corporate borrowing costs, while Lee (2012) examines the impact of readability on equity market efficiency. Ginesti et al. (2018) examine the link between annual report readability and corporate board of director characteristics. Lo et al. (2017) explore the connections between annual report readability and earnings management. Lim et al. (2018) correlate corporate strategy with annual report readability. Other studies focus on investor issues related to annual report readability such as investors' processing fluency (Rennekamp, 2012), small versus large shareholders' trading activity (Miller, 2010), retail investors' trading decisions (Lawrence, 2013), and investor demand for information from foreign firms (Lundholm et al., 2014). Other studies attempt to differentiate between possible competing determinants of annual report readability such as managerial obfuscation versus a firm's underlying operational complexity (see, for example, Guay et al. 2016, and Bushee et al., 2018).

There are also a series of recent studies that examine the readability of other business texts and attempt to make connections with closely-related outcomes. For example, De Franco et al. (2015) examine the possible determinants and implications of analyst report readability. Laksmana et al. (2012) and Hooghiemstra et al. (2017) examine compensation discussion and analysis (CD&A) readability and managerial obfuscation incentives. Inger et al. (2018) examine the association between tax footnote readability and firms' tax avoidance strategies.

While all of these disclosure readability studies acknowledge and control for a wide array of financial, corporate, board, managerial, and investor characteristics in the empirical tests, almost all of these studies delete or ignore the quantitative information contained within the text of the disclosures. However, this almost-universal methodological choice is at odds with almost 50 years of capital markets research that recognizes the prominent role of *quantitative* financial and accounting information and its connection with accounting, financial and economic decisions. Thus, one should expect that the quantitative information *within* the text of corporate disclosures should also be associated with various outcomes and decisions. Thus, the current paradigm in the literature that ignores numbers *within* disclosure texts leads to a correlated omitted variables problem for researchers that can affect inferences about the direct determinants and outcomes of the textual attributes of corporate disclosures.

Second, this study relates to the growing literature that attempts to better define, measure and understand the implications of reporting quality, complexity and comparability. Recent related innovations in this literature have focused on the amount of quantitative information presented in accounting reports. For example, Chen et al. (2015) suggest and implement a new measure of accounting quality based on the amount of disaggregation of reported numbers in a companies' financial statements.⁶ Their evidence suggest that the greater quantity of disaggregated numbers reported in the income statement, balance sheet and statement of cash flows is associated with better capital market outcomes (i.e., more numbers are related to higher accounting quality). Similarly, Hoitash et al. (2017) and Hoitash and Hoitash (2018) focus on the quantity of numbers reported in firms' financial statements. For example, Hoitash and Hoitash (2018) use XBRL tags to tabulate the number of unique quantitative items recognized and reported in firms' financial

⁶ Drake et al. (2016) also count the number of unique, non-missing *Compustat* items in the financial and use it as a control variable in their examination of the use of historical EGDAR filings by investors.

statements. They argue and present evidence consistent with the notion that more (XBRL-tagged) items reported in a firm's financial statements reflects greater accounting complexity (i.e., lower quality) and thus greater difficulty for stakeholders to process the accounting information.

Our study complements and extends this line of research by exploring the amount of quantitative information presented *within* the text of corporate disclosures. In addition, our analyses attempt to connect this quantitative information with other textual attributes and “soft” information contained in the text of firms' disclosures. Related research by Siano and Wysocki (2018b) further explores the links between numbers *disclosed* within the text of a financial report and the numbers *recognized* in the financial statements.

3. Hypotheses

The financial accounting and capital markets literature of the past 50 years has overwhelmingly focused on quantitative information and the numbers *recognized* in firms' financial statements (see, for example, Kothari, 2000; and Lee, 2000). For both economic and pragmatic reasons, this literature has generally avoided dealing with and characterizing the “soft” information contained in the text of corporate disclosures. But, as noted in Section 2 above, the emerging textual analysis literature in accounting and finance has made significant recent advances in analyzing the content and attributes of textual disclosures. However, almost all textual analysis studies use a similar methodology that ignores or removes numbers from the text of accounting and financial documents. We argue that this methodological choice to remove or ignore numbers is problematic because, consistent with the accumulated theory and evidence from the mainstream accounting literature, these numbers are likely to be of primary interest to the users of the financial

disclosure.⁷ While this certainly does not rule an important role for the surrounding text, this text is arguably built on the scaffolding of the disclosed accounting numbers and the surrounding text characterizes and describes the numbers and quantitative information. Thus, we argue that the presence and prevalence of numbers *within* disclosures should, at the very least, be related to the language used in the text of corporate disclosures. Furthermore, while difficult to unequivocally demonstrate, it is likely that the presence of numbers within a disclosure *causally* influence the chosen language and textual attributes of the disclosure.

Our reading of the academic linguistics literature reveals a paucity of discussion, let alone theory and evidence, about the interplay between language and numbers. Similar to the historical aversion of accounting researchers to deal with “soft” language in disclosures, it appears that academic linguists in the humanities have generally ignored hard numbers within corpuses.⁸ Thus, the extant linguistics and textual analysis literatures provides little guidance on the possible links between numbers and words within documents. However, we argue that one should expect a strong link between the presence of numbers in a text and the type of words and the structure of language used to describe the numbers. Specifically, when a text presents and describes measurable and factual quantitative information (i.e., numbers), it seems natural that the associated words are more likely to be objective, concise, precise, free of rhetoric, apply commonly-agreed-upon concepts, unambiguous, and verifiable.⁹ Thus, we would expect that documents that have a greater

⁷ Given the widely-known contracting and valuation roles of accounting numbers, it should be uncontroversial to expect that stakeholders would seek out quantitative information not only in the financial statements, but also *within* the text of accounting reports. Therefore, analyzing the text of an accounting report without considering the quantitative information (i.e., numbers) would an incomplete approach at best.

⁸ The apparent “avoidance” of numbers by academic linguistics is more of an observation about research themes rather than a commentary on the research methods used in the field. It is certainly the case that contemporary linguistics research relies heavily on advanced quantitative, computational and statistical methods.

⁹ Lundholm et al. (2014) argue that the “number of numbers” in the text of an annual report captures the amount of factual information in the disclosure.

prevalence of numbers are less likely to use complex and longer words. This leads to our first hypothesis (stated in null form):

H1: The use of complex words, at both the sentence level and overall document level, is unrelated to the frequency of numbers reported in the document.

