186w2

Missing narratives: An analysis of biases in sample selection and variable choice in textual analysis research[*]

Andrea Bafundi[†], Beatriz García Osma[‡], Encarna Guillamón-Saorín[§], Fengzhi Zhu*

[*] We are grateful for helpful comments and suggestions from Belén Blanco, Hyungjin Cho, as well as from conference and seminar participants at the 2018 EAA Annual Meeting (Milan), Universitat Jaume I, the University of Adelaide, and Queensland University of Technology. We acknowledge financial support by the Spanish Ministry of Innovation and Science (ECO2013-48328, ECO2016-77579 and ECO2016-00501), FEDER (UNC315-EE-3636), and the Madrid Government Region (S2015/HUM-3417).

[†] **Corresponding author:** Andrea Bafundi. Department of Business Administration. Universidad Carlos III de Madrid. c/Madrid 126. 28903 Getafe, Madrid (SPAIN).

[‡] Universidad Carlos III de Madrid. c/Madrid 126. 28903 Getafe, Madrid (SPAIN)

[§] Universidad Carlos III de Madrid. c/Madrid 126. 28903 Getafe, Madrid (SPAIN)

* Universidad Carlos III de Madrid. c/Madrid 126. 28903 Getafe, Madrid (SPAIN)

Missing narratives: An analysis of biases in sample selection and variable choice in textual analysis research

Abstract

We examine plausible biases in textual analysis studies of 10-K documents. The study of financial narratives using automated procedures is a relatively novel development in accounting and finance. Therefore, standardized methods to collect and systematically analyze these data are yet to be developed. We provide detailed step-by-step guidance on how to download and prepare these files for analysis, and study the plausible biases introduced by a number of decisions regarding sample construction, data preparation, and variable choice. In particular, we focus on two widely studied properties of financial narratives: Tone and Readability. We document that a number of these choices introduce biases into the samples studied, as well as induce differences in average observed Tone and Readability. Our results also indicate that a non-trivial proportion of the *Edgar* database population is missing from the textual analyses being conducted.

Keywords: *Narrative disclosure, Textual analysis, Readability, Tone, Sample selection, Measurement choice.*

JEL Classification: *C80, M41*

1. Introduction

The analysis of financial narratives has gained significant traction in recent years, with the development of a number of new proxies to measure qualitative attributes of corporate communication. Most of this research has focused thus far on two qualitative attributes: Tone (e.g. Henry and Leone 2016; Loughran and McDonald 2011), and Readability (e.g. Bonsall et al. 2017; Li 2008; Bonsall and Miller 2017), with a growing literature trying to understand the drivers and consequences of heterogeneity in narrative disclosures (Lo et al. 2017; Kim et al. 2017). While a number of commercial data providers permit access to accounting and finance data with a high assurance of construct validity, the research on narrative disclosure is still in its infancy, and little is known of the biases introduced by researchers through the use of non-standardized procedures.

We study two plausible biases that may impact existing research in the area and that are introduced by 1) sample selection and 2) variable definition choices. To do so, we proceed as follows. First, we review the existing literature on narrative disclosure to identify sample selection choices made by prior researchers, as well as the most commonly used measures of narrative disclosure (focusing on Tone and Readability). Second, we download from the *Edgar* database all available fillings and follow the usual steps taken by prior studies, to identify any significant sample selection biases plausibly introduced by downloading and parsing procedures. Lastly, we compute a number of the most common Tone and Readability measures, to understand whether the same firms are differently classified depending on the measures chosen.

In our final set of analyses, we build on our literature review and classify prior work on narrative disclosure into the main areas that have attracted the most interest thus far, dealing with firm performance, earnings quality, market reactions, and analysts' effects. Once these areas are identified, we download the main variables necessary to study associations between our narrative disclosure measures of Tone and Readability and critical constructs used in each of these lines of research. This process permits understanding whether any additional differences exist between the samples and variables studied in these primary areas of study.

Similar to prior work and to enhance the comparability and tractability of our procedure and findings, we focus on 10-K reports, albeit we also provide limited evidence on other fillings available in *Edgar*. We download all 10-K documents available in the *Edgar* database, and create an initial sample (Sample 0) following the steps detailed in Appendix A. Sample 0 represents the maximum sample of 10-K files that could be examined without imposing any constraints on the data, such as merging the files with commercial databases. This sample is the most extensive dataset that could be used, for example, by researchers interested in pure natural language processing of the documents available, perhaps to create novel measures of narrative disclosure quality, or by researchers in the fields of law, or psychology who would not be inclined to merge these files with accounting or financial data. From this initial dataset, in a number of consecutive steps, we create four subsamples, following steps common in prior research, such as dropping 10-Ks with no data on the Management Discussion and Analysis (MD&A) section (Sample I), and those that cannot be matched back to *Crsp* and *Compustat* (Sample II). Sample III represents the maximum sample of 10-K files that could be used in a study in accounting and finance, where we only impose as a restriction that minimum commonly used variables are available (such as total assets, revenues, and debt). Finally, we create four independent sets of Sample IV, staring from Sample III and imposing different additional minimum requirements of variables needed to conduct analyses in the fields that are the focus of prior literature: firm performance (Sample IV. *Performance*); earnings quality (Sample IV. *Earnings*); market effects (Sample IV.

Market); and finally analysts' usage of qualitative information (Sample IV. *Analysts*).

To identify the aforementioned four areas, we conduct a review of recent research, based on a systematic search of published academic articles in leading Journals related to textual analysis on narrative disclosures in the last decade.[1] In particular, we search by keywords associated with textual or narrative analysis (i.e., textual analysis, readability, language, narrative, and tone).[2] We review these articles and exclude those that do not refer to firm-issued documents as they focus, for example, on press news, analysts' reports, or the U.S. Securities and Exchange Commission (SEC) comment letters. Articles that focus on textual analysis of firm-produced documents are reviewed to extract information on the period of analysis, number of observations, data sources, documents or sections of documents analysed (e.g., 10Ks, 10Q, press releases, MD&A, conference calls), measures of textual analysis (e.g., readability, tone, length, similarity) and the software employed to perform the analyses (see Table 1 Panel A). We identify 56 articles following this procedure and confirm the growing interest in the study of financial narratives, with increasing numbers of papers published throughout the decade (see Table 1 Panels B and C). This review also serves to document the data gathering process of each study, the parsing procedures used, and the variables chosen for analysis (see Table 1 Panel D).

Using our samples and a number of proxies for Tone and Readability, we obtain the following key findings. First, some little-discussed researcher-choices, such as whether to

---

[1] We focus on the period 1997-2017, and consider only published papers (leaving out those that are "in press") in the following journals: Journal of Accounting and Economics (JAE), Journal of Accounting Research (JAR), The accounting Review (TAR), Review of Accounting Studies (RAST), Contemporary Accounting Research (CAR), Accounting Organizations and Society (AOS) and European Accounting Review (EAR), Journal of Finance (JF), Journal of Financial Economics (JFE), and Review of Financial Studies (RFS).

[2] We search using the platform Science Direct which features sophisticated search and retrieval tools to facilitate the search of academic articles. This platform covers three of the journals included in our study (JFE, JAE, and AOS). We use the editor's website to perform the search for the rest of the journals: Wiley Online Library for JF, JAR and CAR, Springer for RAST, Taylor & Francis Online for EAR, American Accounting Association Library for TAR, and Oxford Academic for RFS.

include or remove amended and late filings, or how to deal with duplicates, significantly affect sample sizes. Existing research is almost always silent on these first steps of the sample construction procedure, which can lead to significant differences in final samples. Second, by requiring that accounting and financial data is available in commercial databases, almost two-thirds of all valid observations are lost. We consider a valid observation one that contains full narrative data sufficient to create Tone and Readability measures. Third, the narratives lost when merging the *Edgar* baseline dataset with *Compustat* and *Crsp* are significantly different from those that are retained. This problem is further compounded when additional data constraints are imposed on the data. Finally, we document that the choice of variable measurement may lead to different inferences. Different final outputs might represent a concern for researchers interested in the economic interpretation of the sign and size of their coefficients.

We contribute to the prior literature in a number of ways. First, we provide detailed step-by-step guidance on how to download and prepare *Edgar* fillings for analysis. Second, we document the biases introduced by a set of possible decisions regarding sample construction, data preparation, and variable choice. Our results indicate that a non-trivial proportion of the *Edgar* population is missing from the textual analyses being conducted. On average, these missing narratives appear significantly different from the ones that are retained in standard accounting and finance studies. In particular, we provide evidence of significant differences in two widely studied properties of financial narratives: their Tone and Readability. Further, we document that a number of the variable choices made by researchers also may induce differences in average observed Tone and Readability. Thus, our results question the generalizability of studies in narrative disclosure and also, set the question of what are these missing firms discussing in their annual reports. It appears that existing research may be ignoring much of what is being said.

The remainder of the paper is structured as follows. Section 2 briefly reviews prior literature. Section 3 describes the method and data used while section 4 presents our main results. Section 5 identifies the major lines of research in the existing literature and further studies plausible biases introduced by demanding data merges of commercial databases. Finally, section 6 concludes.

2. Previous literature on database coverage, errors and biases

Increasingly, archival empirical research in financial accounting uses large databases provided by commercial data providers. These underlying data deserve considerable attention as the validity and power of the results depends on the quality of the research-specific datasets. Prior literature in accounting and finance studies and documents significant biases including heterogeneous database coverage that usually leads to smaller firms being less represented in samples as well as survivorship biases, errors in databases, or the use of different metrics to capture underlying constructs with non-trivial impacts on research findings.

One of the main problems described in the literature is the existence of database coverage issues. Databases such as *Crsp* and *Compustat*, while they are doubtlessly the most complete available, have been studied by prior research, documenting the existence of survivorship biases. These studies find that companies excluded from databases are usually small (García Lara et al. 2006; Mutchler and Shane 1995), companies that subsequently are involved in bankruptcy or receive auditing qualified opinions and are audited by non-Big-Eight firms (Mutchler and Shane 1995). Similarly, a study of biases in *ExecuComp* shows that firms included in this database tend to be larger, more complex, followed by more analysts and have less concentrated institutional ownership than other firms (Cadman et al. 2010). Another issue documented in prior work is the existence of differences in firm coverage across databases. Schwarz and Potter (2016) report a lack of overlap between the *SEC Mutual Fund Portfolios* and the *Crsp Mutual Funds Database Portfolios* and when they merge these two datasets with *Thomson Reuters* data, only 39% of portfolios overlap in all three sources for the same universe of funds. These differences are mainly due to voluntary reporting portfolios which may be included in *Thomson Reuters* but not reported to the SEC, and that may or may not be included in *Crsp*. These studies provide evidence that the database choice influences empirical results. Corporate governance studies are also affected by the problems associated with ownership structure data, as prior research has also shown concerns about database choice and coverage (Anderson and Lee 1997).

A particular concern associated with database coverage is the delisting bias. The literature suggests the existence of thousands of delisting returns omitted in *Crsp*. Omitted delisting returns make it difficult to accurately calculate the returns to a feasible portfolio (Shumway 1997). Delisting bias results in confounding empirical outcomes, although it affects mainly NASDAQ rather than NYSE stocks. Research on this issue (Shumway 1997; Shumway and Warther 1999) reveals that correcting for the delisting bias eliminates the size effect considered as an economic phenomenon and first documented by Banz (1981) and Lamoureux and Sanger (1989) and lately by Fama and French (1995), and Berk (1995) among others. Related prior work also documents the effect of survivor bias on the explanatory power of book-to-market equity, earnings yield and cash flow yield with respect to realized stock returns in the case of *Compustat* (Davis 1996) and on returns related to mutual funds in *Crsp* (Elton et al. 2001).

Studies have also acknowledged the existence of errors in databases sufficient to change the nature of the data and suggest a method of quality control for competing databases (Rosenberg and Houglet 1974). Research has documented forecasts error metrics based on reported earnings numbers supplied by forecasts data providers such as *First Call, Zacks Investment Research,* *Crsp*, *Compustat* and *I/B/E/S* (Philbrick 1991; Canina et al. 1998; Rosenberg and Houglet 1974; Abarbanell and Lehavy 2003; Ljungqvist et al. 2009) which leads to inconsistent inferences. Abarbanell and Lehavy (2003) identify two asymmetries in cross-sectional distributions of forecast error observations and demonstrate that analyst's tendency to commit systematic errors is not supported by broader analysis distribution of these errors. Elton et al. (2001) state that *Crsp* return data is biased upward and merger months are inaccurately recorded half of the time. Ljungqvist et al. (2009) find errors evidenced by the widespread changes present in the historical *I/B/E/S* analyst stock recommendation database including alterations of recommendations, additions and deletions of records and removal of analyst names from one download to the next in the period analyzed (2000-2007).

Beyond coverage issues, industry classification is an important element in the methodology of accounting research that has also been studied in this context. Researchers generally use the *Standard Industrial Classification* (SIC) to classify companies into industry sectors but, as previously documented, significant bias can be introduced by the choice of database derived from the differences in data across databases, for example, Guenther and Rosman (1994) and Kahle and Walkling (1996) provide evidence of the bias introduced by the use of SIC codes from *Compustat* or *Crsp*, whereby, more than 36% of the classifications disagree at the two-digit level and nearly 80% at the four-digit level. Similarly, Krishnan (2003) examine the implications of using different industry classification systems by comparing the *North American Industry Classification System* (NAICS) and the SIC. Bhojraj et al. (2003) shows the differences from using the *Global Industry Classifications Standard* (GICS) system popular among financial practitioners and the Fama and French (1997) system used primarily by academics.

<<INSERT TABLE 1 HERE>>

This literature review provides evidence of the high relevance of accurate and reliable data in research. The study of financial narratives using automated procedures is a relatively novel development in accounting and finance, but that is growing rapidly in the last decade (see Table 1 for a summary of the studies published in the main journals of accounting and finance). We are interested in describing plausible biases in textual analysis studies of 10-K documents, to raise awareness on the existing issues that may lead to better measurement and scientific practice.

3. Method and Data

Prior literature shows that large-sample empirical archival research in financial accounting often suffers from biases, errors and coverage problems. We examine the whether these issues also affect narrative disclosure studies, by identifying the common steps taken by researchers studying the textual characteristics of 10K reports, following them, and examining the potential biases derived from sample construction decisions, errors in files, coverage issues and variable construction decisions. To this end, we access the data from *Edgar* provided by the SEC, and follow the procedure detailed in Appendix A. We extract 225,417 observations for the period 1994-2015 from downloading 161,131 individual 10-K reports. After cleaning duplicates, we retain a sample of 159,338 10-K reports, corresponding to 33,466 unique firms. Over half of these 10-K reports use HTML tags (88,860). Table 2 Panel A summarizes the sample selection procedure. Nearly all of these 10-K reports contain the key items under study in prior work: Item 6 (Selected Financial Data) is available for 92% (146,302) of the 10-K reports, Item 7 (Management's discussion and analysis of financial condition and results of operations – MD&A) for 92% (147,303) of the 10-K reports, Item 7A (Quantitative and qualitative disclosures about market risk) for 73% (116,168) of the 10-K reports, and Item 8 (Financial statements and supplementary data) for 93% (147,917) of the 10-K reports. These numbers are in line with prior research in the area, as reviewed in detail in Table 1. We report the results based on the analysis of item 7 of the 10K as this is the section of the 10K more widely analysed in prior research (e.g. Li 2008; Brown and Tucker 2011; Li 2010; Davis and Tama-Sweet 2012; Mayew et al. 2015; Loughran and McDonald 2011; Frankel et al. 2016).

