Essays on the role of narrative disclosures in financial reporting

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Abstract

This thesis contains two essays on the role of narrative disclosures in financial reporting. The first essay, "*Tightening rating standards: The effect of narrative risk-related disclosures*" (co-authored with Argyro Panaretou and Grzegorz Pawlina), examines how narrative disclosures affect rating stringency, a phenomenon where credit rating agencies assign ratings worse than what firm fundamentals justify. Results suggest that narrative disclosures about risk and uncertainty in Form 10-K reports moderate rating stringency. Moreover, this moderating effect is more pronounced when Form 10-K reports have textual attributes that can affect how users contextualize firm risk. The second essay, "*Context matters: The role of fair value footnote narratives*" (co-authored with Argyro Panaretou and Catherine Shakespeare), investigates how narrative disclosures in Form 10-K report footnotes that discuss the measurement of fair values affect investor uncertainty. The findings of this essay show that longer fair value footnote narratives reduce investor uncertainty for opaque fair values, and are particularly informative to sophisticated investors. Further test results suggest that standardized and non-specific fair value narratives increase investor uncertainty for Level 3 fair values, and that fair value narratives offer incremental information to investors relative to tabulated fair value footnote disclosures. Finally, the thesis includes a technical appendix, "*A guide on extracting, processing, and operationalizing Form 10-K report narratives*," on the advantages and challenges in identifying, collecting, and integrating narrative disclosure data from Form 10-K reports into archival accounting studies.

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Declaration of authorship

I hereby declare that this thesis is the result of my own work, and that I have acknowledged all sources used.

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Chapter 1: Thesis introduction

This thesis contains two essays and a technical appendix on narrative disclosures within U.S.-listed firms' annual reports (i.e., Form 10-K reports). Publicly traded firms file these reports annually with the U.S. Securities and Exchange Commission (SEC). By providing a comprehensive overview of a firm's financial performance, operations, risks, and prospects, Form 10-K reports promote transparency and reduce uncertainty in financial markets. Form 10-K reports consist of a narrative and a quantitative component. By presenting both narrative insights and quantitative data, they allow firm outsiders, also known as "users," to gain insights into a firm's financial position, performance, and strategic direction.

The quantitative component of the Form 10-K report includes the financial statements, and other quantitative data that provide numerical representations of a firm's financial position, income, cash flows, and changes in equity. These disclosures constitute "hard" information that is easy to collect, store, and transmit (Liberti and Petersen 2019). The narrative component represents, on average, 80 percent of a Form 10-K report (Li 2010a; Lo, Ramos, and Logo 2017), and contain financial and non-financial information. By providing information on a firm's key performance drivers, risk factors, and industry trends, these disclosures offer valuable insights to users.

Narrative disclosures in Form 10-K reports should help users contextualize the numerical disclosures found in the financial statements and footnotes (Ahn, Hoitash, and Hoitash 2022). Moreover, these disclosures allow firms to discuss various uncertainties that are not quantifiable, such as shifts in market conditions, potential legal issues, and industry-specific challenges. Given the role of accounting disclosures in shaping users' decision-making, better understanding the role of Form 10-K report narrative disclosures can benefit academic researchers, regulators, and financial reporting practitioners.

Chapter 2 examines the role of narrative disclosures in influencing credit rating agencies' (CRAs) assignment of credit ratings. Despite CRAs claiming to use a consistent rating assessment framework, documented trends that rely on quantitative financial information suggest an increasing tightening in rating standards over time (e.g., Blume, Lim, and Mackinlay 1998; Alp 2013; Baghai, Servaes, and Tamayo 2014). However, CRAs also claim that they focus on more than quantitative data to determine credit ratings (S&P Ratings Criteria 2013f), and prior research shows that CRAs use Form 10-K narrative disclosures in their rating analyses (Bozanic, Kraft, and Tillet 2023). The study's findings suggest that risk-related narratives in Form 10-K reports partially explain rating stringency. Furthermore, this effect is more pronounced when Form 10-K report narratives are more specific and readable. This study provides new evidence on the reasons behind rating stringency. Also, by focusing on how linguistic attributes of corporate filings can affect how CRAs interpret public disclosures, this study highlights how narrative disclosure information is also important for sophisticated users with access to private information.