The linguistics and textual analysis literatures have also highlighted the readability of a document as an important document attribute (see, for example, Gunning, 1958, and Li, 2011). One of the more widely-used empirical proxies for document readability is the Gunning (1958) *Fog* measure which captures document “readability” as a combination of the average numbers of words per sentence and the percent complex words (words with more than two syllables):

$$Fog = 0.4 * (Average\ number\ of\ words\ per\ sentence + \% \ Complex\ words) \quad (1)$$

Given the motivating arguments for Hypothesis H1, we would also expect that documents with more numbers within the text to be more “readable” as measured by the *Fog* index (given that the *Fog* index is, in part, mechanically derived from the number of complex words in a document). Thus, our second hypothesis (stated in null form) is:

H2: The readability of a document, as captured by the *Fog* index, is unrelated to the frequency of numbers reported in a business document.

Next, we turn to the possible implications of ignoring numbers with the text of a corporate disclosure. As discussed in section 2, there is a growing body of evidence that disclosure

readability (primarily captured by the *Fog* index) is associated with a host of other accounting, financial and economic outcomes. Two of the more prominent early findings related to disclosure readability are: (i) firms with higher reported profits have higher disclosure readability, as captured by lower *Fog* (Li, 2008), and (ii) firms higher disclosure readability have lower analyst following (Lehavy et al., 2011). Given the expectation of a strong connection between the prevalence of numbers within a disclosure and the readability of a disclosure, empirical tests that ignore the prevalence of numbers may suffer from a correlated omitted variable problem which can bias the estimated association between disclosure readability and other outcomes. The direction of the bias depends on the covariance between the regressors and the omitted variables. Given that we do not have strong priors on the covariance structure of the regressors, we do not form a directional prediction about how controlling for the prevalence of numbers will *directionally* affect the previous unconditional association between disclosure readability and reported profitability or analyst following. However, given the existence of this correlated omitted variable, we do expect that the prevalence of numbers will impact previously-estimated associations, and thus we state our third and fourth hypotheses in null form as:

H3: The prevalence of numbers with the text of a disclosures does not affect the empirical association between reported profitability and disclosure readability.

H4: The prevalence of numbers with the text of a disclosures does not affect the empirical association between disclosure readability and analyst following.

4. Empirical analysis

Our empirical analysis has three main parts related to our four hypotheses. We first examine the links between the numbers and word complexity and readability of generic business texts. We then extend this analysis to corporate filings using a sample of 10-Q reports. Finally, we examine whether controlling for prevalence of numbers within the text of a 10-Q report affects previously-documented findings of a positive link between disclosure readability and reported profitability and a negative relation between disclosure readability and analyst following. In the following subsections, we (a) summarize the data samples used in our empirical tests, (b) describe the main variables used in our analyses, and (c) summarize the results of the regression analyses used to test our hypotheses.

4.1 Data samples

We use two complementary data samples to provide insights on the association between numbers and the readability of business texts. The two samples are described below.

4.1.1. Sample of Wall Street Journal articles

Using the Lexis-Nexis database, we collect a sample of *Wall Street Journal (WSJ)* news articles published in 1992 that are primarily text, but also contain accounting, financial or economic numbers. We use these news articles as a benchmark to determine if there is a foundational association between the prevalence of numbers within a news article and the textual attributes of the news article (at the sentence level). The articles we collect are divided into the following categories: “*Economic News & Indicators*”, “*International Trade*”, “*Monetary Policy*”, and “*Tracking the Economy*”. We also collect a separate sample of *WSJ* articles that

(re)report on a firm's financial accounting performance ("*Corporate Earnings Reports*"), but we treat these news articles separately because they are likely to have content that is influenced by corporate managers' disclosure incentives.¹⁰

4.1.2. 10-Q Filings from the Pre-EDGAR Era

Our second sample is based on a novel set of 10-Q filings for U.S. issuers in the pre-EDGAR (pre-1994) era. We chose this data sample for our initial analyses for three reasons: (1) to introduce and establish the properties of a new data set for textual analysis researchers in accounting and finance, (2) to apply tests that may be less subject to some recent trends in corporate disclosures in the post-1994 era including growing use of boilerplate and bloat in disclosures driven by regulatory compliance (see, for example, Dyer et al., 2017a), and (3) to analyze a sample of machine-readable filings that include fewer tables, graphs and binary files compared to more recent EDGAR filings.¹¹

History of SEC electronic filings in the pre-EDGAR era

In 1983, U.S. Securities and Exchange Commission (SEC) commenced the construction of an electronic disclosure system with the goal to significantly reduce the use of paper filings and to increase transparency and availability of company data. Starting in 1984, companies could file their statements electronically on a voluntary basis. In 1987, Congress requested that the SEC run

¹⁰ Our survey of the contents of *WSJ Corporate Earnings Reports* shows that many articles use very similar language and content as the original 10-K or 10-Q filed by a company. As a result, the content of *Corporate Earnings Reports* likely captures managers' underlying disclosure incentives for the original 10-K or 10-Q filings and these incentives could influence the observed association between the numbers within and readability of a *Corporate Earnings Report* news article.

¹¹ As noted in the section 5 (*Conclusion and future work*) of this paper, we are currently extending the empirical analyses to a sample of EDGAR 10-K filings from 1994-2017.

tests on a significant group of registrants for a period of at least six months before any electronic filing could be mandated for all regulated firms. Between January and June of 1994, the SEC evaluated the filings submitted electronically by firms belonging to the voluntary pilot group and certified the success of the project to the Congress. In December 1994, the SEC made final its rules mandating electronic filing, effective from January 30, 1995 (Release No. 33-7122). The new EDGAR system began to operate in 1995, although electronic filing became mandatory for all companies at the end of 1996, after various phase-in periods.

Data gathering and processing of pre-EDGAR 10-Q filings

The documents investigated are retrieved from the *SEC Online Database* available through *LexisNexis Academic*. Our sample includes filings between 1987, the first year in which data are available in the *SEC Online Database*, and 1993. Represented firms are public companies traded on the New York Stock Exchange, American Stock Exchange, or the National Market System. *SEC Online* provides the full text of filings together with categorical information such as the type of document (e.g. 10-Q, 10-K), the filing date, the document date, the company name, the CUSIP number associated to the company's security, the TICKER symbol, the stock exchange in which securities are traded, the SIC code, the fiscal year end and information on the auditor. Each regulatory filing begins with a marker and has a table of contents which titles divide the documents into sections. Given this convenient and repetitive structure, we are able to download the *SEC Online* filings in bulk and to parse them through text analysis tools.