<<INSERT TABLE 2 HERE>>

Sample I includes all observations with a non-missing Item 7 from *Edgar* 10-K annual reports (147,303 firm-year observations for 31,405 unique firms). Next, we match Sample I data with *Crsp/Compustat Merged Fundamental Annual* to create Sample II. To access these data, we proceed as follows. From Wharton database, we download *Crsp/Compustat Merged Fundamental Annual* for both accounting and financial data. We select output data with the following settings: *Consolidated Level* (Consolidated), *Industry Format* (Standardized), *Population Source* (both Domestic and International), *Currency* (both U.S. and Canadian Dollar), and *Company Status* (both Active and Inactive). Since we extract data from a merged database, we rely on the primary links types provided in Wharton Database: *LC* (link research complete), *LU* (link is unsearched by Crsp), and *LS* (link valid for this security only).[3] On the downloaded data, we exclude those observations not associated with a primary link marker (*Linkprim*) equal to "J" and "N" (joiner secondary issue of a company), and we keep only observations with a primary link "P," and "C". Table 2 Panel B provides details on the sample selection procedure when we match qualitative with quantitative data; it also shows the observations lost when we further impose data requirements.

To obtain Sample II, we follow two parallel methods that either exclude or include the usage

[3] Refer to the supporting manual for a broader description of these links. https://wrds-web.wharton.upenn.edu/wrds/support/Data/_001Manuals%20and%20Overviews/_002Crsp/ccm-overview.cfm

of *Linking Table WRDS-SEC* also provided by *Wharton Database*. We only report on the samples obtained when we use the link table, as this is a more commonly used and replicable procedure, and results are almost identical than when we do not use it. The *Linking Table* associates historical cik from Edgar with the gvkey variable of *Crsp* and *Compustat* databases.[4] This method might alleviate the measurement error of associating qualitative data from *Edgar* with accounting and finance data (Loughran and McDonald 2011). After merger and acquisition operations, companies might either cease to exist or change their identifiers. However, in *Crsp* and *Compustat* there are less missing observations for the gvkey variable compared to the cik, and this condition might improve the possible number of associable observations. Under both the methods, we also rely on both fiscal month and year to identify companies across time. We further impose a number of minimum data availability in terms of accounting variables (lagged, current and forward observations) to run basic analyses and create Sample III.[5] This sample, Sample III, would be representative of the samples used in papers that create narrative disclosure measures, as usually they impose minimum requirements on the additional accounting and finance data needed.

Despite the fact that we only impose minimum data requirements, almost half of the original Sample I is lost in these two steps. Sample II contains 70,489 firm-year observations for 11,293 unique firms, while Sample III contains 66,083 firm-year observations for 10,501 unique companies. We lose 4,406 firm-year observations and 792 firms from Sample II to Sample III.

Finally, we create four subsamples of Sample III. As reported in Table 2 Panel B, we require

[4] To use the Linking Table, we merge Edgar data by cik code, and its output is furtherly matched with Crsp and Compustat adopting gvkey variable as the firm identifier.

[5] The following variables are extracted from "Variable List" of Wharton Database Crsp/Compustat MERGED: AT: Total Assets; cik: Central Identification Number; DLTT: Total Long Term Debt; DLC: Total Short Term Debt; FYEAR: Fiscal Year End; FYR: Fiscal Month End; REVT: Total Revenues.

a minimum accounting and finance data to replicate previous studies investigating the role of qualitative information on firm performance (Sample IV. *Performance*) and earnings quality (Sample IV. *Earnigns*), respectively. We also require that data on two additional databases is available: *Crsp/Compustat Merged Security Daily*, and *I/B/E/S* respectively. Table 2 Panel B provides details on this sample selection procedure, it also shows those observation lost after imposing data availability for daily prices and volumes from *Crsp/Compustat Daily Securities* (Sample IV. *Market*), and analysts' forecasts from *I/B/E/S* (Sample IV. *Analysts*). The latter is our most restrictive sample, as it requires that all data are available. This sample is composed of 13,250 individual 10-K reports.

The simple observation of the large number of narratives that are lost in each recursive step of our procedure may seem very concerning. Of course, this may not be troubling if samples are still representative of the original population (Sample I). To understand whether that is the case, for each of our samples, we compute common measures used in prior research of narrative disclosure. We choose these proxies after careful consideration of the prior literature detailed in our review (see Table 1). In particular, we focus on Tone and Readability. As Table 1 Panel D reveals, these are the most common narrative characteristics studied in prior work. Our analyses reveal the lack of standardized procedures in this field, as that many authors create their own word lists and strategies to systematically conduct content analyses in search for particular meaning, phrases or words. Given however how idiosyncratic these choices are, we focus on the aforementioned characteristics only. Although the literature on these areas is relatively young, it can be readily seen in Panel D that a number of proxies and lists exist to capture these constructs. Next, we detail our approach to measuring them.

3.1. Creation of Samples for empirical analysis

In this section, we briefly describe and justify the requirements that we impose to create each of our samples. To the best of our ability, we try to follow prior work in setting these requirements, i.e., to imitate the process that a researcher would commonly follow when trying to link narrative disclosure quality to its determinants or consequences.

We first start reviewing the work that links firm performance with narratives (Davis et al. 2012; Loughran and McDonald 2011; Allee and Deangelis 2015; Li 2008; Merkley 2014; Huang et al. 2014; Davis et al. 2015), and select a minimum number of variables for running this type of studies.[6] We merge *Edgar* created with *Crsp/Compustat MERGED* using cik(gvkey) fiscal month and year obtained from the Conformed Period of Report included in the 10-K reports. From the full 147,303 observations included in Sample I, we can match 44,947 firm-year observations for7,985 unique firms. This is Sample IV. *Performance*.

Next, following prior work on the links between earnings quality and narratives,[7] we select a minimum number of variables for running this type of studies (Frankel et al. 2016; Huang et al. 2014; Feldman et al. 2010; Lo et al. 2017). From the original Sample I (*Edgar* baseline), we can match 36,183 firm-year observations for 7,360 unique firms. This is Sample IV. *Earnings*.

Finally, we create two final samples, the first one, based on prior work that studies market reaction to firm narratives (Lawrence 2013; Loughran and McDonald 2011; Allee and Deangelis

[6] In particular, the following variables are extracted from "Variable List" of Wharton Database Crsp/Compustat MERGED: AQC: Acquisitions; AT: Total Assets; CEQ: Total Common Ordinary Equity; IB: Income Before Extraordinary Items; MKVALT: Total Fiscal Market Value; OANCF: Net Cash Flow from Operating Activities; NI: Net Income; SSTK: Sale of Common and Preferred Stock

[7] The following variables are extracted from "Variable List" of Wharton Database Crsp: AOLOCH: Other Net Change in Assets and Liabilities; APALCH: Increase/Decrease in Accounts Payable and Accrued Liabilities; AT: Total Assets; IB: Income Before Extraordinary Items; INVT: Inventory; OANCF: Net Cash Flow from Operating Activities; PPEGT: Gross Value of Property, Plan, and Equipment; RECT: Total Receivable; REVT: Total Revenue; TXACH: Increase/Decrease in Income Taxes Accrued; XAD: Advertising Expense; XRD: Research and Development Expense

2015; Koo et al. 2017; Baginski et al. 2016; Campbell et al. 2014; Hope et al. 2016; Segal and Segal 2016; Kothari et al. 2009; Drake et al. 2016; Loughran and McDonald 2013; Lee 2012; You and Zhang 2009; Kravet and Muslu 2013; Huang et al. 2014; Henry and Leone 2016; Miller 2010; Lee 2016; Brochet et al. 2016; Lundholm et al. 2014), and the variables for running this type of studies,[8] we merge *Edgar* created with *Crsp/Compustat* MERGED using cik FYR and FYEAR obtained from the Conformed Period of Report included in 10-K. We then merge matched observations with *Crsp/Compusta*t SECURITY DAILY. The latter database contains daily prices and volumes for listed companies. To merge the two databases, we rely on Filing Date contained in the 10-K reports, on Permno and Permco numbers. We require data to compute returns and volume for a three-day window on the filing date.[9] We are able to match 29,990 firm-year observations belonging to 4,963 unique firms. This is Sample IV. *Market*.

Finally, building on prior work on analysts and firm narratives (Lehavy et al. 2011; Bozanic and Thevenot 2015; Allee and Deangelis 2015), we identify variables to run these type of studies,[10] and merge Sample IV. *Market* with the *I/B/E/S* database. We require at least one observation per company on the variables selected for a forecast horizon of one fiscal year. To merge *Crsp/Compustat* with *I/B/E/S*, we rely on the SAS code "*iclink*" from Wharton Database that allows to create a link table between the two databases. This procedure results in Sample IV. *Analysts* that has 13,250 firm-year observations for 2,224 unique firms.

---

[8] The following variables are extracted from "Variable List" of Wharton Database Crsp/Compustat MERGED: AQC: Acquisitions; AT: Total Assets; CEQ: Total Common Ordinary Equity; IB: Income Before Extraordinary Items; LOC: Current ISO Country Code Headquarters Location; MKVALT: Total Fiscal Market Value; OANCF: Net Cash Flow from Operating Activities; SSTK: Sale of Common and Preferred Stock

[9] The following variables are extracted from "Variable List" of Wharton Database Crsp, and from the help file provided by Crsp to compute return: AJEXDI: Adjustment Factor (Issue); PRCCD: Daily Price Close; TRFD: Daily Total Return Factor; CSHOC: Outstanding Shares; CSHTRD Daily Trading Volume

[10] EPS: Earnings per Share

3.2. Computing Narrative Disclosure Tone

To measure disclosure Tone, a generally used and accepted approach is to count the frequency of certain words contained in the disclosures and compute a score (Henry and Leone 2016). To assess relative frequencies, we use a predefined list of "positive" or "negative" words. In particular, to measure Tone, we review the existing literature to identify all the vocabularies that have been used to classify qualitative information (words) prepared by either companies or analysts. To automatize the process, we use the 2015 version for academic use of the Linguistic Inquiry and Word Count Software (Larcker and Zakolyukina 2012).[11] We extract the various vocabularies from which we compute Tone from articles, online appendixes, and software available. Whenever possible, we look for the sources of vocabulary's data.

First, to have the original list of Diction's vocabularies, we extract wordlists from its software. Diction 7.0 is a software that allows computing optimism (as a result of the differences between positive and negative words).[12] However, it does not report a complete list of positive and negative words. To extract this list, we use both software's settings and the online help manual available for Diction 7.0. Optimism is defined as "*the difference between positive (Praise, Satisfaction, and Inspiration) and negative (Blame, Hardship, and Denial) wordlists*" (Diction 7.0 Manual, page 5). By merely summing the various lists extracted from log files of the software, it is possible to find duplicate words within the same groups of sentiment lists, i.e.,

[11] The main advantage of this software is that it does not require programming skills for researchers that are required by alternative methods such as using Python and UNIX. In particular, it is possible to insert a list of words associated with a vocabulary, and obtain results for every file under analysis. When using alternative software, it is necessary to control for case sensitive search (low and capital letter cases), and non-overlapping search.

[12] Diction 7.0 was the last version available of "Diction: The Text-analysis Program" when we conducted the analyses described in this paper. A link to the online help manual is present on the home page of Diction at "http://www.dictionsoftware.com/". Diction has been extensively used in disclosures such as speeches of politicians, speeches of Federal Reserve policymakers, annual reports and other business documents (e.g. Hart 1984; Yuthas et al. 2002; Hart and Jarvis 1997).

there are words associated with more than one-word list.[13] Not to inflate results, we drop duplicate words since we are interested in the leading group of wordlists: optimistic and pessimistic, respectively. Second, to have the original wordlists of General Inquirer from Harvard University, we select the vocabulary Harvard IV-4 categories.[14] In the file reported, it is possible to find duplicates associated with both positive and negative word lists. The presence of duplicates is mainly due to the different classification that the same word might have across contexts, and also by the fact that General Inquirer has included parallel wordlists in its vocabulary.[15] We keep unique words associated with positive and negative Tone.

Finally, for the remaining vocabularies, we use online appendixes provided in prior research. In particular, to compute forward-looking statements, we rely on the list reported in Appendix B from Li (2010)[16]. For a causations' wordlist, we refer to Panel C provided by Dikolli et al. (2016). For a list of constraining words, we refer to Appendix C in Bodnaruk et al. (2015). For wordlists associated with litigiousness, strength, weakness, uncertainty, optimism, and pessimism, we refer to prior work (Loughran and McDonald 2014, 2011).[17]

<<INSERT TABLE 3 HERE>>

Table 3 provides descriptive statistics for Sample I. We can calculate narrative disclosure

---

[13] For example, in the list that reports positive sentiment, both Inspiration and Satisfaction have the following words in common "charm," "comfort," and "courage." In negative sentiment, both Blame and Hardship share the same words "afraid," "biased," and "cursed." However, this overlap does not necessarily mean that results out of Diction 7.0 suffer from measurement error, as the software may correct for it. By extracting wordlists by software's log files, we might be exposed to measurement error if we do not control for these duplicates.

[14] A complete list is present at the following link http://www.wjh.harvard.edu/~inquirer/spreadsheet_guide.htm by downloading the file named "General Inquirer Augmented Spreadsheet".

[15] In the Excel file provided by Harvard University, it is possible to appreciate the presence of duplicates if we compare the first with the last column that contains description over the word included in a specific vocabulary.

[16] We use the list of positive keywords provided by Li (2010) to compute tone following a dictionary approach. In Li (2010), once the list of forward looking terms is developed, the author uses a Naïve Bayesian Algorithm to infer the content of the text and classify documents based on statistical techniques. Therefore, we use a different methodology and the descriptive statistics are not comparable.