Chapter 3 investigates how the narrative component of fair value footnote disclosures, which can span several pages of a firm's Form 10-K report, affects investor uncertainty about opaque fair values. To help users better understand fair value measurement, accounting standard-setting bodies like the Financial Accounting Standards Board (FASB) and the International Accounting Standards Board (IASB) have mandated additional disclosures in the notes to the financial statements. However, users have raised concerns about the clarity and relevance of these disclosures (FASB 2018 BC38-41). Although earlier research has extensively studied quantitative fair value disclosures, Chapter 3 focuses on the narrative components of the fair value footnote.

This focus uniquely positions this study in the broader discourse on financial reporting. The study's findings suggest that longer fair value narratives decrease uncertainty for more complex and opaque fair values. Moreover, this benefit appears to be driven by sophisticated investors. Further test results show that generic or "boilerplate" narratives can increase investor uncertainty, and emphasize the importance of narrative disclosure quality in financial reporting.

The rest of the thesis is organized as follows: Chapter 2 examines if risk-related narrative disclosures in Form 10-K reports explain why CRAs assign credit ratings below what firm fundamentals justify. Chapter 3 studies if narrative disclosures in Form 10-K report footnotes that discuss fair value measurement affect investor uncertainty regarding the reliability of opaque fair value estimates. Chapter 4 concludes and discusses suggestions for future research.

Chapter 2: Tightening rating standards: The effect of narrative risk-related disclosures

2.1 Chapter 2 summary

This study examines whether soft information, in the form of narrative disclosures, explains rating stringency, a phenomenon where CRAs assign ratings that are stricter than what firm fundamentals justify. Given that CRAs are integral in ensuring the stability of financial markets, it is important to understand how they process and incorporate information into their credit ratings. The study's findings suggest that risk-related narrative disclosures in Form 10-K reports moderate rating stringency. Further tests reveal that this effect is stronger when Form 10-K reports have textual attributes that affect how financial statement users contextualize firm risk. Overall, this study adds new evidence to the discourse around rating stringency, and its findings suggest that academics and practitioners should factor in soft information when assessing corporate credit ratings.

2.2 Introduction

CRAs, such as Standard & Poor's (S&P), Moody's Investors Service (Moody's), and Fitch, harvest and analyze debt issuer information to produce credit ratings, which are forward-looking opinions about the overall creditworthiness of firms seeking debt financing (S&P 2013). CRAs claim that their rating methodologies follow a stable framework that allows for a consistent assessment of creditworthiness across firms and time (Cantor and Falkenstein 2001). Nevertheless, empirical findings show that, over time, CRAs assign credit ratings that are worse than what firm fundamentals justify (Blume et al. 1998; Alp 2013; Baghai et al. 2014). Prior literature refers to this phenomenon as the "tightening of rating standards" or "rating stringency."

This study examines whether the evolution of narrative disclosure information contributes to explaining the documented increase in rating stringency. The causes of rating stringency are largely unexplored by prior literature, with only a few studies explicitly investigating them. On the one hand, Jorion, Shi, and Zhang (2009) offer an accounting-based explanation, and argue that changes in firms' accounting quality over time may explain the phenomenon. On the other hand, Bonsall, Green, and Muller (2018) provide an incentive-based explanation, and suggest that the reputational concerns of CRAs exacerbate rating stringency. These studies suggest that quantitative factors, such as financial statement numbers and ratios, do not capture all aspects of CRAs' rating methodologies. Moreover, CRAs acknowledge that, besides quantitative data, they rely on soft (i.e., non-quantitative) information to determine credit ratings (S&P Ratings Criteria 2013).