We start the data gathering process by downloading all the available *SEC Online* filings, in “.txt” format, between January 1987 and December 1994. The marker [**Summary*], found in the most part of documents, is used to separate one form from the other. In all cases where this

marker is absent, we add it manually to the filings. For our sample, we select only 10-Q filings and only parse the MD&A section of these filings. We do exclude 10-Q amendments from our sample. Our parsing algorithm collects the company's CUSIP number and document date that are found at the beginning of each 10-Q filing. The parsing algorithm then identifies the start and end of the MD&A and extracts and parses all text from this section of each 10-Q filing.

4.2. Description of textual analysis variables

The empirical methods proposed in this paper require identification of the relevant numbers and words from a document. Both *WSJ* news articles and the 10-Q filings (MD&A section) include a wide variety of numbers. They can take the form of monetary amounts, percentage changes, ratios, dates or even numbers expressed in words. For the purpose of our descriptive analysis, we select the numbers most likely to convey quantitative information and only read those. Specifically, our parsing algorithm identifies and counts a number for the following cases: (i) the number is preceded by a dollar sign (“\$”); (ii) the number is followed by the words million/billion; (iii) the number is followed by a percentage sign (“%”) or by the word “percent”. By construction, the primary analyses in this study excludes dates as numbers.¹² With regard to words, we consider all words with the exception of “stop words” listed in a database in the University of Notre Dame Software Repository for Accounting and Finance.

4.2.1. Sentence-based approach

We use a Python program and the Natural Language Toolkit Library (NLTK) to analyze text and implement our textual analysis at the sentence level. To begin with, we tokenize each

¹² As a robustness check, we also include dates in our tabulation of numbers. In unreported regressions, we find very similar results to the regressions presented in Tables 2-5 and all of our inferences and conclusions are unaffected by including dates.

document (either a *WSJ* article or the MD&A section of a 10-Q filing) to separate sentences in each document using punctuation delimiters. Sentences are identified through periods but the Library functions also allow to control for common textual features, within 10-Q filings, that could lead to an improper sentence tokenization such as: (i) the possibility of abbreviations within a sentence (e.g. U.S.A.) or (ii) the presence of decimal numbers which digits are separated by a period (e.g. “increased by 21.5%.”). Once tokens have been created, we remove all the decimals within numbers in order to count them. We then remove all the punctuation found in sentences, split sentences into words, capitalize words (since the word lists used in this paper contain capitalized terms) and finally count words. Numbers and words are evaluated at both the document level and the sentence level. For each document, we count: (i) the total number of words, (ii) the total number of numbers, (iii) the total number of sentences, (iv) the total number of sentences containing quantitative data (i.e., numbers).

The sentence-based approach attempts to more closely link numbers and directly associated words. An alternative to sentence tokenization, is the proximity approach, which consists in the identification and classification of words close enough (e.g. in a range of ± 10 terms) to numbers. A significant limitation of the proximity approach materializes when words surrounding numbers belong to different sentences.

4.2.2. Text measures

In order to provide descriptive evidence on numbers, words, and their possible connections within a document, we create the following variables:

Numbers/Words: the ratio of the “number of numbers” divided by the total count in the relevant section of a document.

Numbers/Sentence: the average of the “number of numbers” in each sentence in a document (an alternate measure of the prevalence of quantitative information in a document).

Words/Sentence: the average of the “number of words” in each sentence in a document (a measure of one dimension of the ‘readability’ of a document and is used as an input into the *Fog* index (Gunning, 1952).

Complex Words/Sentence: the average of the “complex words” in each sentence in a document (complex words are those with more than 2 syllables and this measure is another dimension of the ‘readability’ of a document and also is used as an input into the *Fog* index (Gunning, 1952).

4.2.3. Document readability (*Fog* index)

Similar to numerous recent papers that examine disclosure readability and linguistic complexity, we use the Gunning (1952) *Fog* index to measure the readability of a document. The empirically-derived *Fog* index is derived from the average numbers of words per sentence and the percent complex words (words with more than two syllables):

$$Fog = 0.4 * (Average\ number\ of\ words\ per\ sentence + \% \ Complex\ words) \quad (1)$$

4.2.4. Other variables

In section 4.3, we replicate the baseline regressions and extend the empirical tests of Li (2008) and Lehavy et al. (2011). These tests relate to the association between disclosure readability and two key outcomes: contemporaneous reported profitability (Li, 2008) and analyst following (Lehavy et al., 2011). Therefore, we construct similar control variables to those used in the prior studies. The definitions of the key outcome and control variables are:

Operating earnings: the contemporaneous quarterly (q) Compustat operating earnings scaled by total assets.

Operating earnings volatility: the standard deviation of scaled quarterly operating earnings for the last 12 quarters.

Size: the natural logarithm of beginning of period market value of equity.

M/B: the beginning of period market value of equity divided by its book value.

Analyst following: the number of analysts providing at least one forecast for the fiscal period.

Industry membership: Dummy variables identifying a firm's Fama-French industry membership based on a 17-industry categorization.

4.3. Empirical results

The presentation of our empirical results following the order of our four hypotheses: the connection between numbers and word complexity in generic business texts; the association between the prevalence of numbers in a corporate disclosure and the readability of the corporate disclosure; and the how the prevalence of numbers may affect inferences related to disclosure readability and firm profitability and analyst following.

4.3.1. Relation between numbers, word complexity and readability – *WSJ* articles

Table 1 presents the descriptive statistics for the partitioned subsamples of *Wall Street Journal* news articles from 1992. We consider 1,095 news articles not directly related to corporate earnings reports (hereafter referred to as the sample of *Main News Articles*) comprising the 4 columns labelled “Economic News & Indicators”, “International Trade”, “Monetary Policy”, and “Tracking the Economy”. We also separately consider a sample of 923 *WSJ* news articles that cover “Corporate Earnings Reports” (presented as a holdout sample in the last column). On

average, the ratio of numbers to words for the *Main News Articles* is 9.6% (with a high of 13.1% for “Tracking the Economy” articles).