[17] https://www3.nd.edu/~mcdonald/Word_Lists.html. For our analysis, we rely on both lists from 2011 and 2014.

quality measures for all of our samples, and can thus assess any differences in the average narrative dimensions across samples. Panel A shows that for the average firm in our sample the reporting month is December (month 12). Panel A also provides evidence on the heterogeneous sizes of 10-K files, with a distribution that is heavily skewed to the right. The size of the 10K itself has been used as a measure of disclosure quality, with higher values being considered of greater disclosure quality. Table 3 Panel B provides descriptive statistics of Sample I for the calculations our Tone measures based on Diction (Diction Neg. and Diction Pos.), (Loughran and McDonald 2014, 2011).[18] (LM Neg. and LM Pos.), and General Inquirer (Inquirer Neg. Inquirer Pos.). We report results obtained for the analysis of Item 7 (MD&A), similar findings are obtained for the other items. It can be readily seem that the use of General Inquirer is likely to return a more positive Tone, and also the highest negative Tone on average. This suggests that wordlist use is an important determinant of average Tone observed, as noted by Loughran and McDonald (2011). Table 3 Panel C provides descriptive statistics for our calculations of additional scores associated with word lists commonly used in prior work (see Table 1 Panel D), in particular, we calculate a score for constraining vocabulary (Constraining), four word lists in Loughran and McDonald (2011) (LM Litigious, Strong, Weak and Uncertainty), and scores for the use of causation (Causation (Dikolli)) and forward-looking (ForwardLook (Li)) vocabularies. While these scores are not comparable directly between themselves, they are in line with those reported in prior research (e.g. Law and Mills 2015), and will be used to understand differences between our Samples.

[18] https://www3.nd.edu/~mcdonald/Word_Lists.html. For our analysis, we rely on both lists from 2011 and 2014. The means reported in Table 3 are similar to those in prior research focusing on item 7 of the 10K for all the measures of tone (Loughran and McDonald, 2011).

3.3. Computing Narrative Disclosure Readability

The clarity of written language can be quantified using Readability formulas, which estimate the understandability of written texts. The assumption in prior work is that better written documents include less ambiguity and lead to better corporate valuation which reflects on lower price volatility of the stocks after the filling of 10Ks (Loughran and McDonald 2014). We focus on three indicators of Readability which have been primarily used in previous studies: Gunning Fog index, Flesch reading ease score, and Flesch–Kincaid grade level (Brochet et al. 2016; Li 2008; Law and Mills 2015; De Franco et al. 2015). First, we compute the Fog index as the sum of words per sentence and percentage of complex words (Gunning 1952).[19] The score of the index is associated with a scale reporting the minimum number of years a reader would need to interpret information. Second, we calculate the Flesch reading ease score as the difference between number of words per sentence and syllables per words (Flesch 1948).[20] The index reinterprets the presence of "complex" words by measuring the total number of syllables. Readability is associated with a minimum educational level which readers might need to attain to understand a text. Lastly, we compute the Flesch-Kincaid grade as the sum of words per sentence and syllables per sentence (Kincaid et al. 1988).[21] Similar to the previous index, it associates Readability to U.S. grade school levels. However, the interpretation is different: higher values of both Fog index and Flesch–Kincaid grade level indicate lower Readability. In contrast, higher Flesch reading scores are associated with higher Readability. Consistent with Li (2008), we use Perl (package named Fathom::EG) to measure Readability. We extract the following variables

[19] [(Number of words per sentences + Percentage of complex words) * (0.4)]. Where percentage of complex words is computed as number of complex words over total words. A word would be "complex", if it is composed by three or more syllables.

[20] [206.835 – (1.015 * Number of words per sentences) – (84.6 * Syllables per words)]

[21] [-15.59 + (0.39 * Number of words per sentences) + (11.8 * Syllables per words)]

for computing Readability indexes: number of words, number of sentences, the percentage of complex words, and total syllables per sentence respectively. Table 3 Panel D presents average values of these indexes. All scores are within the expected values reported in prior literature (Law and Mills 2015; Loughran and McDonald 2014; Li 2008).

4. Main results

As described in the above sections, we first construct three separate samples (Samples I, II, and III) of 10-K reports. For each of these samples, we compute, at the individual 10-K report level, three measures of Tone (Diction, LM and Inquirer) segregated by positive (Pos.) and negative (Neg.), four measures of Readability (Fog, Flesh, Flesch-Kincaid, No. of words), and seven measures of content analyses (constraining, litigious, strong, weak, uncertainty, causation and forward looking). Using these samples and measures, we study whether samples commonly used in prior research in accounting and finance (i.e., our Sample IV) can be generalized as compared to both Sample I (the full usable *Edgar*) and Sample III (the subsample with the minimum requirement of accounting data) and whether the narratives not commonly studied in prior research (henceforth, the 'missing narratives') are, on average, different from those that are under the increasing scrutiny of research.

<<INSERT FIGURE 2 HERE>>

The selection procedure to create samples II to IV is included in Appendix C. Figure 2 Panels A and B provides a visual and initial representation of coverage issues with the procedure followed to create the subsamples. After calculating our narrative disclosure measures of Sample I, we assign them into deciles, so that, for example, the observations with the more positive tone would be classified in the first decile of Diction (Pos.) and the ones with the least positive tone in the last decile. We then observe how sample reductions affects coverage by examining what percentage of the original deciles are retained. To illustrate, if 40% of all Sample I observations are lost when we construct Sample II and there are no distributional biases, we should observe that around 40% of observations are lost of *each* of the deciles, so that 60% of the original observations in each of the original deciles would be retained. Figure 2 Panel A shows that around 60% of the observations belonging to deciles 1 to 4 are retained in Sample II. However, after decile 4, there is a steady decline in the percentages retained, which is greatest at decile 9, where only around 30% of the original observations are retained in Sample II. Similar patterns can be observed for the other Samples. Panel B shows comparable evidence, but linking Sample III (full data on *Crsp/Compustat*) with the four Sample IV subsamples. It is apparent in this Panel that extreme observations are lost: over 70% of decile 2 to 8 observations from Sample III are retained in Sample IV. *Performance*, while less that 50% of decile 10 are retained.

<<INSERT TABLE 4 HERE>>

Table 4 formally compares the textual characteristics of the missing narratives between Samples I and II. Panel A compares mean and median Tone, Panel B compares mean and median scores of commonly used content analyses variables, and Panel C of Readability measures. It can be readily seen that differences systematically exist. In fact, they differences are significant in all Panels. Missing narratives appear to contain more negative words on average than those that are kept in Sample II. They also show signs of having lower complexity in terms of Readability. This may indicate that these are smaller firms, less likely to use optimistic Tone in an opportunistic way and potentially more inclined to use simple language. Overall, the evidence in this table contains compelling evidence that the missing narratives are not alike the narratives commonly studied in accounting and finance, and suggest that sample selection procedures likely bias the findings, impeding generalizing the results to the general population of firms.

<<INSERT TABLE 5 HERE>>

Table 5 shows the differences between Sample III and Sample I. We observe a similar pattern compared with Table 4 suggesting that previous results are generalizable to those observations containing the minimum requirement of accounting data, and not just the match with *Crsp/Compustat* database.

5. Further analyses based on research lines

As noted above, we build on our literature review (see Table 1 Panels B to D) to identify the main lines of research that have been the focus of the literature in textual and narrative analysis thus far. Without aiming to be exhaustive, we identify four main lines of interest for our study, studies that link narratives to financial reporting quality, performance, market reactions, analysts' information environment. We follow the same procedure and in Tables 6, 7, 8 and 9 we provide evidence of the new missing narratives. These are 10-K reports that are lost in the process of comparing Sample III with the data required to conduct the analyses that are common in prior literature (Sample IV). Again, the results are split into three panels, Panel A shows differences for Tone, Panel B for usual content scores, and finally, Panel C for Readability.

<<INSERT TABLE 6 HERE>>

<<INSERT TABLE 7 HERE>>

Across the various tables in Panel A, it can be readily seen that again differences systematically exist between Sample III and the various Sample IV except Table 7. In this case, the difference regarding negative Tone for both Diction and Inquirer tend to be less statistically significant compared with the other subsamples of Sample IV. On the magnitude of Tone for all these subsamples, Missing Narratives include observations that have lower both negative and positive words. However, the average reduction in both negative and positive words is asymmetrical suggesting that net optimism, computed as the difference between positive and negative words, might still be significantly different across paired samples (missing and non-missing narratives). Whether at the Tone level it is possible to appreciate a clear difference in terms of mean and median across missing and non-missing narrative, the same does not hold for other vocabularies and Readability. As reported in Panel B and C, mean and median tend to be more similar, and less significant differences compared with results of Panel A.

<<INSERT TABLE 8 HERE>>

<<INSERT TABLE 9 HERE>>

Overall, the evidence in these tables again indicates that the missing narratives are different from those commonly studied in accounting and finance, and suggest that sample selection procedures likely bias the findings, impeding generalizing the results to the general population of firms. Furthermore, we observe that by augmenting those restrictions of both accounting and finance data, the differences introduced by *Linking Tables* tend to disappear: across the various Sample IV mean and median seem to be similar.

5.1. Within sample choice of variables

Thus far, we have shown that significant differences appear to exist between the narratives that are commonly studied in current research and those that are not studied. A further issue is whether differences in measurement using the different proxies and thus, the choice of proxies, could potentially influence the results of studies that examine the determinants and consequences of narratives. Errors in measurement that are not systematic would lead to biased coefficients but may still provide insights into whether associations are positive or negative. However, if different proxies classify observations differently, so that, for example, using one measure of Tone classifies a firm/manager as using highly positive Tone, and using another measure as using highly negative Tone, the choice of proxy would influence not only the size of the coefficient, but also its sign. To understand whether this is the case, we create, within samples, decile rankings of all proxies. Then, we produce frequency tables by deciles, where the diagonal shows the percentage of firms classified in a particular decile for a narrative measure that are classified in the same decile using a different proxy of the same narrative property. If observations are exactly classified, this diagonal would have percentages close to 100%.

<<INSERT TABLE 10 HERE>>

Table 10 provides the results of this analysis. We report full frequency data, and in a separate, last, column, we measure the percentage of observations similarly classified (as belonging to the same decile, one decile lower or higher). For simplicity, we only tabulate four comparisons for Sample I, two of tone (one positive, one negative) and two of readability, but results are usually similar when we move to the smaller samples. Panel A and B show results for tone. As can be readily seen, a large number of observations are significantly classified in different deciles. Panel C and D report results for readability. The evidence suggests lower differences for these measures, albeit the distributions in the deciles surrounding the diagonal do not show clear decreases for several deciles away from the diagonal. The evidence of this table would suggest choice of variable could significantly affect the results of empirical studies.

6. Discussion and Conclusions

We study plausible biases in textual analysis studies of 10-K documents. The study of financial narratives using automated procedures is a relatively novel development in accounting and finance. Therefore, standardized methods to collect and systematically analyse these data are yet to be developed. We provide detailed step-by-step guidance on how to download and prepare these files for analyses, and study the biases introduced by a number of decisions regarding sample construction, data preparation, and variable choice. This is particularly interesting given the lack of standardised procedures in prior research. In particular, we focus on two widely studied properties of financial narratives: their Tone and Readability. We document that a number of these choices introduce significant biases into the samples studied, as well as induce differences in average observed Tone and Readability. Our results also indicate that a non-trivial proportion of the *Edgar* population is missing from the textual analyses being conducted.

We contribute to the prior literature in a number of ways. First, we provide detailed step-by-step guidance on how to download and prepare *Edgar* fillings for analysis. Second, we document the biases introduced by a number of decisions regarding sample construction, data preparation, and variable choice. Our results indicate that a non-trivial proportion of the *Edgar* population is missing from the textual analyses being conducted. On average, these missing narratives appear significantly different from the ones that are retained in common accounting and finance studies. In particular, we provide evidence of significant differences in two widely studied properties of financial narratives: their Tone and Readability. Further, we document that a number of the variable choices made by researchers also may induce differences in average observed Tone and Readability. Thus, our results question the generalizability of studies in narrative disclosure and also, set the question of what are these missing firms discussing in their 10-K reports? It appears that existing research may be ignoring much of what is being said.

Appendix A. Detailed downloading and parsing procedures

We investigate the content of 10-K reports released by the Stock Exchange Commission (SEC). In this appendix, we provide detail on the procedure used to download and parse the data.

I. Downloading Documents

Step One: Access to Edgar Database

<<INSERT FIGURE 1 HERE>>

The *Edgar* database stores all documents released by the SEC since 1993. Prior work usually focuses on: 10-K, 10-Q, 8-K, and 20-F. Appendix B provides descriptive evidence on the documents available for downloading in the *Edgar* database between 1994 and 2015.[22] It can be readily seen that sample sizes vary depending on the document type, with 8-K fillings being the more numerous. We show data both for the original files and their amendments. Figure 1 Panel A graphically shows time-trends in 10-K fillings, which are the focus of this study, while Panel B provides details on the percentage of amended documents. Amendments can be easily identified as they are labelled differently (/A documents). Unsurprisingly, late filings (NT documents) are less likely to be amended. Only 1.58% (0.88%) of late 10-Ks (10-Qs) fillings are amended, relative to 25.44% (8.24%) of on-time 10-Ks (10-Qs). To download 10-K reports, we connect to the *Edgar* website. In its archive, web links to SEC's documents are stored in files that are divided by year and by quarters respectively (master files).[23]

Step Two: Download Master Files

Since we ignore the exact quarter in which 10-K have been released, we download all the files containing web links for every quarter folder from 1994 to 2015 (both included). To automatize downloading, UNIX allows creating a batch file that recursively opens and downloads 10-K reports.[24] To use UNIX on Windows, we download and install Cygwin.[25] After installing and updating Cygwin, we can download all the weblinks' files automatically[26].

Step Three: Select Documents

Downloaded files are structured in tables with the same variables across quarters and years: Form Type, Company Name, cik, Date Filed, and File Name, respectively. Since our master files contain different types of documents released by the SEC, we extract only those links to documents for the Form Type "10-K." Then, we remove headings that include description file. Second, we select only those web links associated to a 10-K. To handle these two tasks, we download Powergrep 5.[27]

---

[22] We exclude 1993 for being a transitional year i.e. the first year *Edgar* was reporting companies' information.

[23] *Edgar* website: https://www.sec.gov/edgar.shtml; Archives: https://www.sec.gov/Archives/edgar/full-index/

[24] Parallel automatic approaches might be useful, but we decide to rely on UNIX, and more specifically on a command named "Wget" for being the most effective and user friendly method we found.

[25] Cygwin is a freeware software allows Windows' users to have a UNIX's interface without having to install the UNIX's operating system. After having downloaded Cygwin, it is important to update the software by including the wget package. Cygwin itself does not contain all the packages we might need to use for our goals.

[26] The command "wget" on the Cygwin interface (without quotes) downloads the master file of 1993 for the first quarter in our folder "downloads" with the name "masteridx_1993_1.txt". To make the command recursive, it would be sufficient to replace the year from the weblink.

[27] Powergrep is not a freeware software. However, it is possible to obtain the same functions of Powergrep from other

By using Powergrep, from our files, we extract only those lines that contain web links for downloading "10-K"[28].

Step Four: Download Documents

Once all previous steps are complete, we have a full list of 10-K reports. To download them, we follow the approach used to obtain the master files. The SEC associates a unique File Name to every document. This File Name partially contains the link to download the document but also some identifiers of the company. To have a complete match between the master files and the downloaded documents, we use part of the File Name as the filename for storing 10-K files.