Prior literature argues that although CRAs are sophisticated users of financial information that can also source private information from debt issuers, they use narrative disclosure information from Form 10-K reports as credit rating inputs (Bozanic et al. 2023). Nevertheless, narrative disclosures constitute soft information, and thus have high processing costs (e.g., Liberti and Petersen 2019). Moreover, prior research shows that credit analysts often disregard costly-to-process information sources, such as financial statement footnotes (Basu and Naughton 2020). Furthermore, even if rating analysts use narrative disclosure information as rating inputs (Bozanic et al. 2023), there is no guarantee that the weight they place on this information will substantially affect rating stringency.

The study relies on risk-related narrative disclosures in Form 10-K reports as a proxy for soft information because these disclosures have been increasing in length over time, and exhibit a negative tone (e.g., Bonsall and Miller 2017; Campbell, Chen, Dhaliwal, Lu, and Steele 2014).[1] Also, given the asymmetric payoff function of creditors relative to equity investors, CRAs should be more sensitive to downside risk information (Bozanic et al. 2023). Furthermore, CRAs acknowledge that they consider risk-related qualitative information (e.g., business and legal risks) when determining credit ratings (S&P Ratings Criteria 2013). To quantify risk-related narratives, we use the risk dictionary of Campbell et al. (2014). Using a sample of non-financial firms that file disclosures with the SEC, from 2001 to 2015, we find evidence that narrative risk-related disclosures in Form 10-K reports moderate rating stringency. Moreover, when we account for the type of issuer, we find that this effect is more pronounced for investment-grade firms.[2]

Narrative disclosures are unstructured and more ambiguous than quantitative disclosures (Loughran and McDonald 2014; Liberty and Petersen 2019). Moreover, prior literature suggests that textual attributes of corporate filings can affect CRAs opinions about debt issuer default risk

[1] These are characteristics that soft information needs to possess to explain rating stringency (Baghai et al. 2014)
[2] Investment-grade credit ratings signify that a firm's debt carries relatively low default risk for its interest payments and principal repayment. On the other hand, non-investment-grade (i.e., speculative-grade) credit ratings indicate a higher default risk for a firm's debt. Consequently, to compensate investors for the increased risk, debt issued by speculative-grade firms typically offers higher yields.

(Bonsall and Miller 2017). Therefore, the effect we document should be more pronounced for Form 10-K reports that use language that can facilitate the reader's understanding of firm risk. Thus, in further tests, we partition the sample based on two textual properties that possess this characteristic: specificity and readability. In line with expectations, the moderating effect of risk-related narratives on rating stringency is stronger when the language of Form 10-K reports is more specific or readable.

This study contributes to several research streams. By showing that narrative disclosure information moderates rating stringency, it adds to the rating stringency literature, and supplements recent research on how CRAs contextualize public disclosure information (Kraft 2015; Bozanic et al. 2023). Moreover, by showing that the effect of risk-related narrative disclosures on rating analysts' risk perceptions is more pronounced when Form 10-K report language is more specific and readable, it contributes to the literature that examines risk information in public filings using textual analysis (e.g., Loughran and McDonald 2011; Campbell et al. 2014; Campbell, Cecchini, Cianci, Ehinger, and Werner 2019).

The rest of the study is organized as follows. Section 2.3 provides the institutional background and hypothesis development. Section 2.4 outlines the sample selection process. Section 2.5 describes the variable measurement process and the research design. Section 2.6 presents the empirical results. Section 2.7 concludes.