Using this *Main News Articles* sample, we compare the textual properties of sentences that contain numbers (quantitative sentences) to those that do not contain numbers (non-quantitative sentences). We first examine average sentence length as a dimension of text readability. As indicated in the row labelled *Mean # words per sentence*, there are some differences in the average sentence length between quantitative (i.e., contains at least one number) and non-quantitative sentences. On average, there is just over one more word per sentence for quantitative sentences compared to non-quantitative sentences for the full sample of 1,095 *Main News Articles*. Given that the average sentence length of the non-quantitative sentences is 10.8 words, this means that, on average, quantitative sentences are 9.3% longer than non-quantitative sentences as measured by words. This suggests that quantitative sentences are “less readable” along the sentence length dimension.

We next turn to the use of complex words (words that are more than two syllables). As indicated in the next row labelled *Mean # complex words per sentence*, there are also differences between quantitative and non-quantitative sentences. On average, there are 0.35 more complex words per sentence for non-quantitative sentences compared to quantitative sentences for the full sample of 1,095 *Main News Articles*. This is an economically meaningful difference because the average number of complex words per sentence for non-quantitative sentences is 2.96. This means that quantitative sentences use, on average, 11.8% fewer complex words than non-quantitative sentences. This finding suggests that quantitative sentences are “more readable” based on this second dimension of fewer complex words. These findings are consistent with the arguments behind *Hypothesis H1*. Specifically, we predicted that quantitative sentences would be use fewer

long complex words because quantitative information is more compatible with language that is concise, precise, unambiguous, and free of rhetoric; and applies uses commonly-agreed-upon verifiable concepts.

The most-commonly used measure of sentence and document readability is the *Fog* index (Gunning, 1952). Therefore, we also compare the *Fog* index for quantitative and non-quantitative sentences for the full sample of 1,095 *Main News Articles*. Given that the *Fog* index is essentially a linear combination of sentence length and complex words, one might conclude that the opposing effects of sentence length and word complexity across quantitative and non-quantitative sentences would “cancel each other out” for this sample. However, the empirical *Fog* index (equation (1)) places an order of magnitude more weight on a 1% difference in word complexity compared to a 1% difference in sentence length to rate the overall composite “readability” of a sentence. Thus, as summarized in the next row in Table 2 labelled *Mean Fog of sentences*, there is a very large difference between the overall *Fog* “readability” of quantitative versus non-quantitative sentences. On average, the *Fog* index is almost 4 points higher (or 24.6%) higher for nonquantitative sentences compared to quantitative sentences (i.e., sentences that include numbers) for the sample of *Main News Articles*. This difference is both economically and statistically significant (p-value <0.01). In other words, nonquantitative sentences are far more “*Foggy*” and thus less readable than quantitative sentences. These findings are consistent with the arguments behind *Hypothesis H2* and the results suggest that the predicted *Fog* differences between quantitative and nonquantitative sentences are driven by differences in word complexity.

As discussed earlier, the above findings for the sample of 1,095 *Main News Articles* provides insights on the association between numbers and readability for articles that are unlikely to be affected by corporate reporting incentives. However, we also perform the readability

comparisons for a separate sample of 923 *WSJ* news articles focused on *Corporate Earnings Reports*. As shown in the last column of Table 1, we find even stronger readability differences between quantitative and non-quantitative sentences for this sample. On average, the *Fog* index is 53% (7.89 points) higher for nonquantitative sentences compared to quantitative sentences within *WSJ Corporate Earnings Reports*.

4.3.2. Relation between prevalence of numbers and disclosure readability - 10-Q evidence

We next turn to the sample of 10-Q filings for the years 1987-1993 in the pre-EDGAR era. The main sample consists of 20,154 firm-quarter observations with available data to calculate the *Fog* index from the text of the MD&A section of a firm's 10-Q filing and matching *Compustat* data to calculate the key control variables: scaled *Operating earnings*, *Operating earnings volatility*, firm *Size*, *M/B* ratio, and the *SIC* code to determine *Fama-French-17 industry* membership.

Table 2 presents the correlations among the main variables. The key correlation of interest captures the possible association between the commonly-used *Fog* index (used to capture disclosure readability) and the prevalence of numbers *within* the text of the MD&A disclosure (captured by the ratio *Num/Words*). Consistent with the arguments motivating *Hypothesis H2*, we find that the Pearson correlation is -0.46. This is economically significant and it is larger than any of the other correlations presented in Table 2 (or even in other studies examining the properties of disclosure readability). Given the possible concern that *Num/Words* may just capture the overall length of a disclosure (the denominator of this variable), we also present the correlation between *Fog* and the inverse of the length of a disclosure in words (*1/Words*). As shown in Table 2, this correlation is +0.39 and is opposite in sign to the *Fog – Num/Words* correlation. Also, the correlation between *Num/Words* and *1/Words* is only +0.13. This evidence supports our hypothesis

that the prevalence of numbers within a disclosure is a unique and potentially very important (both economically and statistically) correlated omitted variable that has the potential to affect inferences about previously-documented associations between disclosure readability and other outcomes.

4.3.3. *The impact of numbers on the profitability-readability relation - 10-Q evidence*

Table 3 presents a replication of the profitability-readability regression originally estimated in Li (2008). We use a sample of 20,254 firm-quarter observations derived from 10-Q filings between 1987 and 1993. In column (1) of Table 3, we estimate a regression that is very similar to Table 3 in Li (2008) using similar *Compustat* explanatory variables. The dependent variable is the *Fog* index for the MD&A section of a firm's 10-Q filing. Similar to Li (2008), we control for *Size*, *MTB*, *Earnings Volatility*, *Industry Fixed Effects*, and *Period (year-quarter) Fixed Effects*. Consistent with the findings of Li (2008), we find in regression column (1) that the MD&A *Fog* is strongly negatively related to contemporaneous reported firm profitability (i.e., a statistically-significant negative coefficient on *Operating Earnings* of -1.97). Thus, this finding is consistent with the original findings in Li (2008) that firms with lower profitability tend to have less readable (higher *Fog*) disclosures.

However, the regression in column (1) of Table 3 does not control for the prevalence of numbers in the MD&A section of the 10-Q filing. Therefore, in column (2) of Table 3 we include the ratio of *Numbers/Words* in the MD&A as an additional explanatory variable. Not surprisingly, the explanatory power of the regression increases from 13.9% to 32.8%. More importantly, the association between firm profitability and *Fog* is no longer significant (and the point estimate of the coefficient on *Operating Earnings* becomes positive). Thus, the claimed association between disclosure readability and firm profitability does not appear to be as robust as previous evidence might suggest. Clearly, the prevalence of quantitative disclosures within the MD&A text is an

important correlated (and previously-omitted) disclosure characteristic. It appears that the claimed connection between profitability and readability is not as direct as claimed by Li (2008).