II. Parsing Documents

Step Five: Recognize HTML vs. NON-HTML files

We download all 10-K reports as TXT files. Although it would be possible to download HTML documents, HTML tags allow us to extract the various sections of 10-K reports. However, not all 10-Ks have HTML tags. We use Powergrep to recognize those files that contain HTML tags by using specific keywords, such as <a>, <body>, <dir>, <h1>, or <href>.

Step Six: Extract Specific Sections

We focus on four sections of the 10-K report: Item 6 (Selected Financial Data), Item 7 (Management's discussion and analysis of financial condition and results of operations), Item 7A (Quantitative and qualitative disclosures about market risk), and Item 8 (Financial statements and supplementary data). However, to simply the paper we report the results based on Item 7, which is the most widely section of 10Ks or 10Qs analysed in prior research (e.g. Li 2008; Brown and Tucker 2011; Li 2010; Davis and Tama-Sweet 2012; Mayew et al. 2015; Loughran and McDonald 2011; Frankel et al. 2016).

For files without HTML tags, we use regular expressions (regexes) that allow capturing titles of the various sections.[29] For files with HTML tags, we use HTML tags' scheme for extracting titles' sections. First, we remove potential confounding titles that might be used as references in different parts of the 10-K.[30] Second, we use some paths associated with the use of HTML to include titles in texts.[31] The approach includes and develops techniques used to exploit the HTML tags used by firms (Campbell et al. 2014). Contrary to Li (2008), we use the words included in the titles of the items under analysis only as the last step of our extraction (if the methodology of using HTML tags does not provide results). By using those words that define the title of our items, we face two

---

software such as Python, as they share the same usage of regular expressions (regexes). The main advantage of Powergrep is being more user-friendly, and having windows commands that allow visualizing of software's output. Therefore, Powergrep is recommended for those users who do not have a proficient skill in software's coding.

[28] In the Library section of Powergrep, it is possible to find a command that allows extracting only those lines that contain a specific word: Collect lines containing a search term. In Powergrep, as a "Search type," we select "Literal text" and as a "Search" the word "|10-K|" (without quotes). This would prevent us from selecting other Form Types such 10-K/A, NT 10-K, 10-K405, and 10-K405/A that contain the same word 10-K.

[29] E.g., "ITEM 6"; "^ITEM 6"; "^\s+ITEM 6"; "ITEM\s+6"; "^ITEM \s+6"; "^\s+ITEM\s+6". We rely on a regex that can capture titles of 10-K sections written in capital letters, at the beginning of the line, and after several spaces with all the possible combinations.

[30] E.g., "HREF" followed by "ITEM 6", and "HREF" followed by "Selected financial statement"

[31] E.g., "a name" followed by "ITEM 6", "style" and "ITEM 6", "link1" and "ITEM 6", "link2" and "ITEM 6", "font" and "ITEM 6", "size" and "ITEM 6".

possible scenarios. First, we have to edit in advance the 10-K files by confounding titles (Li 2008). This process would increase the time and resources devoted to parsing documents. Second, we would face the risk of extracting titles of sections which do not refer to the beginning of the section but instead refer to a continued section. We use those keywords suggested by Feldman et al. (2010) (item number, titles, surrounding language, and new item number) to extract both the beginning and end of our sections.

Step Six (Bis): Robustness Tests

We run some robustness tests to reduce the likelihood of extracting wrong sections. A possible error is associated with having selected either a title of contents' table or a section's reference. To assess this eventuality, a solution is either to count the number of words or to look at the file's size. Both low numbers of words and a small file's size are indicative of possible missteps. A further solution is to look at the presence of non-consecutive items.[32] Furthermore, we might not find some or even all items. This might be the case for smaller firms or if they consolidate information of one item into a further one.[33] The latter might be the case if a company decides only to provide a reference to the section.

Step Seven: Remove Tables

Consistent with previous studies (Bonsall et al. 2017; Miller 2010; Li 2008), we remove all tables. We use a regex that accounts for how tables are reported.[34] We erase tables as self-defined by firms. However, we do not drop lines with special characters such as <s> and <c> (Loughran and McDonald 2011). HTML <s> identifies no longer useful text, <c> states for HTML code. We leave these tags intact, not to remove those parts of the 10-K that are lists of elements and might contain words associated with our vocabularies. Furthermore, applying the same regex even to non-HTML files is possible. Indeed, there is a consistent amount of non-HTML files for which tables are reported using HTML tags. However, it is important to highlight a possible limitation to this approach. In both types of files, we can extract and remove tables that are self-reported by the firm. Tables may be copied and pasted on the 10-K (this scenario is more probable for non-HTML tags that use tags only for inserting tables) without using HTML tags.

Step Eight: Generate Readable Files

After removing tables from all the sections, we convert TXT files with HTML tags into readable text files. First, we convert TXT 10-Ks into HTML files.[35] This process generates readable HTML files without tags. Second, we convert HTML files into readable TXT files.[36]

---

[32] For example, the presence of Item 7A into the file that contains Item 6.

[33] The Item 7A is, on average, the section which is most time consolidated into Item 7.

[34] For example, in 10-K tables usually starts with "<table" and end with "/table>".

[35] A batch file in Windows can copy and paste all the files in folder from txt format with HTML tags to HTML.

[36] In Cygwin, both "w3m" and "-dump" commands convert HTML into readable TXT files dropping HTML tags.

Appendix B. *Edgar* fillings with at least 150 observations in any year between 1994-2015.

	SEC Filling													
Year	**10-K**	**10-K/A**	**10-K405**	**10-K 405/A**	**10-Q**	**10-Q/A**	**20-F**	**20-F/A**	**8-K**	**8-K/A**	**NT 10-K**	**NT 10-K/A**	**NT 10-Q**	**NT 10-Q/A**
1994	1,912	616	11	5	6,632	558	0	0	3,623	375	51	1	68	3
1995	2,218	933	1,018	190	14,131	1,692	0	0	6,339	798	187	6	373	7
1996	4,315	1,495	1,944	317	25,758	2,319	9	7	15,736	2,155	749	21	1,261	16
1997	6,698	2,152	3,201	538	29,024	2,036	39	4	24,143	2,858	1,533	36	1,757	16
1998	6,930	1,943	3,357	589	29,254	2,135	108	28	28,004	3,285	1,687	41	1,828	18
1999	6,761	1,798	3,361	610	28,701	2,426	144	21	27,946	2,941	1,815	36	1,940	36
2000	6,652	1,530	3,217	483	28,301	1,926	195	55	29,747	2,946	2,285	41	3,705	37
2001	6,248	1,578	3,000	494	26,012	1,722	281	57	35,333	2,805	2,493	49	4,046	38
2002	6,762	2,010	2,168	123	24,111	1,778	1,131	148	45,136	3,165	2,455	43	4,114	49
2003	8,468	2,021	0	0	21,876	1,694	1,031	189	67,746	3,742	2,310	34	3,632	33
2004	8,567	2,096	0	0	20,878	1,704	1,004	234	91,445	4,191	2,061	58	3,604	53
2005	9,017	2,180	0	0	20,676	1,946	1,028	331	116,353	5,497	2,540	37	4,377	41
2006	8,852	1,510	0	0	20,049	1,574	980	233	106,390	5,009	2,357	43	4,575	36
2007	8,574	1,470	0	0	20,054	1,065	883	214	101,389	4,479	2,278	17	4,062	32
2008	8,746	1,801	0	0	27,047	1,517	820	193	90,993	3,505	2,308	27	3,681	25
2009	9,839	2,320	0	0	27,822	2,195	768	188	82,043	3,119	2,122	36	3,422	18
2010	9,165	2,213	0	0	26,556	2,060	746	217	80,519	2,923	1,817	21	3,079	15
2011	8,840	1,995	0	0	25,677	3,539	748	226	78,904	3,998	1,704	21	3,179	25
2012	8,393	1,840	0	0	24,192	3,045	723	267	77,417	2,908	1,574	10	2,908	25
2013	8,105	1,765	0	0	23,260	1,829	702	197	76,440	2,931	1,542	19	2,701	12
2014	8,084	1,557	0	0	22,883	1,420	676	90	76,996	2,735	1,423	8	2,502	10
2015	7,985	1,258	0	0	22,174	1,095	691	81	76,482	2,410	1,332	7	2,239	8

We exclude 10-KT and NT 20-F (and their amendments). The maximum number of 10-KT (NT 20-F) fillings is 41 (120) in 2014 (2003).

Appendix C. Selection procedure to create Samples II to IV

	Sample I		Sample II		Sample III		Sample IV. Performance			Sample IV. Earnings			Sample IV. Market			Sample IV. Analysts		
Deciles	Obs	%	Obs	% over Sample I	Obs	% over Sample I	Obs	% over Sample I	% over Sample III	Obs	% over Sample I	% over Sample III	Obs	% over Sample I	% over Sample III	Obs	% over Sample I	% over Sample III
1	14,730	10	7,984	54.20	7,484	50.81	4,242	28.80	56.68	4,071	27.64	54.4	2,918	19.81	38.99	1,097	7.45	14.66
2	14,730	10	8,659	58.78	8,119	55.12	5,719	38.83	70.44	4,388	29.79	54.05	3,832	26.01	47.20	1,622	11.01	19.98
3	14,731	10	8,412	57.10	7,900	53.63	5,825	39.54	73.73	4,256	28.89	53.87	3,899	26.47	49.35	1,815	12.32	22.97
4	14,730	10	8,448	57.35	7,911	53.71	6,040	41.00	76.35	4,327	29.38	54.7	3,983	27.04	50.35	1,802	12.23	22.78
5	14,730	10	7,981	54.18	7,491	50.86	5,676	38.53	75.77	4,175	28.34	55.73	3,651	24.79	48.74	1,717	11.66	22.92
6	14,731	10	6,616	44.91	6,160	41.82	4,683	31.79	76.02	3,507	23.81	56.93	2,927	19.87	47.52	1,438	9.76	23.34
7	14,730	10	5,563	37.77	5,172	35.11	3,851	26.14	74.46	3,078	20.9	59.51	2,363	16.04	45.69	1,130	7.67	21.85
8	14,731	10	5,281	35.85	4,914	33.36	3,429	23.28	69.78	2,934	19.92	59.71	2,240	15.21	45.58	969	6.58	19.72
9	14,730	10	4,909	33.33	4,605	31.26	2,631	17.86	57.13	2,698	18.32	58.59	1,766	11.99	38.35	713	4.84	15.48
10	14,730	10	6,636	45.05	6,327	42.95	2,851	19.36	45.06	2,749	18.66	43.45	2,411	16.37	38.11	947	6.43	14.97
Total	**147,303**	**100**	**70,489**	**47.85**	**66,083**	**44.86**	**44,947**	**30.51**	**68.02**	**36,183**	**24.56**	**54.75**	**29,990**	**20.36**	**45.38**	**13,250**	**9.00**	**20.05**

References

Abarbanell, J., and R. Lehavy. 2003. Biased forecasts or biased earnings? The role of reported earnings in explaining apparent bias and over/underreaction in analysts' earnings forecasts. *Journal of Accounting and Economics* 36:105-146.

Allee, K. D., and M. D. Deangelis. 2015. The structure of voluntary disclosure narratives: Evidence from tone dispersion. *Journal of Accounting Research* 53 (2):241-274.

Anderson, R. C., and D. S. Lee. 1997. Ownership studies: The data source does matter. *Journal of Financial and Quantitative Analysis* 32 (3):311-329.

Baginski, S., E. Demers, C. Wang, and J. Yu. 2016. Contemporaneous verification of language: evidence from management earnings forecasts. *Review of Accounting Studies* 21 (1):165-197.

Banz, R. W. 1981. The relationship between return and the market value of common stocks. *Journal of Financial Economics* 9:103-126.

Berk, J. 1995. A critique of size-related anomalies. *Review of Financial Studies* 8:275-286.

Bhojraj, S., C. M. C. Lee, and D. K. Oler. 2003. What's my line? A comparison of industry classification schemes for capital market research. *Journal of Accounting Research* 41 (5):745-774.

Bodnaruk, A., T. Loughran, and B. McDonald. 2015. Using 10-K Text to Gauge Financial Constraints. *Journal of Financial and Quantitative Analysis* 50 (4):623–646.

Bonsall, S. B., A. J. Leone, B. P. Miller, and K. Rennekamp. 2017. A plain English measure of financial reporting readability. *Journal of Accounting and Economics* 63 (2):329-357.

Bonsall, S. B., and B. P. Miller. 2017. The impact of narrative disclosure readability on bond ratings and the cost of debt. *Review of Accounting Studies* 22 (2):608-643.

Boone, A. L., I. V. Floros, and S. A. Johnson. 2016. Redacting proprietary information at the initial public offering. *Journal of Financial Economics* 120 (1):102-123.

Bozanic, Z., and M. Thevenot. 2015. Qualitative Disclosure and Changes in Sell-Side Financial Analysts' Information Environment. *Contemporary Accounting Research* 32 (4):1595-1616.

Brochet, F., M. Loumioti, and G. Serafeim. 2015. Speaking of the short-term: disclosure horizon and managerial myopia. *Review of Accounting Studies* 20 (3):1122-1163.

Brochet, F., P. Naranjo, and G. Yu. 2016. The capital market consequences of language barriers in the conference calls of non-U.S. firms. *The Accounting Review* 91 (4):1023-1049.

Brown, S. V., and J. W. Tucker. 2011. Large-sample evidence on firms' year over year MD&A modifications. *Journal of Accounting Research* 49 (2):309-346.

Bushman, R. M., B. E. Hendricks, and C. D. Williams. 2016. Bank competition: Measurement, decision-making, and risk-taking. *Journal of Accounting Research* 54 (3):777-826.

Cadman, B., S. Klasa, and S. Matsunaga. 2010. Determinants of CEO pay: A comparison of ExecuComp and non-ExecuComp firms. *The Accounting Review* 85 (5):1511-1543.

Campbell, J. L., H. Chen, D. S. Dhaliwal, H.-m. Lu, and L. B. Steele. 2014. The information content of mandatory risk factor disclosures in corporate filings. *Review of Accounting Studies* 19 (1):396-455.

Canina, L., R. Michaely, R. Thaler, and K. Womack. 1998. Caveat Compounder: A warning about using the daily CRSP equal-weighted index to compute long-run excess returns. *The Journal of Finance* 53 (1):403-416.

Davis, A., and I. Tama-Sweet. 2012. Managers' use of language across alternative disclosure outlets: Earnings press releases versus MD&A. *Contemporary Accounting Research* 29 (3):804-837.

Davis, A. K., W. Ge, D. Matsumoto, and J. L. Zhang. 2015. The effect of manager-specific optimism on the tone of earnings conference calls. *Review of Accounting Studies* 20 (2):639-673.