2.3 Institutional background and hypothesis development

Credit ratings serve as indicators of firm credit quality, and aid in securities pricing and debt contracting. (e.g., Holthausen and Leftwich 1986; Hand, Holthausen, and Leftwich 1992;

Kliger and Sarig 2000; Boot, Milbourn, and Schmeits 2006; Kisgen and Strahan 2010). Moreover, credit ratings are integral in capital markets and financial regulations, often determining whether and how much institutional investors can invest in a firm's securities (Kisgen 2007). Thus, CRAs act as gatekeepers of capital markets, and ensure their effective functioning (Roychowdhury and Srinivasan 2019).

In the U.S. market, corporate credit ratings, which are issuer-specific and not instrument-specific (e.g., bond ratings), appear to deteriorate over time. Specifically, prior literature documents a tightening of rating standards from 1978 to 1995 for investment-grade firms (Blume et al. 1998; Jorion et al. 2009). Alp (2013) corroborates these findings and documents that speculative-grade and investment-grade firms experienced a structural break toward more stringent rating standards after 2002. Moreover, Baghai et al. (2014) show that firms affected by rating stringency have lower growth, issue less debt, and hold more cash.

CRAs argue that their rating methodologies remain stable over time (Cantor and Falkenstein 2001). However, they have strong incentives to be conservative with the ratings they assign to debt issuers. Specifically, according to the SEC, CRAs have incentives to avoid untimely or inflated ratings to safeguard their reputation, which is one of their key assets (SEC 2003). Consistent with this argument, Dimitrov, Palia, and Tang (2015) suggest that to protect their reputation CRAs may issue ratings below the levels dictated by the debt issuer's fundamentals. Moreover, Beaver, Shakespeare, and Soliman (2006) suggest that CRAs tend to be conservative because they cater to the downside risk aversion of debt market participants.

However, an enduring criticism of CRAs is that they have strong incentives to inflate credit ratings to attract more business (e.g., Bolton, Freixas, and Shapiro 2012; Sangiorgi and Spatt

2017). Specifically, the main revenue stream of CRAs comes from the issuers of the debt products that they rate. Therefore, even in the presence of reputational concerns, CRAs have incentives to inflate credit rating (e.g., Mathis, McAndrews, and Rochet 2009; Jiang, Stanford, and Xie 2012; Xia 2014). Moreover, the issuer-pays model allows for "rating shopping," where debt issuers solicit credit ratings from multiple CRAs and then choose the most favourable ones. Thus, to maintain their revenues and market share, CRAs can respond to the competitive pressure that rating shopping introduces by loosening their rating standards (Griffin, Nickerson, and Tang 2013).

Most studies that explore the impact of accounting information on credit ratings focus on quantitative financial statement data. However, to determine credit rating, CRAs also collect soft information about debt issuers through various channels (S&P Ratings Criteria 2013; Liberti and Petersen 2019; Bozanic et al. 2023). Among the studies examining the tightening of rating standards, only Baghai et al. (2014) discuss, albeit briefly, soft information as a potential reason behind the phenomenon when they argue that for soft factors to be a determinant of rating stringency, they need to have a negative tone.

According to prior research, narrative information can facilitate the contextualization of the content of corporate filings by firm stakeholders (Li 2010a), can affect the precision of private information (Bozanic and Thevenot 2015), and can incrementally predict future firm performance (Li 2008; Li 2010b). Furthermore, Mayew, Sethuraman, and Venkatachalam (2015) show that narrative disclosures in the Management, Discussion, and Analysis (MD&A) section of a firm's Form 10-K report provide valuable incremental information beyond financial statement numbers, that enable predictions about a firm's likelihood of continuing as a going concern. Moreover, Bozanic et al. (2023) argue that rating analysts use the narrative disclosure content from Form 10-K reports to complement their private information.