To help provide a more complete picture of the association between the prevalence of numbers, readability, and profitability, we also estimate another set of regressions in Table 4. The regressions use the same *Compustat* explanatory variables as Table 3, but the dependent variable in Table 4 is the prevalence of numbers within the MD&A (ratio of *Numbers/Words*). Column (1) of Table 4 shows the regression results without including *Fog* as an explanatory variable. We find that the ratio of *Numbers/Words* shows a strong positive association with contemporaneous reported firm profitability (i.e., a statistically-significant positive coefficient on *Operating Earnings* of 0.06). This finding suggests an important link between the level of profitability and the propensity of managers to include quantitative disclosures *within* the MD&A. However, *Fog* is clearly a correlated omitted variable. Therefore, in column (2) of Table 4, we include the MD&A *Fog* as an additional explanatory variable. Again, not surprisingly, the explanatory power of the regression increases from 4.5% to 25.5% and the coefficient on *Fog* is negative and strongly significant. However, the more interesting finding is that the coefficient on *Operating Earnings* remains essentially unchanged and remains strongly significant. Overall, these findings suggest a fundamental and robust link between profitability and the disclosure of quantitative information in the MD&A text. Moreover, this link appears to mediate the previously-claimed relation between profitability and MD&A readability. Overall, these findings are consistent with the issues raised in *Hypothesis H3* and suggest that the benchmark findings in Li (2008) are not as robust as previously thought and the claimed links between firm performance and disclosure readability are more nuanced than indicated by prior research.

4.3.4. Relation between analyst following and disclosure readability - 10-Q evidence

Table 5 outlines a replication of the analyst following regressions originally presented in Lehavy et al. (2011). We use a sample of 15,383 firm-quarter observations derived from 10-Q filings between 1987 and 1993 and match the firms with analyst forecast data from I/B/E/S. In column 1 of Table 5, we estimate a regression that is very similar to Lehavy et al. (2011) using similar *Compustat* explanatory variables. The dependent variable is the *Number of Analysts* who follow a firm during the period. Similar to Lehavy et al. (2011), we control for *Size*, *MTB*, *Earnings Volatility*, *Industry Fixed Effects*, and *Period (year-quarter) Fixed Effects*. Consistent with the findings of Lehavy et al. (2011), we find in column (1) of Table 5 that analyst following is positively related to the MD&A *Fog* of the contemporaneous 10-Q filing (i.e., a statistically-significant positive coefficient on *Fog* of 0.04). Thus, this finding is consistent with the original finding in Lehavy et al. (2011) that firms with less readable (higher *Fog*) disclosures tend to attract more analysts and this finding is consistent with an information intermediary/processing role for analysts.

However, the regression in column (1) of Table 5 does not control for the prevalence of numbers in the MD&A section of the 10-Q filing. Thus, we cannot be certain that readability is the disclosure attribute that is directly associated with analyst following. Alternately, analyst following could be influenced by the (lack of) quantitative information in a firm's disclosures. Therefore, in column (2) of Table 5 we replace *Fog* with the ratio of *Numbers/Words* in the MD&A as an explanatory variable for analyst following. In this regression specification, we find that analyst following is negatively related to the prevalence of numbers in the MD&A *Fog* of the contemporaneous 10-Q filing (i.e., a statistically-significant negative coefficient on *Fog* the ratio of *Numbers/Words* of -5.36). Thus, this finding supports the notion that firms with fewer disclosed

numbers in the MD&A tend to attract more analysts and also consistent with an information intermediary/processing role for analysts.

Finally, in column (3) of Table 5, we include both *Fog* and the ratio of *Numbers/Words* in the MD&A as explanatory variables for analyst following. This specification is motivated by *Hypothesis H4* on the possible confounding effects of the prevalence of numbers on the explanatory role of document readability. Consistent with our hypothesis, we find that the previously-significant relation between *Analyst Following* and *Fog* is no longer significant after controlling for *Number/Words* in the regression. Interestingly, the coefficient on the ratio of *Numbers/Words* is almost unchanged and remains statistically significant. Thus, the claimed association between analyst following and disclosure readability documented in Leavy et al. (2011) does not appear to be robust. On the other hand, the prevalence of numbers in the MD&A is more robust and it appears to subsume and explain the Leavy et al. (2011) *Fog* effect.

5. Conclusions and Future Work

The majority of accounting and finance research over the past 50 years has focused on the determinants and use of *quantitative* information for investment, contracting and business decisions. Only more recently has the literature started to better understand and characterize the non-quantitative and textual information in accounting and financial documents and communications. Researchers have made significant advances using textual analysis tools to document the associations between the textual attributes of accounting and financial documents and various economic outcomes. However, existing textual analysis techniques almost universally remove or ignore *quantitative* information from the text of accounting and financial disclosures.

Consistent with quantitative focus of the traditional literature, we argue that numbers *within* the text of accounting and financial disclosures should be of primary interest for stakeholders and

that the surrounding text is likely to play a secondary role of describing the disclosed numbers. Thus, we argue that the prevalence of numbers within disclosures should be related to, if not a prime determinant of, the language used in the text of corporate disclosures. We present empirical evidence that strongly supports this view.

We utilize document datasets from *Wall Street Journal* articles and firms' 10-Q filings to document a strong association between the prevalence of numbers in a business document and the complexity and readability of the document. These associations are found even at the sentence level of business documents and disclosures. More importantly, we present empirical evidence that two key findings from the textual analysis literature are affected by the presence of numbers within firms' disclosures. Specifically, the associations between disclosure readability and reported profitability and analyst following (see, Li, 2008, and Lehavy et al., 2011) become insignificant after one accounts for the prevalence of numbers *within* the text of the disclosures. Overall, these results are consistent with the view that numbers disclosed within the body of textual disclosures are key correlates that are linked to firm's disclosure strategies and the outcomes of these strategies. This reinforces the historical view of the central role of quantitative information in accounting and financial reports.