Davis, A. K., J. M. Piger, and L. M. Sedor. 2012. Beyond the numbers: Measuring the information content of earnings press release language. *Contemporary Accounting Research* 29 (3):845-868.

Davis, J. L. 1996. The cross-section of stock returns and survivorship bias: Evidence from delisted stocks. *Quarterly Review of Economics & Finance* 36 (3):365-375

De Franco, G., O.-K. Hope, D. Vyas, and Y. Zhou. 2015. Analyst Report Readability. *Contemporary Accounting Research* 32 (1):76-104.
Dikolli, S. S., T. Keusch, W. J. Mayew, and T. D. Steffen. 2016. A Linguistic-Based Approach to Measuring Innate Executive Traits: The Case of CEO Integrity: Duke Univesity.
Drake, M. S., D. T. Roulstone, and J. R. Thornock. 2016. The usefulness of historical accounting reports. *Journal of Accounting and Economics* 61 (2–3):448-464.
Dyer, T., M. Lang, and L. Stice-Lawrence. 2017. The evolution of 10-K textual disclosure: Evidence from Latent Dirichlet Allocation. *Journal of Accounting and Economics* 64 (2):221-245.
Elton, E. J., M. J. Gruber, and C. Blake, R. . 2001. A first look at the accuracy of the CRSP mutual fund database and a comparison of the CRSP and morningstar mutual fund databases. *Journal of Finance* 56 (6):2415-2430
Fama, E. F., and K. R. French. 1995. Size and book-to-market factors in earnings and returns. *Journal of Finance* 50:131-155.
Fama, E. F., and K. R. French. 1997. Industry costs of equity. *Journal of Financial Economics* 43 (2):153-193.
Feldman, R., S. Govindaraj, J. Livnat, and B. Segal. 2010. Management's tone change, post-earnings announcement drift and accruals. *Review of Accounting Studies* 15 (4):915-953.
Flesch, R. 1948. A new readability yardstick. *Journal of Applied Psychology* 32 (3):221-233.
Frankel, R., J. Jennings, and J. Lee. 2016. Using unstructured and qualitative disclosures to explain accruals. *Journal of Accounting and Economics* 62 (2–3):209-227.
García Lara, J. M., B. García Osma, and B. Gill de Albornoz Noguer. 2006. Effects of database choice on international accounting research. *Abacus* 42 (3/4):426-454.
Goel, S., J. Gangolly, S. R. Faerman, and O. Uzuner. 2010. Can linguistic predictors detect fraudulent financial filings? *Journal of Emerging Technologies in Accounting* 7:25–46.
Guay, W., D. Samuels, and D. Taylor. 2016. Guiding through the Fog: Financial statement complexity and voluntary disclosure. *Journal of Accounting and Economics* 62 (2–3):234-269.
Guenther, D. A., and A. J. Rosman. 1994. Differences between COMPUSTAT and CRSP SIC codes and related effects on research. *Journal of Accounting and Economics* 18 (1):115-128.
Gunning, R. 1952. *the technique of clear writing*. New York: McGraw-Hill.
Hart, R. P. 1984. *Verbal style and the presidency: A computer-based analysis*

Orlando, FL: Academic Press, Inc. .
Hart, R. P., and S. Jarvis. 1997. Political Debate: Forms, Styles, and Media. *American Behavioral Scientist* 40:1095-1122.
Henry, E. 2006. Market reaction to verbal components of earnings press releases: event study using a predictive algorithm. *Journal of Emerging Technologies in Accounting* 3 (1):1-19.
Henry, E. 2008. Are investors influenced by how earnings press releases are written? *Journal of Business Communication* 45 (4):363-407.
Henry, E., and A. J. Leone. 2016. Measuring qualitative information in capital markets research: Comparison of alternative methodologies to measure disclosure tone. *The Accounting Review* 91 (1):153-178.
Hoberg, G., and V. Maksimovic. 2015. Redefining financial constraints: A text-based analysis. *The Review of Financial Studies* 28 (5):1312-1352.
Hoberg, G., and G. Phillips. 2010. Product market synergies and competition in mergers and acquisitions: A text-based analysis. *The Review of Financial Studies* 23 (10):3773-3811.
Hope, O.-K., D. Hu, and H. Lu. 2016. The benefits of specific risk-factor disclosures. *Review of Accounting Studies* 21 (4):1005-1045.
Huang, X., S. H. Teoh, and Y. Zhang. 2014. Tone management. *The Accounting Review* 89 (3):1083-1113.
Humpherys, S. L., K. C. Moffitt, M. B. Burns, J. K. Burgoon, and W. F. Felix. 2011. Identification of fraudulent financial statements using linguistic credibility analysis. *Decision Support Systems* 50 (3):585–594.

Hwang, B.-H., and H. H. Kim. 2017. It pays to write well. *Journal of Financial Economics* 124 (2):373-394.

Irani, R. M., and D. Oesch. 2013. Monitoring and corporate disclosure: Evidence from a natural experiment. *Journal of Financial Economics* 109 (2):398-418.

Kahle, K. M., and R. A. Walkling. 1996. The impact of industry classifications on financial research *Journal of Financial and Quantitative Analysis* 31 (3):309-335.

Kim, J., Y. Kim, and J. Zhou. 2017. Languages and earnings management. *Journal of Accounting and Economics* 63 (2):288-306.

Kincaid, J. P., R. Braby, and J. E. Mears. 1988. Electronic Authoring and Delivery of Technical Information. *Journal of Instructional Development* 11 (2):8-13.

Kolk, A., D. Levy, and J. Pinkse. 2008. Corporate responses in an emerging climate regime: The institutionalization and commensuration of carbon disclosure. *European Accounting Review* 17 (4):719-745.

Koo, D. S., J. Julie Wu, and P. E. Yeung. 2017. Earnings Attribution and Information Transfers. *Contemporary Accounting Research* 34 (3):1547-1579.

Kothari, S. P., X. Li, and J. E. Short. 2009. The effect of disclosure my management, analysts and business press on cost of capital, return volatility, and analysts forecasts: A study using content analysis *The Accounting Review* 84 (5):1639-1670.

Kravet, T., and V. Muslu. 2013. Textual risk disclosures and investors' risk perceptions. *Review of Accounting Studies* 18 (4):1088-1122.

Krishnan, J. a. E. P. 2003. The North American industry classification system and its implications for accounting research. *Contemporary Accounting Research* 20 (4):685-717.

Lamoureux, C. G., and G. C. Sanger. 1989. Firm size and turn-of-the-year effects in the OTC/Nasdaq market. *Journal of Finance* 44:1219-1245.

Lang, M., and L. Stice-Lawrence. 2015. Textual analysis and international financial reporting: Large sample evidence. *Journal of Accounting and Economics* 60 (2–3):110-135.

Larcker, D., and A. Zakolyukina. 2012. Detecting deceptive discussions in conference calls. *Journal of Accounting Research* 50 (2):495-540.

Law, K. K. F., and L. F. Mills. 2015. Taxes and Financial Constraints: Evidence from Linguistic Cues. *Journal of Accounting Research* 53 (4):777-819.

Lawrence, A. 2013. Individual investors and financial disclosure. *Journal of Accounting and Economics* 56 (1):130-147.

Lee, J. 2016. Can investors detect managers' lack of spontaneity? Adherence to predetermined scripts during earnings conference calls. *The Accounting Review* 91 (1):229-250.

Lee, Y.-J. 2012. The effect of quarterly report readability on information efficiency of stock prices. *Contemporary Accounting Research* 29 (4):1137-1170.

Lehavy, R., F. Li, and K. Merkley. 2011. The effect of annual report readability on analyst following and the properties of their earningsforecasts. *The Accounting Review* 86:1087-1115.

Li, F. 2008. Annual report readability, current earnings, and earnings persistence. *Journal of Accounting and Economics* 45 (2/3):221-247.

Li, F. 2010. The information content of forward-looking statements in corporate filings - A naive bayesian machine learning approach. *Journal of Accounting Research* 48 (5):1049-1102.

Li, F., R. Lundholm, and M. Minnis. 2013. A measure of competition based on 10-K filings. *Journal of Accounting Research* 51 (2):399-436.

Li, F., M. Minnis, V. Nagar, and M. Rajan. 2014. Knowledge, compensation, and firm value: An empirical analysis of firm communication. *Journal of Accounting and Economics* 58 (1):96-116.

Ljungqvist, A., C. Malloy, and F. Marston. 2009. Rewriting history. *Journal of Finance* 64 (4):1935-1960.

Lo, K., F. Ramos, and R. Rogo. 2017. Earnings management and annual report readability. *Journal of Accounting and Economics* 63 (1):1-25.

Loughran, T., and B. McDonald. 2011. When is a liability not a liability? Textual analysis, dictionaries, and 10-Ks. *Journal of Finance* 66 (1):35-65.

Loughran, T., and B. McDonald. 2013. IPO first-day returns, offer price revisions, volatility, and form S-1 language. *Journal of Financial Economics* 109 (2):307-326.

Loughran, T., and B. McDonald. 2014. Measuring readability in financial disclosures. *Journal of Finance* 69:1643-1671.

Lundholm, R., R. Rogo, and J. L. Zhang. 2014. Restoring the tower of babel: how foreign firms communicate with US investors. *The Accounting Review* 89 (4):1453-1485.

Mayew, W. J., M. Sethuraman, and M. Venkatachalam. 2015. MD&A disclosure and the firm's ability to continue as a going concern. *The Accounting Review* 90 (4):1621-1651.

Merkley, K. 2014. Narrative disclosure and earnigns performance: Evidence from R&D disclosures. *The Accounting Review* 89 (2):725-759.

Miller, B. 2010. The effects of reporting complexity on small and large investor trading. *The Accounting Review* 85:2107-2143.

Mukherjee, A., M. Singh, and A. Žaldokas. 2017. Do corporate taxes hinder innovation? *Journal of Financial Economics* 124 (1):195-221.

Mutchler, J., and P. Shane. 1995. A comparative analysis of firms included in and excluded from the NAARS database. *Journal of Accounting Research* 33 (1):193-202.

Newman, M., J. Pennebaker, D. Berry, and R. J. 2003. Lying words: Predicting deception from linguistic styles. *Personality and Social Psychology Bulletin* 29 (5):665–675.

Philbrick, D. R. a. W. E. R. 1991. Using value line and IBES analyst forecasts in accounting research. *Journal of Accounting Research* 29 (2):397-417.

Purda, L., and D. Skillicorn. 2015. Accounting cariables, deception, and a bag of words: Assessing the tools of fraud detection. *Contemporary Accounting Research* 32 (3):1193-1223.

Rosenberg, B., and M. Houglet. 1974. Error rates in CRSP and compustat data bases and their implications. *Journal of Finance* 29 (4):1303-1310.

Schwarz, C. G., and M. E. Potter. 2016. Revisiting mutual fun portfolio disclosure. *Review of Financial Studies* 29 (12):3519-3544.

Segal, B., and D. Segal. 2016. Are managers strategic in reporting non-earnings news? Evidence on timing and news bundling. *Review of Accounting Studies* 21 (4):1203-1244.

Shumway, T. 1997. The delisting bias in CRSP data. *Journal of Finance* 52 (1):327-340.

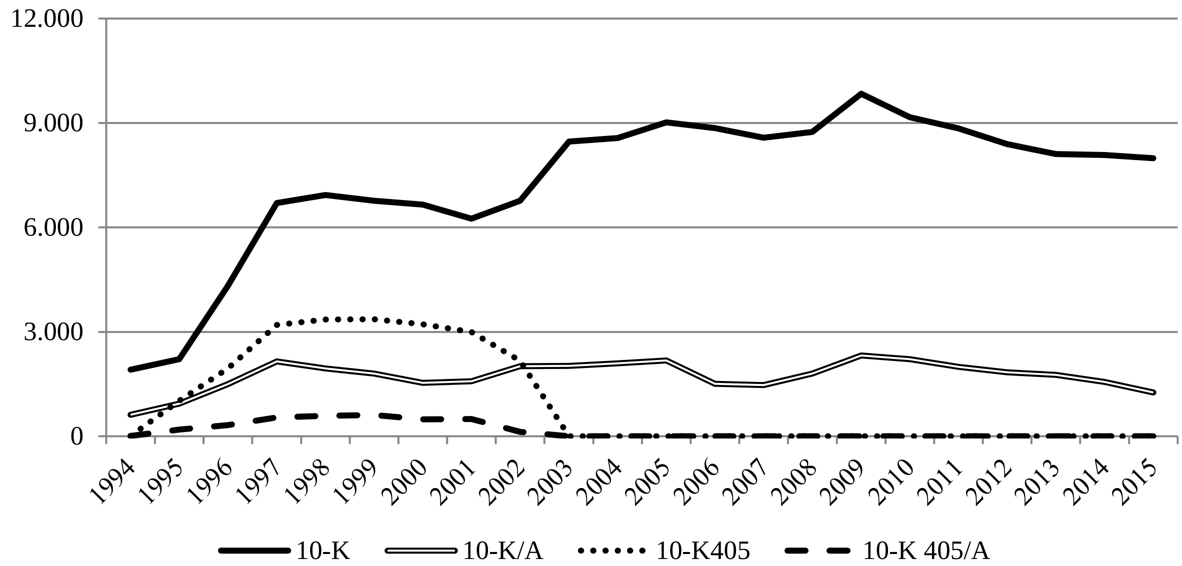
Shumway, T., and V. A. Warther. 1999. The delisting bias in CRSP's Nasdaq data and its implications for interpretation of the size effect. *Journal of Finance* 54 (6):2361-2379.

You, H., and X. Zhang. 2009. Financial reporting complexity and investor underreaction to 10-K information. *Review of Accounting Studies* 14:559-586.

Yuthas, K., R. Rogers, and J. F. Dillard. 2002. Communicative action and corporate annual reports. *Journal of Business Ethics* 41 (1/2):141-157.