Prior literature suggests that CRAs view certain disclosures as more relevant for their analyses. Specifically, Bonsall and Miller (2017) offer indicative evidence that risk-related disclosures are relevant for rating agencies. Moreover, prior research finds that risk-related narratives are consistently negative in tone (Campbell et al. 2014), and help credit investors to assess firm credit risk (Chiu, Guan, and Kim 2018). Furthermore, because of judicial concerns and regulatory pressures, firms have progressively increased the amount of risk-related information they include in their annual reports over time (e.g., Campbell et al. 2014; Cazier, McMullin, and Treu 2021).[3] Thus, we posit that risk-related narrative disclosures in Form 10-K reports have characteristics that can moderate the reported phenomenon of tightening rating standards over time.

H1: Ceteris paribus, accounting for risk-related narrative disclosure intensity reduces rating stringency over time.

Although risk-related narrative disclosures in corporate filings have increased over time, prior research suggests that they have also become, on average, less informative (Dyer, Lang, and Stice-Lawrence 2017; Beatty, Cheng, and Zhang 2019). Moreover, narrative risk-related disclosures are a noisier risk signal compared to quantitative disclosures that communicate risk levels to financial statement users (Kravet and Muslu 2013). Theoretical work on risk disclosures argues that more precise risk signals receive greater weight from information users (Heinle and Smith 2017). Consistent with this argument, Hope, Hu, and Lu (2016) empirically show that equity investors pay more attention to risk-related public disclosures when these are more specific. In

[3] The Private Securities Litigation Reform Act (PSLRA) of 1995 offers a statutory safe harbor for forward-looking statements accompanied by cautionary risk descriptions. Moreover, from 2005 onwards, the SEC mandated firms to discuss significant risks in Item 1A of their Form 10-K reports.

addition, they show that more specific risk-related disclosures help financial analysts to assess the fundamental risk of disclosing firms. Thus, for the second hypothesis, we posit that the moderating effect of narrative risk-related disclosures on rating stringency is stronger when Form 10-K report narrative disclosures are more specific.

H2a: Ceteris paribus, the effect of risk-related narrative disclosures on rating stringency over time increases with the specificity of Form 10-K narrative disclosures.

Prior literature shows that less readable financial disclosure inhibits the interpretation of filing content by analysts (Lehavy, Li, and Merkley 2011). Furthermore, You and Zhang (2009) find that investors underreact to the information in Form 10-K reports when reporting complexity is high. In the case of CRAs, anecdotal evidence suggests that disclosure quality can affect rating decisions (Ganguin and Bilardello 2004). Consistent with this argument, Bonsall and Miller (2017) show that more complex narrative disclosures lead to rating disagreements between the two largest agencies, S&P and Moody's. As a result, we argue that readable narrative disclosures facilitate users' interpretation of risk-related information. Thus, as an extension to the second hypothesis, we posit that the moderating role of risk-related narrative disclosures in explaining rating stringency is stronger when Form 10-K report narratives are more readable (i.e., less complex).

H2b: Ceteris paribus, the effect of risk-related narrative disclosures on rating stringency over time increases with the readability of Form 10-K narrative disclosures.

2.4 Sample selection

The sample consists of 11,379 firm-year observations, and includes firms with S&P long-term issuer credit ratings between 2001 and 2015. Prior research shows a structural shift toward more stringent ratings following the introduction of the Sarbanes-Oxley Act in 2002 (Alp 2013). Thus, we use 2001 as the baseline year for the analyses.[4] Because of data limitations, the sample ends in 2015.

The technical appendix discusses how we source Form 10-K report data in detail. Financial statement and credit rating data are sourced from Compustat, and stock information from CRSP. Consistent with prior studies, we exclude financial firms from analyses as they are heavily regulated and follow a distinct business model (e.g., Alp 2013; Baghai et al. 2014). Given the focus of the study, we keep only firms that file Form 10-K reports with the SEC in the sample. Furthermore, we drop firm-year observations with a negative book value of assets or missing control variable data.