Overall, our initial findings suggest that ignoring numbers within the text of corporate disclosures will likely to impact researchers' inferences about the links between textual attributes and various accounting, finance and economic outcomes. Our findings can help researchers (re)interpret past findings about the possible determinants and outcomes related to the textual attributes of corporate disclosures. Furthermore, our initial evidence suggests that future research on disclosure readability should explicitly model or control for the prevalence of numbers within the text of disclosures. Overall, we suggest that future textual analysis research should embrace,

rather than avoid, numbers. We are currently undertaking extensions to the analyses presented in this version of the paper to examine the robustness of the findings in other samples (i.e., 10-K filings from 1994-2017) and their associations with other textual attributes of corporate disclosures such as tone (i.e., Allee and DeAngelis, 2015), plain-English use (i.e., Bonsall et al., 2017), and ambiguity (i.e., Friberg and Seiler, 2017).

Our empirical findings also suggest that greater amounts of quantitative information *within* the text of a disclosures are associated with a higher quality disclosure. This finding aligns with the financial statement measure of Chen et al. (2015) which based on greater disaggregation of financial numbers in the income statement, balance sheet and statement of cash flows. On the other hand, our findings and those of Chen et al. (2015) contrast with the Hoitash and Hoitash (2018) finding that more numbers (based on XBRL coding) reported in the financial statements is associated with greater accounting complexity (i.e., lower accounting quality).

References

- Allee, K., and M. DeAngelis, 2015. The structure of voluntary disclosure narratives: evidence from tone dispersion. *Journal of Accounting Research* 53, 241–74.
- Asay, S., B. Elliott, and K. Rennekamp, 2017. Disclosure readability and the sensitivity of investors' valuation judgments to outside information. *The Accounting Review*.
- Bonsall, S., A. Leone, B. Miller, and K. Rennekamp, 2017. A plain English measure of financial reporting readability. *Journal of Accounting and Economics* 63, 329–57.
- Bonsall, S., and B. Miller, 2017. The impact of narrative disclosure readability on bond ratings and the cost of debt capital. *Review of Accounting Studies*.
- Bushee, B., Gow, I., Taylor, D., 2018. Linguistic complexity in firm disclosures: obfuscation or information? *Journal of Accounting Research*.
- Cazier, R., and R. Pfeiffer, 2016. Why are 10-K filings so long? *Accounting Horizons* 30, 1-21.
- Chen, S., B. Miao, and T. Shevlin, 2015. A new measure of disclosure quality: The level of disaggregation of accounting data in annual reports. *Journal of Accounting Research* 53, 1017-54.
- Das, S., 2014. Text and context: language analytics in finance. *Foundations and Trends in Finance* 8, 145–261.
- De Franco, G., O. Hope, D. Vyas, and Y. Zhou, 2015. Analyst report readability. *Contemporary Accounting Research* 32, 76–104.
- Drake, M., D. Roulstone, and J. Thornock, 2016. The usefulness of historical accounting reports. *Journal of Accounting and Economics* 61, 448-64.
- Dyer, T., M. Lang, and L. Stice-Lawrence. 2017a. The evolution of 10-K textual disclosure: evidence from latent dirichlet allocation. *Journal of Accounting and Economics*.
- Dyer, T., M. Lang, and L. Stice-Lawrence. 2017b. What have we learned and where do we go with textual research? A discussion of Cazier and Pfeiffer. *Journal of Financial Reporting*.
- Ertugrul, M., J. Lei, J. Qiu, and C. Wan, 2017. Annual report readability, tone ambiguity, and the cost of borrowing. *Journal of Financial and Quantitative Analysis* 52, 811-836.
- Friberg, R., and T. Seiler, 2017. Risk and ambiguity in 10-Ks: An examination of cash holding and derivatives use. *Journal of Corporate Finance* 45, 608-631.
- Ginesti, G., C. Drago, R. Macchioni, and G. Sannino, 2018. Female board participation and annual report readability in firms with boardroom connections. *Gender in Management*.
- Guay, W., D. Samuels, and D. Taylor, 2016. Guiding through the fog: financial statement complexity and voluntary disclosure.” *Journal of Accounting and Economics* 62, 234–69.
- Gunning, R., 1952. The technique of clear writing. New York, NY: *McGraw-Hill International Book Co.*
- Healy, P. and K. Palepu, 2001. Information asymmetry, corporate disclosure and the capital markets: A review of the empirical disclosure literature. *Journal of Accounting and Economics* 31.
- Hoitash, R., U. Hoitash, A. Kurt, and R. Verdi, 2017. An XBRL-based measure of financial statement comparability. *MIT Sloan School of Management Working Paper*.
- Hoitash, R., and U. Hoitash, 2018. Measuring accounting reporting complexity with XBRL. *The Accounting Review*.
- Hooghiemstra, R., Y. Kuang, and B. Qin, 2017. Does obfuscating excessive CEO pay work? The influence of remuneration report readability on say-on-pay votes. *Accounting and Business Research*.
- Hwang, B., and H. Kim, 2017. It pays to write well. *Journal of Financial Economics*.