Figure 1. Edgar Fillings

Panel A. Trends in 10-K fillings in the period 1994-2015



Panel B. Percentage of amended *Edgar* fillings in the period 1994-2015

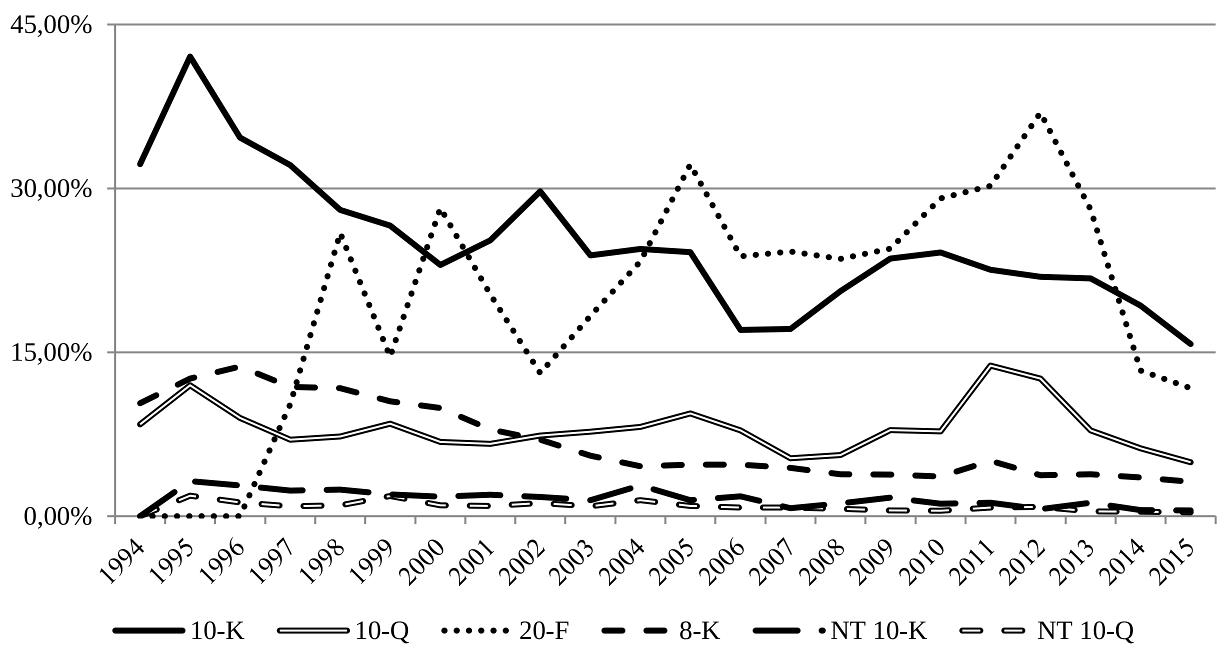
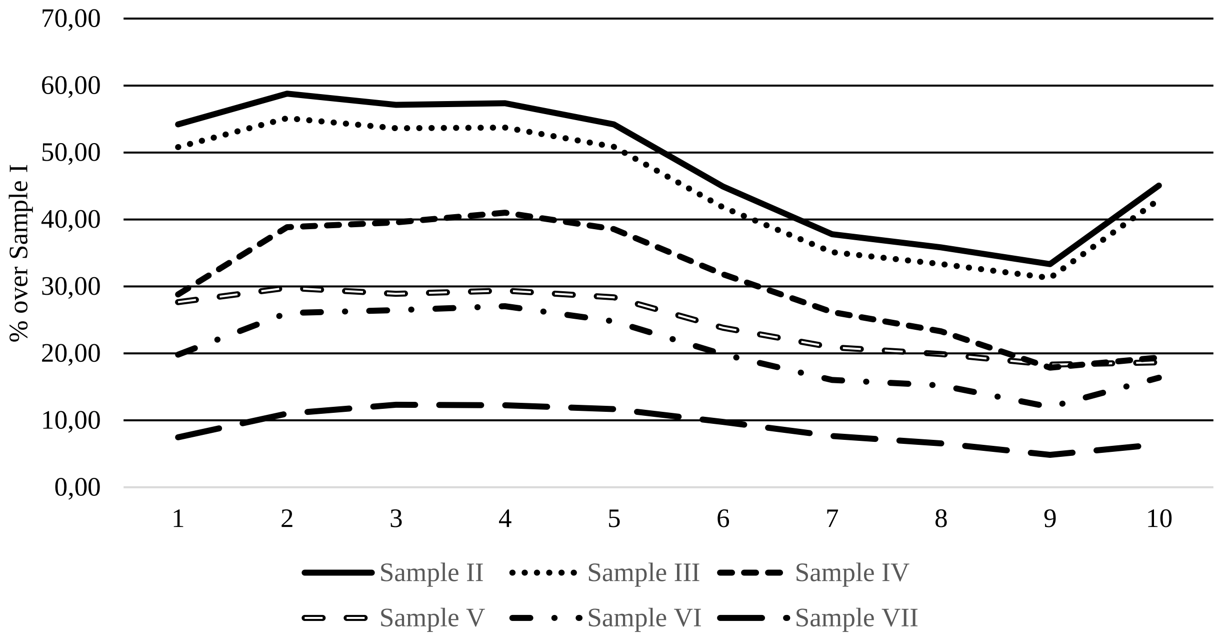


Figure 2. Deciles evolution of observations across samples

Panel A. Deciles evolutions with Link Table *to Crsp/Compustat over Sample I*



Panel B. Deciles evolutions with Link Table *to Crsp/Compustat over Sample III*

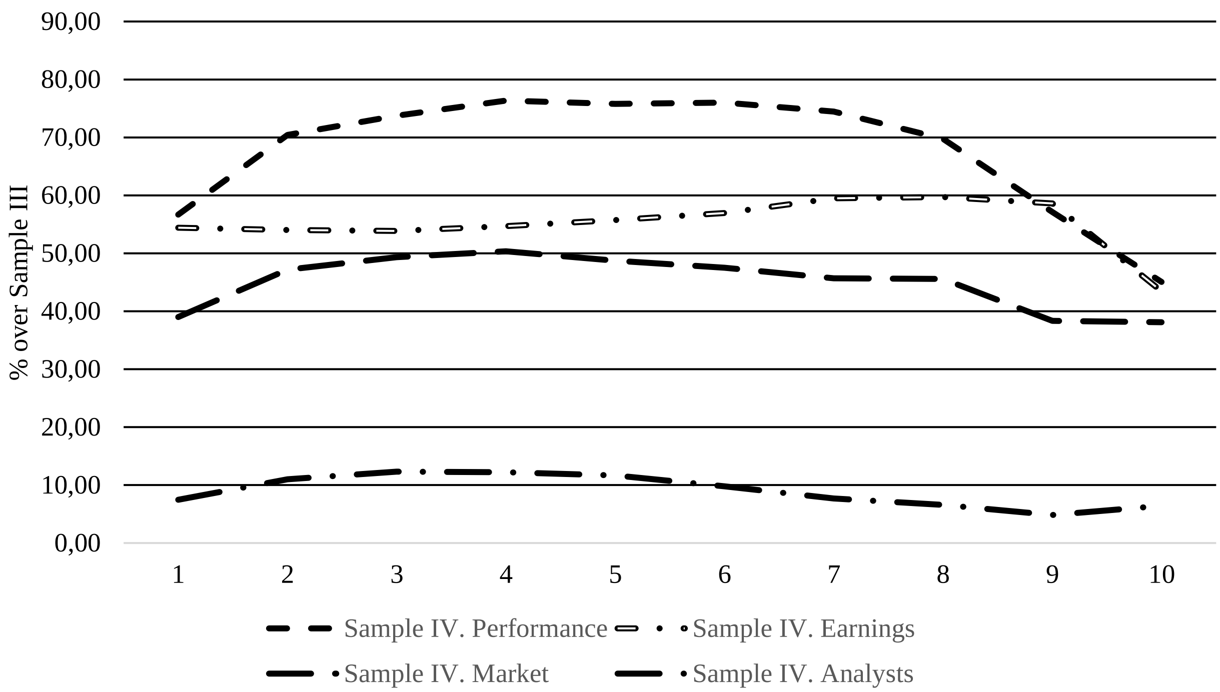


Table 1. Summary of Literature Review

Panel A. Total articles containing keywords related with firm narratives (2007-2017)

Keyword	**JFE**	**JF**	**RFS**	**JAE**	**JAR**	**TAR**	**CAR**	**AOS**	**RAST**	**EAR**	**TOTAL**
Textual analysis	19	39	2	16	29	3	19	34	16	1	178
Readability	96	69	1	23	29	11	28	8	13	2	280
Language	81	441	16	40	58	7	86	187	19	30	965
Narrative	19	102	0	10	33	3	40	124	16	17	364
Tone	20	85	3	20	43	6	45	66	17	5	312

Panel B. Total article published by leading Journals (2007-2017)

	JFE	**JF**	**RFS**	**JAE**	**JAR**	**TAR**	**CAR**	**AOS**	**RAST**	**EAR**	**TOTAL**
Articles published	5	2	2	10	8	10	6	1	10	2	56

Panel C. Total article published by year (2007-2017)

	2008	**2009**	**2010**	**2011**	**2012**	**2013**	**2014**	**2015**	**2016**	**2017**	**TOTAL**
Articles published	2	2	4	4	5	5	7	8	12	7	56

Journal of Accounting and Economics (JAE), Journal of Accounting Research (JAR), The accounting Review (TAR), Review of Accounting Studies (RAST), Contemporary Accounting Research (CAR), Accounting Organizations and Society (AOS) and European Accounting Review (EAR), Journal of Finance (JF), Journal of Financial Economics (JFE), and Review of Financial Studies (RFS).

Panel D. Articles details

			Sample		Measures		
Authors	**Journal**	**Year**	**Period**	**No. Observations**	**Readability**	**Tone**	**Others**
Hwang & Kim	JFE	2017	2003-2013	92 equity close-end funds; 6,507 monthly-yrs.	Readability (Fog index, Flesch-Kincaid index), passive verbs, hidden verbs, legal words, wordy phrases, overwriting, abstract words	.	File size
Mukherjee, Singh & Žaldokas	JFE	2017	1990-2006	47,632 firm-yrs press releases	.	.	Press releases on "New Products"
Boone, Floros, & Johnson	JFE	2016	1996-2011	2,199 IPOs, 875 redacting firms	.	.	Registration statements uses term "confidential"
Irani & Oesch	JFE	2013	1994-2005	39,384 firm-yrs 10Ks	Fog index and number of words, Li (2008)	.	.
Loughran & McDonald	JFE	2013	1997–2010	1,887 IPOs	.	Uncertain, weak, negative, positive, legal, and strong words.	.
Li	JAE	2008	1994-2004	55,719 firm-yrs MD&A	Fog index and average length of sentence	.	.
Lang & Stice-Lawrence	JAE	2015	1998-2011	15,000 firms, 87,608 obs., 42 non-US countries annual reports	Fog index	.	Length, boiler plate, comparability and complexity
Frankel, Jennings, & Lee	JAE	2016	1994-2013	71847 firm-yrs MD&A	Fog index	.	File size, length
Drake, RoulsTone & Thornock	JAE	2016	2003-2012	24,617 firm-yrs 10Ks, 10Qs.			total number of words (table characters)
Lo, Ramos, & Rogo	JAE	2017	2000-2012	4,855 firms, 26,967 firm-yrs MD&A	Fog index	.	.
Bonsall IV, Leone, & Miller	JAE	2017	1994-2011	46,424 firm-yrs 10Ks	Bog index, Fog index	.	Plain English index, sentence length, passive voice, weak verbs, overused and complex words, jargon
Guay, Samuels, &Taylor	JAE	2016	1995-2012	72,366 firm-yrs 10Ks	REadIndex (Flech, LIX, RIX, Fog index, ARI, SMOG) principal component. Readability	.	Length 10K
Lawrence	JAE	2013	1994-	95,107 firm-yrs 10Ks	Fog index (Li, 2008)		

Dyer, Lang & Stice-Lawrence	JAE	2017	1996-2013	10,452 firms, 75,991 firm-yrs 10Ks	Fog index		Boilerplate, length, redundant words, sticky words
Li, Minnis, Nagar, & Rajan	JAE	2014	2003-2007	17,419 conference calls	.	.	length of text, number of comments
Cho, Roberts, & Patten	AOS	2010	2002	190 firms 10Ks	.	Optimism and certainty (Diction dictionary)	
Loughran & McDonald	JF	2011	1994-2008	50,115 10Ks, 37,287 MD&A		Uncertain, weak, negative, positive, legal, strong words and Harvard General Inquirer word list	
Loughran & McDonald	JF	2014	1994-2011	66,707 firm-yrs 10Ks	Fog index		length, words per sentence, % complex, common, financial words
Gruning	EAR	2011	2005-2008	127,895 firm-yrs corporate reports	.	.	AIMD (Artificial Intelligence measurement of disclosure). N-Gram
Kolk, Levy, & Pinkse	EAR	2008	2003-2007	FT500 firms/380 responding firms questionnaires	.	.	Carbon disclosure project (CDP 5)
Lundholm, Rogo, & Zhang	TAR	2014	2000-2012	3,499 (1,582) foreign firm-yrs (press releases) and 37,344 (21,976) from US	Fog index		length
Brochet, Naranjo, & Yu	TAR	2016	2002-2010	25,830 conference calls	Fog index	.	length
Lehavy, Li, & Merkley	TAR	2011	1995-2006	57,642 firm-yrs 10Ks	Fog index	.	.
Miller	TAR	2010	1995-2006	13,000 10Ks	Fog index	.	.
Huang, Teoh, & Zhang	TAR	2014	1997-2007	14,475 firm-yrs Earnings press releases	.	Positive and negative words following Loughran and McDonald (2011), Henry (2008) Harvard General Inquirer word list	.
Lee	TAR	2016	2002-2011	40,820 conference calls	.	.	cosine-similarity
Mayew, Sethuraman, & Venkatachalam	TAR	2015	1995-2012	45,265 (460) Non-(bankrupt) firm-yrs MD&A		Positive and negative words following Loughran and McDonald (2011)	
Merkely	TAR	2014	1996-2007	22,482 firm-yrs 10Ks	.	.	Dictionary of common R&D keywords

Henry & Leone	TAR	2016	2004-2012	143,972 earnings announcements	.	Positive and negative words following Henry (2006, 2008), Diction, Harvard General Inquirer word list, Loughran and McDonald (2011)	.
Kothari, Li, & Short	TAR	2009	1996-2001	326,357 texts, 889 firms and 5,350 firm-yrs 10Ks, analysts reports, briefings, press releases	.	Harvard General Inquirer word list	Market, firm, organizational, reputational, performance, & regulatory risks
Hoberg, & Phillips	RFS	2010	1997-2006	50,104 firm-yrs 10Ks	.	.	cosine-similarity
Hoberg & Maksimovic	RFS	2014	1997-2009	48,512 10Ks	.	.	cosine-similarity, boiler plate, constraints scores
Feldman, Gvindaraj, Kivnaat & Segal	RAST	2010	1993-2007	153,988 10K, 10Q	.	Loughran and McDonald (2011)	.
Segal, & Segal	RAST	2016	2005-2013	335,328 8Ks	.	Loughran and McDonald (2011)	.
Kravet, & Muslu	RAST	2013	1994-2007	28,110 firm-yrs 10Ks	.	.	risk-related sentences
Hope, Hu, & Lu	RAST	2016	2006-2011	14,865 firm yrs 10Ks	.	.	specificity
Davis, Ge, Matsumoto, & Zhang	RAST	2015	2002-2009	25 firms, 121 CEOs & CFOs conference calls	.	Positive and negative words using Diction and also following Henry (2006, 2008) and Loughran and McDonald (2011)	.
Campbell, Chen, Dhaliwal, Lu, & Steele	RAST	2014	2005-2009	9,076 10Ks	.	.	risk-related list
Brochet, Loumioti, & Serafeim	RAST	2015	2002-2008	70,042 conference calls	.	.	short-term keywords.
Bonsall IV, & Miller	RAST	2017	1994-2014	3,659 10Ks	Bog index Bonsall et al. (2016)	Forward-looking (Bozanic et al. 2015) Tone, Uncertainty (Loughran and McDonald, 2011)	Risk disclosures (Kravet and Muslu 2013; Campbell et al. 2014).
Baginski, Demers, Wang & Yu	RAST	2016	1997-2006	1,764 mngt earnings forecasts	.	Diction, Loughran and McDonald (2011),	.
You, & Zhang	RAST	2009	1995-2005	123,449 10Ks	complexity	.	.