2.5 Variable measurement and research design

2.5.1 Variable measurement

To measure risk-related disclosures, we use the risk dictionary of Campbell et al. (2014), which classifies risk into five subcategories: idiosyncratic risk, systematic risk, financial risk, legal and regulatory risk, and tax risk. Moreover, we use the latest dictionary version, which Campbell et al. (2019) use. To construct the dictionary, the authors draw from risk-related phrase lists from prior literature, and also use Latent Dirichlet Allocation (LDA) to identify additional risk-related phrases that appear in Item 1A, a part of the Form 10-K report where firms qualitatively discuss risk. By incorporating these additional phrases, they enhance their dictionary's coverage. Appendix 2.B provides a comprehensive list of these dictionary entries.

[4] The primary test results are similar when we use 2002 as the baseline year.

Dictionary methods are not considered the most sophisticated textual analysis techniques available. Specifically, textual analysis dictionaries can never be exhaustive and do not evolve with changing language trends. Moreover, they can miss idioms or jargon terms. Another limitation is that, unless specified otherwise, all dictionary entries carry the same weight. Nevertheless, the dictionary of Campbell et al. (2014) has a suitable fit with the hypotheses tested for several reasons: i) Because of its domain and granularity, it is particularly well-suited for the quantification of risk-related narrative disclosure content of Form 10-K reports, ii) Since a dictionary approach requires no subjective interpretation of text, it allows for the construction of easy-to-calculate and replicable measures.

Most dictionaries label their entries as "keywords." However, the longest Campbell et al. (2014) dictionary entry is four words long. Therefore, for each risk subcategory, we quantify risk-related narratives at the quadgram level (i.e., four-word sequence) as the natural logarithm of the count of risk-related quadgrams in a firm's Form 10-K report. Specifically, we break down the narrative component of the Form 10-K report, and for each quadgram, we use Python regular expressions to programmatically search if it contains a risk-related phrase.

Because the five risk subcategories are highly correlated, we use principal component analysis to identify a latent risk factor (*RISKD_10K*).[5] While *RISKD_10K* may potentially overlook the context in which risk-related words appear in a Form 10-K report, it should, at a minimum, capture the intensity of risk-related discussions and exhibit a positive correlation with the level of firm riskiness.[6]

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[5] The technical appendix provides more information on the calculation of *RISKD_10K*. Appendix 2.C plots the evolution of *RISKD_10K* over the sample period.

[6] Using the logarithm of the aggregate mention count of the five risk-related categories does not alter the conclusions of the main analyses.

To control for firm complexity and operational flexibility, we use the logarithm of the book value of assets (*SIZE*), rental payments divided by total assets (*RENT*), net property, plant, and equipment divided by total assets (*PPE*), and capital expenditures divided by total assets (*CAPEX*). Moreover, we use EBITDA divided by sales (*PROFIT*), and the volatility of profitability over the previous five years (*VOL*) to control for firm performance. In addition, we account for the ability of the firm to service its debt obligations through the following controls; interest coverage ratio, which we calculate as operating income before depreciation and amortization divided by net interest paid (*INTCOV*), cash and marketable securities divided by total assets (*CASH*), total debt liabilities divided by total assets (*TLEV*), convertible debt divided by total assets (*CONVD*), total debt divided by EBITDA (*DEBT/EBITDA*), an indicator variable equal to one if the debt to EBITDA ratio is negative and zero otherwise (*NDEBT/EBITDA*), firm systematic risk (*BETA*), and firm idiosyncratic risk (*RMSE*). Consistent with Blume et al. (1998) and Baghai et al. (2014), we standardize *BETA* and *RMSE* each year by dividing them by their annual sample averages.

We also account for the richness of a firm's external information environment, and events that might be associated with risk-related disclosures. Specifically, we control for the number of analysts that follow the firm over the fiscal year (*FOLLOW*), the disclosure of a SOX 404 internal control weakness by the firm in the last three years (*ICW*), the occurrence of an accounting restatement by the firm in the last three year (*RESTATE*), and the filing of a federal class action lawsuit against the firm in the last three years (*LAWSUIT*). Moreover, because prior research shows that business press coverage affects rating stringency (Bonsall et al. 2018), we also introduce a control variable that accounts for its effects (*LCOVER).*

In subsequent tests relating to Hypothesis 2 (*H2a*), we measure narrative disclosure specificity (*SPECIFICITY_10K*) following Hope et al. (2016). The framework of Hope et al.