- Inger, K., M. Meckfessel, M., Zhou, and W. Fan, 2018. An examination of the impact of tax avoidance on the readability of tax footnotes. *Journal of the American Taxation Association*.
- Kearney, C. and S. Liu, 2014. Textual sentiment in finance: A survey of methods and models. *International Review of Financial Analysis* 33, 171–85.
- Kothari, S., X. Li, and J. Short, 2009. The effect of disclosures by management, analysts, and business press on cost of capital, return volatility, and analyst forecasts: A study using content analysis. *The Accounting Review* 84, 163970.
- Laksmmana, I., W. Tietz, and Y. Yang, 2012. Compensation discussion and analysis (CD&A): readability and management obfuscation. *Journal of Accounting and Public Policy* 31, 185-203.
- Lang, M., and L. Stice-Lawrence, 2015. Textual analysis and international financial reporting: Large sample evidence. *Journal of Accounting and Economics* 60, 110–35.
- Lawrence, A., 2013. Individual investors and financial disclosure. *Journal of Accounting and Economics* 56, 130-147.
- Lee, Y., 2012. The effect of quarterly report readability on information efficiency of stock prices. *Contemporary Accounting Research*.
- Lehavy, R., F. Li, and K. Merkley, 2011. The effect of annual report readability on analyst following and the properties of their earnings forecasts. *The Accounting Review* 86, 1087–115.
- Leuz, C. and Wysocki, 2016. The economics of disclosure and financial reporting regulation: evidence and suggestions for future research. *Journal of Accounting Research* 54, 525-622.
- Li, F., 2008. Annual report readability, current earnings, and earnings persistence. *Journal of Accounting and Economics* 45, 221–47.
- Li, F., 2011. Textual analysis of corporate disclosures: A survey of the literature. *Journal of Accounting Literature* 29.
- Lim, E., K. Chalmers, and D. Hanlon, 2018. The influence of business strategy on annual report readability. *Journal of Accounting and Public Policy*.
- Lo, K., F. Ramos, and R. Rogo, 2017. Earnings management and annual report readability. *Journal of Accounting and Economics* 63.
- Loughran, T., and B. McDonald, 2011. When is a liability not a liability? Textual analysis, dictionaries, and 10-Ks. *Journal of Finance* 66, 35–65.
- Loughran, T., and B. McDonald, 2014. Measuring readability in financial disclosures. *Journal of Finance* 69, 1643–71.
- Loughran, T., and B. McDonald, 2016. Textual analysis in accounting and finance: A survey. *Journal of Accounting Research* 54, 187–230.
- Lundholm, R., R. Rogo, and, J. Zhang, 2014. Restoring the tower of Babel: how foreign firms communicate with US investors. *The Accounting Review* 89, 1453-1485.
- Miller, B., 2010. The effects of reporting complexity on small and large investor trading. *The Accounting Review* 85, 2107–43.
- Rennekamp, K., 2012. Processing fluency and investors' reactions to disclosure readability. *Journal of Accounting Research* 50, 1319–54.
- Siano, F., and P. Wysocki, 2018b. Recognition versus disclosure of numbers in 10-K filings: Measures, determinants and outcomes. *Boston University*.
- You, H., and X. Zhang, 2009. Financial disclosure complexity and investor underreaction to 10-K information. *Review of Accounting Studies* 14, 559–86.

Table 1: Differences in Textual Attributes Across Quantitative and Non-Quantitative Sentences in *WSJ* News Articles

		Category of Wall Street Journal Article (Year = 1992)				
		<i>Main News Articles</i> (1,095 new articles)				<i>Holdout Sample</i>
		Economic News & Indicators	International Trade	Monetary Policy	Tracking the Economy	Corporate Earnings Reports
Number of articles		776	238	30	51	923
Mean ratio #’s/words	Full Article	9.0%	11.6%	3.4%	13.1%	14.2%
Mean # words per sentence	Sentence includes #’s	11.26*	11.73	13.35*	19.75*	11.89
	Sentence without #’s	10.68	11.11	11.79	10.46	11.94
Mean # complex words per sentence	Sentence includes #’s	2.75*	2.09*	3.05*	2.64*	2.08*
	Sentence without #’s	2.90	2.87	3.27	4.17	3.37
Mean <i>Fog</i> of Sentences	Sentence includes #’s	16.96*	16.48*	16.69*	14.68*	14.77*
	Sentence without #’s	20.57	21.38	20.51	20.27	22.66

This table presents across sub-sample comparisons of sentence-level textual attributes for a sample of *Wall Street Journal* news articles from Lexis-Nexis for the calendar year 1992. The main sample (*Main News Articles*) consists of 1,095 news articles that contain both text and financial information. Sentences within each article are divided into quantitative sentences (includes numbers) and nonquantitative sentences (without numbers). The *mean ratio #’s/Words* captures the average ratio of “number of numbers” to “number of words” within each category (quantitative vs. nonquantitative sentences). *Complex words* are defined as words with more than 2 syllables. The *mean ratio # complex words per sentence* captures the average number of *complex words per sentence* within each sentence category (quantitative vs. nonquantitative sentences). *Fog* is the Gunning (1952) *Fog* index calculated as $0.4 * (\text{words per sentence} + \text{percent of complex words})$ for each sentence in a document for each sentence category (quantitative vs. nonquantitative sentences). * indicates significant differences in mean of a variable across quantitative (sentences with #’s) and non-quantitative (sentences without #’s) subsamples at <0.01 level.

Table 2: Correlations Among Key Variables for 10-Q MD&A Sample

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	
	Fog	Num/Words	1/Words	Num/Sent	1/Sent	Operating Earnings scaled	Operating Earnings Volatility	Log Size	M/B	
(1)	Fog	1.00								
(2)	Num/Words	(0.46)	1.00							
(3)	1/Words	0.39	0.13	1.00						
(4)	Num/Sent	(0.15)	0.19	(0.09)	1.00					
(5)	1/Sent	0.44	0.04	0.65	(0.08)	1.00				
(6)	Operating Earnings scaled	(0.06)	0.06	0.09	0.01	0.05	1.00			
(7)	Operating Earnings Volatility	0.12	(0.06)	0.04	(0.02)	0.02	(0.17)	1.00		
(8)	Log Size	(0.22)	0.01	(0.20)	0.02	(0.12)	0.33	(0.31)	1.00	
(9)	M/B	0.03	(0.01)	0.07	(0.01)	0.03	0.31	0.20	0.25	1.00

This table shows Pearson correlations between the key variables used in the 10-Q disclosure analyses. Sample of 20,154 quarterly observations from pre-EDGAR filings from 1987-1993. *Fog* is the Gunning (1952) *Fog* index calculated as $0.4 * (\text{avg. words per sentence} + \text{percent of complex words})$ of the MD&A section of a firm's 10-Q filing. The *Num/Words* ratio is calculated as the number of numbers over the number of words (excluding numbers and stop words) within the MD&A text of the 10-Q filing. *1/Words* is the inverse of the number of words (excluding numbers and stop words) contained in the MD&A section of a firm's 10-Q filing. The *Num/Sent* ratio is calculated as the average number of numbers per sentence in the MD&A text of the 10-Q filing. *1/Sent* is the inverse of the number of sentences contained in the MD&A section of a firm's 10-Q filing. *Operating earnings* are the contemporaneous quarterly Compustat operating earnings scaled by total assets. *Operating earnings volatility* is the standard deviation of scaled quarterly operating earnings for the last 12 quarters. *Size* is the natural logarithm of beginning of period market value of equity. *M/B* is the beginning of period market value of equity divided by its book value. section of firms' 10-Q filings. The aforementioned explanatory variables are winsorized at the 1% level. Correlations with absolute magnitude greater than 0.03 are statistically significant with p-value <0.01.