Bozanic & Thevenot	CAR	2015	1984-2012	1,838 firm yrs 160 unique firms.	Fog index, complex words	.	similarity (Brown and Tucker, 2010) Diversity (Goel et al. 2010, Humphreys et al. 2011)
Purda, & Skillicorn	CAR	2015	1994-2006	240 firms, 4,895 10Ks and 10Q	.	Uncertainty, negativity, litigation (Loughran and McDonald 2011)	deception (Newman et al. 2003)
Lee	CAR	2012	2001-2007	60,161 earnings announcements	Fog index, Length	.	.
Koo, Wu, & Yeung	CAR	2017	2001-2007	1,765 mngt forecasts	.	.	attribution phrases
Davis, Piger, & Sedor	CAR	2012	1998-2003	23,017 firm-quarter quarterly earnings press releases		Optimistic and pessimistic tone using Diction	
Davis, & Tama-Sweet	CAR	2012	1998-2003	11, 826 firm-quarters MD&A in 10Ks and 10Qs and earnings press releases	.	Optimistic and pessimistic tone using Diction	.
Li, Lundholm, & Minnis	JAR	2013	1995-2009	33,492 firm-yrs 10Ks	.	Tone	length, competition keywords
Li	JAR	2010	1994-2007	145,479 firms quarters MD&A of 10Qs and 10Ks	Fog index	Positive and negative tone using LIWC and Diction	Risk,Forward-looking words using Diction, General Inquirer and LIWC
Law, & Mills	JAR	2015	1994-2011	5,418 firm-years (2,340 firms) 10Ks	Fog index, No. of words, Flesch Reading Ease, Kincaid Readability	Uncertainty, Strong, litigious, Constraints words using Loughran and McDonald (2011) summary file	Negotiation words
Larcker, & Zakolyukina	JAR	2012	2003-2007	29,663 conference calls	.	LIWC, emotions words list	References, Calculation Cognitive Process, Other Cues from LIWC and self-constructed word list
Bushman, Hen-dricks & Williams	JAR	2016	1996-2012	14,633 bank-quarters 10Ks	.	.	competition words from Li et al. (2013)
Brown & Tucker	JAR	2011	1997-2006	28,279 firm years MD&A and earnings announcements	.	.	similarity cosine
Allee, & Deangelis	JAR	2015	2004-2014	73,201 conference calls transcripts resulting in 40,428 observations for 3,345 firms	.	Positive and negative tone following Loughran and McDonald (2011)	.

Loughran & McDonald	JAR	2016	1994-2011	66,707 observations 10Ks	Non-GAAP

Table 2. Sample selection procedure

Panel A. Procedure to create Sample I

	Firms (cik)	Observations	%
Total observations from 10-K files 1994-2015		225,417	
Possible duplicates		(64,286)	
10-K fillings in *Edgar*		161,131	
Missing Conformed Period of Report		(1,759)	
Duplicates (cik, FYEAR, FYR)		(913)	
Final Observations (Sample 0)	**33,466**	**159,338**	
Presence of HTML tags		88,860	56%
Item 6		146,545	92%
Item 7		147,303	92%
Item 7A		116,168	73%
Item 8		147,917	93%

Panel B. Selection procedure to creates Sample from I to IV

Sample name	**Sample type**	**10K reports withTable Link available**	**Description**	
Sample I		147,303	Item 7 observations	All the 10K containing Item 7 section.
Sample II	Subsample of Sample I	70,489	(1) Merge with CRSP/COMPUSTAT	Observations containing Central Index Key (cik), Fiscal Year (fyear), Fiscal Month (fyr), link to Compustat (linkprim equals to "P", and "C"), and Stock ownership code (no subsidiary).
Sample III	Subsample of Sample I	66,083	(2) Merge with CRSP/COMPUSTAT	Current and lagged values of Total assets (at), Revenues (revt), Short term debt (dlc), and Long term debt (dltt).
Sample IV. *Performance*	Subsample of Sample III	44,947	Performance	Current and lagged values of Net income (ni), Income Before Extraordinary Items (ib), Acquisition (aqc), Sale of Common and Preferred Stock (sstk), Common Ordinary Equity (ceq), Net Cash Flow from Operating Activities (oancf), Market Value (mkvalt).
Sample IV. *Earnings*	Subsample of Sample III	36,183	Earnings	Current and lagged values of Before Extraordinary Items (ib), Net Cash Flow from Operating Activities (oancf), Advertising Expenses (xad), Research and Development Expenses (xrd), Net Change Assets and Liabilities (aoloch), Accounts Payable (ap), Invetories (invt), PPE (ppegt), Receivables (rect), Accrued Income Taxes (txach).
Sample IV. *Market*	Subsample of Sample III	29,990	Market	Current and lagged values of Income Before Extraordinary Items (ib), Common Ordinary Equity (ceq), Market Value (mkvalt), Net Cash Flow from Operating Activities (oancf), Sale of Common, Preferred Stock (sstk), and adjustements for computing firms returns.
Sample IV. *Analysts*	Subsample of Sample III	13,250	Analysts	Current and lagged values of Income Before Extraordinary Items (ib), Common Ordinary Equity (ceq), Market Value (mkvalt), Net Cash Flow from Operating Activities (oancf), Sale of Common and Preferred Stock (sstk), and earnings per share in U.S. currency.

Table 3. Descriptive statistics of Tone and Readability measures for Sample I (N=147,303).

Panel A. Average file size and number of years available

VARIABLES	Mean	Median	Sd	Min	P25	P75	Max
Reporting month	10	12	3	1	9	12	12
File size (KB)	3,262	541	123,434	0	155	1,321	19,339,000

Panel B. Tone as measured by Diction, Loughran and McDonald (2011) and Inquirer.

VARIABLES	Mean	Median	Sd	Min	P25	P75	Max
Diction Neg.	0.0147	0.0116	0.0197	0	0.0084	0.0155	0.2727
Diction Pos.	0.0091	0.0099	0.0061	0	0.0055	0.0128	0.0909
LM Neg.	0.0124	0.011	0.0143	0	0.0066	0.0152	0.375
LM Pos.	0.0049	0.005	0.0035	0	0.0027	0.0069	0.0426
Inquirer Neg.	0.0179	0.0202	0.0103	0	0.0143	0.0245	0.0926
Inquirer Pos.	0.1201	0.1201	0.0452	0	0.1022	0.1386	0.9375

Panel C. Content analysis of other attributes.

VARIABLES	Mean	Median	Sd	Min	P25	P75	Max
Constraining	0.0055	0.0054	0.0049	0	0.0027	0.0073	0.0976
LM Litigious	0.0061	0.0044	0.0071	0	0.0023	0.0072	0.1315
LM Strong	0.0024	0.0021	0.0022	0	0.001	0.0032	0.06
LM Weak	0.0033	0.0028	0.0036	0	0.0013	0.004	0.1112
LM Uncertainty	0.0112	0.0114	0.0077	0	0.0074	0.0147	0.2223
Causation (Dikolli)	0.0341	0.0302	0.0161	0	0.0262	0.0357	0.2
Forward Look (Li)	0.0075	0.0072	0.0061	0	0.0039	0.01	0.1667

Panel D. Readability measures

VARIABLES	Mean	Median	Sd	Min	P25	P75	Max
Fog Index	18.9637	18.5429	3.8728	0	17.022	20.5724	88.8067
Flesch Index	22.606	26.7765	14.3684	-178.0791	20.0605	31.2249	115.1627
Flesch Kincaid index	14.4483	14.2818	2.9151	-2.1218	13.0137	15.6375	82.5664

Table 4. Tone and Readability differences between Sample I and Sample II.

Panel A. Differences in Tone as measured by Diction, Loughran and McDonald (2011) and Inquirer between Missing Narratives and Sample II

	Missing Narratives (Obs. 76,814)		Sample II (Obs. 70,489)		T-test	Wilcoxon rank-sum	Nonparametric medians
VARIABLES	Mean	Median	Mean	Median	T-stat	Z-stat	Fisher's p
Diction Neg.	0.0182	0.0122	0.011	0.0112	70.84	44.45	0.00
Diction Pos.	0.0084	0.0092	0.0098	0.0105	-44.29	-48.89	0.00
LM Neg.	0.0136	0.0109	0.0111	0.0111	33.97	-5.02	0.00
LM Pos.	0.0044	0.0044	0.0054	0.0054	-55.67	-64.26	0.00
Inquirer Neg.	0.0164	0.0192	0.0195	0.0211	-57.38	-52.58	0.00
Inquirer Pos.	0.117	0.119	0.1236	0.121	-28.24	-23.17	0.00

Panel B. Differences in Content analysis of other attributes between Missing Narratives and Sample II

	Missing Narratives (Obs. 76,814)		Sample II (Obs. 70,489)		T-test	Wilcoxon rank-sum	Nonparametric medians
VARIABLES	Mean	Median	Mean	Median	T-stat	Z-stat	Fisher's p
Constraining	0.005	0.0049	0.006	0.0058	-39.19	-51.57	0.00
LM Litigious	0.0052	0.0038	0.0071	0.0049	-51.20	-71.97	0.00
LM Strong	0.0025	0.0021	0.0023	0.0021	21.82	-4.20	0.52
LM Weak	0.003	0.0025	0.0036	0.0029	-35.96	-43.54	0.00
LM Uncertainty	0.0103	0.0107	0.0121	0.012	-44.36	-52.97	0.00
Causation (Dikolli)	0.036	0.0303	0.032	0.0302	48.46	9.86	0.08
Forward Look (Li)	0.0075	0.007	0.0075	0.0074	-1.03	-19.74	0.00

Panel C. Differences in Readability measures of other attributes between Missing Narratives Sample II

	Missing Narratives (Obs. 76,814)		Sample II (Obs. 70,489)		T-test	Wilcoxon rank-sum	Nonparametric medians
VARIABLES	Mean	Median	Mean	Median	T-stat	Z-stat	Fisher's p
Fog Index	19.430	19.333	18.456	17.940	48.58	86.56	0.00
Flesch Index	20.393	25.327	25.017	27.955	-62.52	-63.49	0.00
Flesch Kincaid index	14.612	14.680	14.270	13.903	22.54	57.36	0.00

Table 5. Tone and Readability differences between Sample I and Sample III.

Panel A. Differences in Tone as measured by Diction, Loughran and McDonald (2011) and Inquirer between Missing Narratives and Sample III

	Missing Narratives (Obs. 81,220)		Sample III (Obs. 66,083)		T-test	Wilcoxon rank-sum	Nonparametric medians
VARIABLES	Mean	Median	Mean	Median	T-stat	Z-stat	Fisher's p
Diction Neg.	0.0178	0.0122	0.011	0.0112	67.16	43.23	0.00
Diction Pos.	0.0085	0.0093	0.0098	0.0105	-39.53	-44.23	0.00
LM Neg.	0.0134	0.0108	0.0111	0.0112	31.12	-7.98	0.00
LM Pos.	0.0044	0.0045	0.0054	0.0055	-52.42	-61.48	0.00
Inquirer Neg.	0.0166	0.0193	0.0195	0.0212	-54.33	-52.21	0.00
Inquirer Pos.	0.1172	0.119	0.1237	0.1211	-27.53	-23.53	0.00

Panel B. Differences in Content analysis of other attributes between Missing Narratives and Sample III

	Missing Narratives (Obs. 81,220)		Sample III (Obs. 66,083)		T-test	Wilcoxon rank-sum	Nonparametric medians
VARIABLES	Mean	Median	Mean	Median	T-stat	Z-stat	Fisher's p
Constraining	0.005	0.0049	0.006	0.0058	-38.98	-50.65	0.00
LM Litigious	0.0052	0.0039	0.0072	0.005	-51.96	-70.93	0.00
LM Strong	0.0025	0.0022	0.0022	0.0021	27.26	3.36	0.00
LM Weak	0.003	0.0026	0.0036	0.0029	-30.38	-37.05	0.00
LM Uncertainty	0.0104	0.0108	0.0121	0.012	-40.72	-49.17	0.00
Causation (Dikolli)	0.0357	0.0302	0.0321	0.0302	43.33	6.50	0.68
Forward Look (Li)	0.0076	0.007	0.0074	0.0073	5.47	-12.18	0.00

Panel C. Differences in Readability measures of other attributes between Missing Narratives Sample III

	Missing Narratives (Obs. 81,220)		Sample III (Obs. 66,083)		T-test	Wilcoxon rank-sum	Nonparametric medians
VARIABLES	Mean	Median	Mean	Median	T-stat	Z-stat	Fisher's p
Fog Index	19.3696	19.2401	18.4648	17.9339	44.90	81.69	0.00
Flesch Index	20.7352	25.5605	24.9052	27.9167	-55.98	-57.66	0.00
Flesch Kincaid index	14.5849	14.68	14.2805	13.9033	19.96	53.44	0.00

Table 6. Tone and Readability differences between Sample III and Sample IV. Performance

Panel A. Differences in Tone as measured by Diction, Loughran and McDonald (2011) and Inquirer between Missing Narratives and Sample IV.Performance

	Missing Narratives (Obs. 21,136)		Sample IV (Obs. 44,947)		T-test	Wilcoxon rank-sum	Nonparametric medians
VARIABLES	Mean	Median	Mean	Median	T-stat	Z-stat	Fisher's p
Diction Neg.	0.0093	0.0098	0.0117	0.0116	-50.11	-49.13	0.00
Diction Pos.	0.0083	0.009	0.0105	0.0109	-48.34	-46.58	0.00
LM Neg.	0.0092	0.0091	0.012	0.0118	-50.69	-51.36	0.00
LM Pos.	0.0048	0.005	0.0057	0.0056	-31.49	-29.51	0.00
Inquirer Neg.	0.0166	0.0192	0.0208	0.0219	-56.49	-46.85	0.00
Inquirer Pos.	0.1293	0.1272	0.1211	0.1191	26.41	34.46	0.00

Panel B. Differences in Content analysis of other attributes between Missing Narratives and Sample IV.Performance