(2016), is based on the notion that references with unambiguous meanings provide more firm-specific information to the reader. For example, references such as "England" are more specific relative to "neighbouring country." To this end, they use the Stanford Named Entity Recognizer (NER), which achieves close to human accuracy levels in identifying named entities, on Item 1A "Risk Factor" narrative disclosures.[7]

For example, in the below passage, the Stanford NER algorithm identifies bold terms in brackets as named entities:

For similar reasons, during the years ended ***[December] [31]****,* ***[2016]*** *and* ***[2015]****, we transferred* ***[$] [34] [million]*** *and* ***[$] [181] [million]****, respectively, of securities issued by the* ***[U.S.]*** *government and government-sponsored entities from Level 1 to Level 2.*

Using the Stanford NER algorithm to quantify narrative disclosure specificity is straightforward. Nevertheless, as with many textual analysis techniques, it is subject to certain limitations. Deploying the algorithm on large texts requires time and computational resources. Moreover, as the algorithm is case-sensitive, the researcher should carefully evaluate the casing of text that they provide as an input. Specifically, the algorithm will often classify uppercased words as a named entity, and label them as a *Person* or an *Organization*. The algorithm might also misclassify a term. For example, "Washington capital" could be classified as a *Location* and not an *Organization*. Ideally, the researcher should first test the algorithm's output so that they can identify misclassification patterns that can affect their hypotheses testing, and correct them.

[7] The Stanford NER algorithm classifies narrative disclosures into seven categories: Time, Location, Organization, Person, Money, Percentage, and Date.

Finally, if the researcher chooses to scale the measure by the non-stopword count, they should ensure that the list of stopwords they use is appropriate for their setting.

When using the Hope et al. (2016) framework to calculate narrative disclosure specificity, we also length-adjust the resulting measure. Specifically, we follow Brown and Tucker (2011), and regress specificity on the first five polynomials of narrative disclosure length, which we measure as the number of words that comprise the narrative disclosure of interest (i.e., Form 10-K report). Subsequently, we de-length the raw specificity measure by subtracting the fitted measure from it. This adjustment allows for a better identification of specificity as a linguistic attribute, which should not be affected by narrative disclosure length, a factor that can vary considerably across firms.

Finally, for the purposes of Hypothesis 2 (*H2b*), we measure Form 10-K report readability (*GFOG_10K*) using the Gunning Fog index formula, which generates a readability score based on factors such as word complexity, and sentence length. Narrative disclosure readability measures can help researchers examine the quality and impact of financial disclosures. The Gunning Fog index represents a proxy of the number of years of formal education a reader needs to comprehend a text on their first try. Thus, a higher Gunning Fog Index score indicates less readable Form 10-K report narrative disclosures.

$$G.Fog\ index\ = 0.4 * \left[\left(\frac{number\ of\ words}{number\ of\ sentences}\right) + 100 * \left(\frac{number\ of\ complex\ words}{number\ of\ words}\right)\right]$$

Methods like the Gunning Fog index have the benefit of being replicable and easy to use, but also have limitations. For example, complex language can both inform and confuse the reader (Bushee, Gow, and Taylor 2018). More advanced methods can measure readability through machine-learning models and human-annotated readability text. However, these methods might not generalize across texts or reader types (Bochkay et al. 2023). Moreover, these methods are rarely used in accounting research settings, and are resource-consuming.