Table 3: Replication of Li (2008) of the Association between 10-Q MD&A Readability and Quarterly Reported Profitability

Explanatory Variable	Pred. Sign from Li (2008)	Dependent Variable: 10-Q MD&A <i>Fog</i>	
<i>Operating Earnings (q)</i>	(-)	-1.97*** [-2.9]	0.52 [0.9]
<i>Operating Earnings Variability</i>	(+)	3.72*** [3.7]	0.91 [1.0]
<i>Size</i>	(-)	-0.29*** [-27.7]	-0.29*** [-31.5]
<i>MTB</i>	(+)	0.24*** [11.2]	0.22*** [11.4]
<i>Numbers/Words</i>	(-) Our Hypotheses H1 and H2		-39.31*** [-75.3]
FF-17 Industry Fixed Effects		Included	Included
Year-Quarter Fixed Effects		Included	Included
# Obs.		20,154	20,154
<i>Adj. R</i> ²		13.9%	32.8%

This table shows the regression results of the *Fog* index (10-Q MD&A) on the Compustat determinants from Li (2008) and period and industry fixed effect. Sample of quarterly observations from pre-EDGAR filings from 1987-1993. *Fog* is the Gunning (1952) *Fog* index calculated as $0.4 * (\text{avg. words per sentence} + \text{percent of complex words})$ of the MD&A section of a firm's 10-Q filing. The *Numbers/Words* ratio is calculated from the MD&A text of the 10-Q filing. *Operating earnings* are the contemporaneous quarterly Compustat operating earnings. *Operating earnings volatility* is the standard deviation of quarterly operating earnings for the last 12 quarters. *Size* is the natural logarithm of beginning of period market value of equity. *MTB* is the beginning of period market value of equity divided by its book value. section of firms' 10-Q filings. The aforementioned explanatory variables are winsorized at the 1% level. Industry Fixed Effects are based on Fama French 17-industry definitions. All regressions are estimated with an intercept included, but the intercept is not reported. Robust t-statistics reported in [] parentheses. *** indicates significance at <0.01.

Table 4: The Association between the Prevalence of Numbers within MD&A and Quarterly Reported Profitability

Explanatory Variable	Pred. Sign	Dependent Variable: <i>Numbers/Words</i> in 10-Q MD&A	
<i>Operating Earnings (q)</i>	(+)	0.06*** [7.9]	0.05*** [7.4]
<i>Operating Earnings Variability</i>	(-)	-0.07*** [6.0]	-0.05*** [-4.8]
<i>Size</i>	(?)	-0.00 [-0.3]	-0.02*** [-14.8]
<i>MTB</i>	(?)	-0.001** [-2.3]	0.001*** [3.3]
<i>Fog</i>	(-) Our Hypotheses H1 and H2		-0.006*** [-75.3]
FF-17 Industry Fixed Effects		Included	Included
Year-Quarter Fixed Effects		Included	Included
# Obs.		20,154	20,154
<i>Adj. R</i> ²		4.5%	25.5%

This table shows the regression results of the *Numbers/Words* (10-Q MD&A) on Compustat determinants from Li (2008) and period and industry fixed effect. Sample of quarterly observations from pre-EDGAR filings from 1987-1993. The *Numbers/Words* ratio is calculated from the MD&A text of the 10-Q filing. *Fog* is the Gunning (1952) *Fog* index calculated as 0.4*(avg. words per sentence + percent of complex words) of the MD&A section of a firm's 10-Q filing. *Operating earnings* are the contemporaneous quarterly Compustat operating earnings. *Operating earnings volatility* is the standard deviation of quarterly operating earnings for the last 12 quarters. *Size* is the natural logarithm of beginning of period market value of equity. *MTB* is the beginning of period market value of equity divided by its book value. section of firms' 10-Q filings. The aforementioned explanatory variables are winsorized at the 1% level. Industry Fixed Effects are based on Fama French 17-industry definitions. All regressions are estimated with an intercept included, but the intercept is not reported. Robust t-statistics reported in [] parentheses. *** indicates significance at <0.01, and ** indicates significance at <0.05.

Table 5: The Association between Analyst Following and 10-Q MD&A Readability

Explanatory Variable	Predicted Sign from Lehavy et al. (2011)	Dependent Variable is I/B/E/S <i>Analyst Following</i>		
<i>Operating earnings (q)</i>	(?)	-15.25*** [-7.9]	-14.85*** [-7.7]	-14.88*** [-7.7]
<i>Operating Earnings Volatility</i>	(+)	18.81*** [6.4]	18.47*** [6.3]	18.51*** [6.3]
<i>Size</i>	(+)	4.68*** [61.1]	4.68*** [62.2]	4.68*** [60.2]
<i>MTB</i>	(+)	-0.58*** [-10.1]	-0.58*** [-3.6]	-0.58*** [-2.8]
<i>FOG</i>	(+)	0.04** [2.5]		0.02 [0.8]
Numbers/Words	(-) From Our Hypothesis 4		-5.36*** [-3.6]	-4.71*** [-2.8]
FF-17 Industry Fixed Effects		Included	Included	Included
Year-Quarter Fixed Effects		Included	Included	Included
# Obs.		15,383	15,383	15,383
<i>Adj. R</i> ²		67.3%	67.3%	67.3%

This table shows the regression results of the *I/B/E/S Analysts Following* (# analysts issuing at least one forecast for the period) on Compustat determinants from Lehavy et al. (2011) and period and industry fixed effect. The data sample includes quarterly 10-Q filings from pre-EDGAR filings from 1987-1993. *Fog* is the Gunning (1952) *Fog* index calculated as 0.4*(avg. words per sentence + percent of complex words) of the MD&A section of a firm's 10-Q filing. The *Numbers/Words* ratio is calculated from the MD&A text of the 10-Q filing. *Operating earnings* are the contemporaneous quarterly Compustat operating earnings. *Operating earnings volatility* is the standard deviation of quarterly operating earnings for the last 12 quarters. *Size* is the natural logarithm of beginning of period market value of equity. *MTB* is the beginning of period market value of equity divided by its book value. section of firms' 10-Q filings. The aforementioned explanatory variables are winsorized at the 1% level. Industry Fixed Effects are based on Fama French 17-industry definitions. All regressions are estimated with an intercept included, but the intercept is not reported. Robust t-statistics reported in [] parentheses. *** indicates significance at <0.01, and ** indicates significance at <0.05.