	Missing Narratives (Obs. 21,136)		Sample IV (Obs. 44,947)		T-test	Wilcoxon rank-sum	Nonparametric medians
VARIABLES	Mean	Median	Mean	Median	T-stat	Z-stat	Fisher's p
Constraining	0.0053	0.0042	0.0064	0.0063	-28.56	-69.07	0.00
LM Litigious	0.0081	0.0045	0.0067	0.0051	21.98	-12.45	0.00
LM Strong	0.002	0.0018	0.0023	0.0022	-23.27	-34.03	0.00
LM Weak	0.0033	0.0024	0.0038	0.0031	-14.26	-49.04	0.00
LM Uncertainty	0.0102	0.0105	0.0129	0.0125	-49.01	-52.44	0.00
Causation (Dikolli)	0.034	0.0308	0.0312	0.03	31.37	18.00	0.00
Forward Look (Li)	0.0058	0.0057	0.0081	0.0078	-60.03	-66.14	0.00

Panel C. Differences in Readability measures of other attributes between Missing Narratives Sample IV.Performance

	Missing Narratives (Obs. 21,136)		Sample IV (Obs. 44,947)		T-test	Wilcoxon rank-sum	Nonparametric medians
VARIABLES	Mean	Median	Mean	Median	T-stat	Z-stat	Fisher's p
Fog Index	18.9552	18.2163	18.2342	17.8518	23.13	20.11	0.00
Flesch Index	22.0588	26.8847	26.2437	28.2235	-40.02	-24.37	0.00
Flesch Kincaid index	14.6015	14.0584	14.1296	13.8514	18.89	13.63	0.00

Table 7. Tone and Readability differences between Sample III and Sample IV Earnings

Panel A. Differences in Tone as measured by Diction, Loughran and McDonald (2011) and Inquirer between Missing Narratives and Sample IV.Earnings

	Missing Narratives (Obs. 29,990)		Sample IV (Obs. 36,183)		T-test	Wilcoxon rank-sum	Nonparametric medians
VARIABLES	Mean	Median	Mean	Median	T-stat	Z-stat	Fisher's p
Diction Neg.	0.0108	0.0111	0.0111	0.0112	-5.31	-3.40	0.01
Diction Pos.	0.0099	0.0108	0.0097	0.0102	4.67	14.10	0.00
LM Neg.	0.0109	0.0112	0.0113	0.0112	-8.95	-5.37	0.30
LM Pos.	0.0051	0.0053	0.0057	0.0056	-24.31	-21.45	0.00
Inquirer Neg.	0.0184	0.0207	0.0203	0.0216	-25.94	-21.61	0.00
Inquirer Pos.	0.1229	0.1211	0.1244	0.1211	-4.86	-3.47	0.86

Panel B. Differences in Content analysis of other attributes between Missing Narratives and Sample IV.Earnings

	Missing Narratives (Obs. 29,990)		Sample IV (Obs. 36,183)		T-test	Wilcoxon rank-sum	Nonparametric medians
VARIABLES	Mean	Median	Mean	Median	T-stat	Z-stat	Fisher's p
Constraining	0.0062	0.0059	0.0059	0.0057	8.75	5.02	0.00
LM Litigious	0.0077	0.005	0.0067	0.005	17.61	5.31	0.94
LM Strong	0.0019	0.0019	0.0025	0.0023	-43.74	-45.15	0.00
LM Weak	0.0034	0.0028	0.0038	0.003	-15.01	-23.08	0.00
LM Uncertainty	0.0116	0.0119	0.0124	0.0122	-14.80	-13.34	0.00
Causation (Dikolli)	0.0324	0.03	0.0318	0.0304	6.42	-5.93	0.00
Forward Look (Li)	0.0066	0.0068	0.0081	0.0078	-41.04	-41.79	0.00

Panel C. Differences in Readability measures of other attributes between Missing Narratives Sample IV.Earnings

	Missing Narratives (Obs. 29,990)		Sample IV (Obs. 36,183)		T-test	Wilcoxon rank-sum	Nonparametric medians
VARIABLES	Mean	Median	Mean	Median	T-stat	Z-stat	Fisher's p
Fog Index	18.6159	17.9336	18.3399	17.9344	9.42	4.19	0.99
Flesch Index	23.7567	27.7041	25.8543	28.1002	-21.22	-12.38	0.00
Flesch Kincaid index	14.3901	13.8773	14.1899	13.9244	8.53	2.02	0.01

Table 8. Tone and Readability differences between Sample III and Sample IV Market

Panel A. Differences in Tone as measured by Diction, Loughran and McDonald (2011) and Inquirer between Missing Narratives and Sample IV.Market

	Missing Narratives (Obs. 36,093)		Sample IV (Obs. 29,990)		T-test	Wilcoxon rank-sum	Nonparametric medians
VARIABLES	Mean	Median	Mean	Median	T-stat	Z-stat	Fisher's p
Diction Neg.	0.0105	0.0109	0.0115	0.0114	-21.59	-19.58	0.00
Diction Pos.	0.0093	0.0099	0.0104	0.011	-27.93	-33.18	0.00
LM Neg.	0.0106	0.0106	0.0117	0.0118	-21.64	-24.83	0.00
LM Pos.	0.0053	0.0054	0.0055	0.0056	-9.97	-11.57	0.00
Inquirer Neg.	0.0188	0.0207	0.0203	0.0218	-20.54	-21.21	0.00
Inquirer Pos.	0.1268	0.1238	0.12	0.1186	23.27	28.57	0.00

Panel B. Differences in Content analysis of other attributes between Missing Narratives and Sample IV.Market

	Missing Narratives (Obs. 36,093)		Sample IV (Obs. 29,990)		T-test	Wilcoxon rank-sum	Nonparametric medians
VARIABLES	Mean	Median	Mean	Median	T-stat	Z-stat	Fisher's p
Constraining	0.0057	0.0053	0.0064	0.0063	-20.30	-41.55	0.00
LM Litigious	0.0072	0.0048	0.0072	0.0052	0.06	-14.65	0.00
LM Strong	0.0023	0.0022	0.0021	0.0021	12.80	8.86	0.00
LM Weak	0.0036	0.0028	0.0036	0.003	-1.80	-12.19	0.00
LM Uncertainty	0.0115	0.0117	0.0128	0.0124	-23.74	-24.20	0.00
Causation (Dikolli)	0.0325	0.0303	0.0315	0.0301	11.92	5.93	0.00
Forward Look (Li)	0.0072	0.0071	0.0076	0.0075	-12.16	-15.37	0.00

Panel C. Differences in Readability measures of other attributes between Missing Narratives Sample IV.Market

	Missing Narratives (Obs. 36,093)		Sample IV (Obs. 29,990)		T-test	Wilcoxon rank-sum	Nonparametric medians
VARIABLES	Mean	Median	Mean	Median	T-stat	Z-stat	Fisher's p
Fog Index	18.555	18.019	18.3562	17.8428	6.78	9.52	0.00
Flesch Index	24.4533	27.8328	25.4492	27.9977	-10.05	-3.14	0.01
Flesch Kincaid index	14.3221	13.955	14.2304	13.8423	3.90	5.75	0.00

Table 9. Tone and Readability differences between Sample III and Sample IV Analysts

Panel A. Differences in Tone as measured by Diction, Loughran and McDonald (2011) and Inquirer between Missing Narratives and Sample IV.Analysts

	Missing Narratives (Obs. 52,833)		Sample IV (Obs. 13,250)		T-test	Wilcoxon rank-sum	Nonparametric medians
VARIABLES	Mean	Median	Mean	Median	T-stat	Z-stat	Fisher's p
Diction Neg.	0.0108	0.0111	0.0116	0.0115	-12.90	-12.17	0.00
Diction Pos.	0.0096	0.0103	0.0104	0.0109	-14.87	-16.11	0.00
LM Neg.	0.011	0.0111	0.0118	0.0116	-12.27	-12.82	0.00
LM Pos.	0.0053	0.0054	0.0058	0.0057	-14.67	-14.61	0.00
Inquirer Neg.	0.1255	0.1228	0.1165	0.1157	25.10	32.99	0.00
Inquirer Pos.	0.0192	0.021	0.0206	0.0218	-15.55	-14.55	0.00

Panel B. Differences in Content analysis of other attributes between Missing Narratives and Sample IV.Analysts

	Missing Narratives (Obs. 52,833)		Sample IV (Obs. 13,250)		T-test	Wilcoxon rank-sum	Nonparametric medians
VARIABLES	Mean	Median	Mean	Median	T-stat	Z-stat	Fisher's p
Constraining (Bodn.)	0.006	0.0057	0.0064	0.0062	-9.64	-22.95	0.00
LM Litigious	0.0072	0.0049	0.0069	0.0052	3.92	-10.31	0.00
LM Strong	0.0022	0.0021	0.0023	0.0022	-3.93	-6.47	0.00
LM Weak	0.0035	0.0028	0.004	0.0031	-12.43	-22.97	0.00
LM Uncertainty	0.0117	0.0118	0.0133	0.0128	-24.30	-26.98	0.00
Causation (Dikolli)	0.0322	0.0302	0.0315	0.0303	7.23	-0.56	0.38
Forward Look (Li)	0.0072	0.0071	0.0082	0.008	-23.08	-26.83	0.00

Panel C. Differences in Readability measures of other attributes between Missing Narratives Sample IV.Analysts

	Missing Narratives (Obs. 52,833)		Sample IV (Obs. 13,250)		T-test	Wilcoxon rank-sum	Nonparametric medians
VARIABLES	Mean	Median	Mean	Median	T-stat	Z-stat	Fisher's p
Fog Index	18.4987	17.9693	18.3296	17.8228	4.64	6.75	0.00
Flesch Index	24.7229	27.9596	25.6324	27.7887	-7.38	0.56	0.01
Flesch Kincaid index	14.2851	13.9088	14.2621	13.8761	0.79	1.51	0.15

Table 10. Tone and Readability differences in classification of observations

Panel A. Differences L.M vs. Diction Negative

	1	2	3	4	5	6	7	8	9	10	[-1 D, +1 D]
1	**42.6**	15.7	1.5	1.1	0.7	0.8	1.1	1.0	1.6	33.8	58.3
2	34.2	**26.2**	6.4	3.0	2.2	1.9	1.7	1.5	1.9	21.1	66.8
3	0.1	22.1	**24.2**	16.1	11.3	8.5	6.8	5.3	3.7	2.0	62.3
4	0.2	10.5	20.6	**18.1**	15.9	12.5	9.4	6.4	4.4	2.0	54.6
5	0.5	6.9	15.0	16.8	**15.7**	14.9	11.7	9.6	6.4	2.6	47.4
6	0.1	4.6	11.9	14.5	15.5	**15.2**	14.2	11.8	9.2	3.2	44.8
7	0.1	3.4	8.8	12.3	14.0	15.7	**15.5**	14.7	12.3	3.4	45.9
8	0.1	2.5	6.5	9.8	12.3	14.6	16.4	**17.9**	14.7	5.3	49.0
9	0.1	1.6	3.8	6.6	9.6	11.7	15.7	20.3	**22.8**	7.7	50.8
10	22.0	6.5	1.3	1.9	2.9	4.3	7.5	11.5	23.2	**19.0**	42.1

Panel B. Differences L.M vs. Diction Positive

	1	2	3	4	5	6	7	8	9	10	[-1 D, +1 D]
1	**49.1**	44.8	1.4	0.4	0.3	0.3	0.2	0.3	0.5	2.8	93.9
2	45.3	**47.9**	1.5	0.4	0.3	0.5	0.3	0.3	0.5	3.1	94.6
3	4.9	5.5	**23.4**	14.1	10.5	9.4	8.6	7.2	6.8	9.6	43.1
4	0.1	0.3	14.2	**14.0**	13.1	11.7	12.6	12.3	11.3	10.3	41.3
5	0.1	0.2	11.5	12.3	**13.0**	12.8	12.8	12.9	13.0	11.4	38.0
6	0.1	0.3	11.0	12.4	12.4	**13.1**	12.7	13.5	13.2	11.3	38.3
7	0.1	0.2	9.9	12.0	13.2	12.9	**13.1**	13.4	13.9	11.3	39.5
8	0.1	0.2	8.8	12.0	13.2	13.4	13.9	**13.7**	13.2	11.7	40.8
9	0.1	0.3	8.8	11.7	12.9	13.3	13.4	13.6	**13.4**	12.6	39.5
10	0.3	0.3	9.6	10.7	11.2	12.7	12.4	12.7	14.3	**15.9**	30.1

Panel C. Differences Fog vs. Flesch

	1	2	3	4	5	6	7	8	9	10	[-1 D, +1 D]
1	**65.6**	19.4	4.1	0.8	0.2	0.1	0.1	0.5	9.4	0.0	84.9
2	20.4	**40.7**	24.0	8.2	2.9	0.6	0.2	0.4	2.6	0.0	85.1
3	7.7	19.9	**30.7**	24.2	9.7	3.0	1.6	0.6	2.5	0.0	74.9
4	4.0	10.0	19.0	**27.9**	23.7	10.9	3.2	1.0	0.3	0.0	70.6
5	1.6	6.3	11.3	17.3	**26.9**	23.1	9.0	2.6	1.7	0.1	67.3
6	0.5	3.0	7.8	13.0	18.4	**26.7**	22.1	5.7	2.7	0.3	67.2
7	0.1	0.6	2.7	6.9	13.5	21.7	**28.8**	16.2	8.9	0.6	66.7
8	0.0	0.1	0.4	1.6	4.2	12.4	26.7	**30.9**	18.8	4.9	76.3
9	0.0	0.0	0.0	0.1	0.4	1.5	8.2	37.1	**24.4**	28.2	89.7
10	0.0	0.0	0.0	0.0	0.0	0.0	0.1	5.2	28.8	**65.9**	94.7

Panel D. Differences Flesch Kinkeid vs. Flesch

	1	2	3	4	5	6	7	8	9	10	[-1 D, +1 D]
1	**67.7**	17.9	2.9	0.6	0.3	0.2	0.3	0.8	9.4	0.0	85.5
2	20.9	**43.0**	23.0	6.7	1.7	0.6	0.4	1.1	2.7	0.0	86.8
3	6.6	20.8	**31.8**	21.7	8.4	2.1	0.8	0.8	6.9	0.0	74.3
4	3.1	10.2	21.5	**29.2**	20.3	7.5	2.0	1.5	4.5	0.0	71.0
5	1.1	5.1	11.9	20.7	**28.6**	19.4	6.2	1.7	5.3	0.1	68.6
6	0.4	2.3	5.8	11.9	19.9	**25.0**	14.2	3.1	13.7	3.8	59.1
7	0.1	0.6	2.4	6.8	13.6	24.5	**24.2**	6.7	2.8	18.2	55.4
8	0.1	0.1	0.7	2.0	6.0	16.2	33.1	**21.2**	6.9	13.7	61.2
9	0.0	0.0	0.1	0.4	1.0	4.5	18.2	47.6	**16.7**	11.5	75.8
10	0.0	0.0	0.0	0.0	0.1	0.2	0.7	15.4	31.0	**52.7**	83.7