2.5.2 Research design

To examine the effect of narrative disclosure information on rating stringency, we estimate an ordered logistic regression where we model S&P long-term credit ratings (*RATING3M*) as a function of firm characteristics, and industry and year indicator variables (Baghai et al. 2014).[8] To ensure that CRAs have the latest available data when they determine credit ratings, we match credit ratings at the fiscal year-end date with financial statement data lagged by three months. Because CRAs typically assign default ratings ex-post, we drop observations from the sample where *RATING3M* denotes default (i.e., SD or D). In addition, we transform ratings from alphanumerical levels to numerical rating codes (C- to AAA transforms from 1 to 21, respectively). Thus, higher values of *RATING3M* represent higher firm creditworthiness.[9]

To examine the effect of risk-related narrative disclosures on rating stringency, we estimate the following equation:[10]

$$RATING3M_{i,t} = \beta 1\, RISKD\_10K_{i,t} + \beta 2\, Controls_{i,t} + \beta 3\, Industry_j + \beta 4\, Year_t + e_{i,t} \quad (1)$$

Consistent with prior research, we focus on coefficient estimate sign of $Year_t$ to evaluate rating stringency and exclude the year indicator (i.e., year intercept) corresponding to the first year

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[8] Our findings are similar when we use an ordered probabilistic regression or an Ordinary Least Squares (OLS) model.
[9] S&P classifies long-term issuer ratings into alphanumerical categories: The highest rating is AAA, whereas the lowest rating is C. Overall, a lower rating signifies lower firm creditworthiness.
[10] Appendix 2.A summarizes all model variable in more detail.

in the sample (e.g., Blume et al. 1998; Alp 2013; Baghai et al. 2014). Specifically, a series of consistently negative coefficient estimates for the year indicators represents a tightening of the rating standards relative to the baseline year (i.e., 2001). In our results, we do not report model constants (i.e., cut points) for ease of presentation.

2.6 Results

2.6.1 Descriptive statistics

Table 2.1 presents the sample distribution of issuer credit ratings over time. For ease of presentation, we tabulate ratings into nine categories by pooling all the "+" and "–" ratings with the middle alphanumerical rating. For example, the AA rating category contains firms rated AA+, AA, and AA−. Overall, the annual number of firms in each rating category does not fluctuate substantially over the sample period. Moreover, the proportion of speculative-grade firms (i.e., credit ratings below BBB-) in the sample remains relatively stable over time, and ranges from 52.40 to 56.73 percent.

[Table 2.1]

Table 2.2 presents sample descriptive statistics. The mean value of *RATING3M* is 11.08, which corresponds to a BB+ credit rating, and its standard deviation is 3.28. These values supplement the data shown in Table 2.1, and suggest a moderate level of consistency in the ratings of these entities in the sample. On a more granular level, we find that, on average, credit ratings range from 10.72 to 11.27 over the sample years (untabulated). Predictably, the lower end of the range corresponds to the 2008 financial crisis. Our risk-related proxy, *RISKD_10K*, which we construct through principal component analysis, exhibits a mean close to zero but shows variation, evidenced by a standard deviation of 1.89.

[Table 2.2]

Figure 2.1 shows that firms have been discussing risk more frequently in their Form 10-K reports over time. Conversely, non-risk-related disclosures have remained stable in length. Moreover, apart from financial risk narratives, which do not increase much relative to 2001, the other four risk-related disclosure categories of the Campbell et al. (2014) dictionary substantially increase in length over time.[11] In unreported results, we also confirm that risk-related mentions are overwhelmingly negative in tone. Specifically, the net tone of the sentences surrounding a risk-related mention is negative in 99 percent of observations. These results suggest that risk-related narratives have characteristics that can explain rating stringency.

[Figure 2.1]

Table 2.3 presents Pearson correlations for the main test variables. *RATING3M* correlates positively with *SIZE.* This finding suggests that larger firms generally have higher ratings. Consistent with the notion that greater risk-related discussion intensity signifies higher firm risk, *RISKD_10K* correlates negatively with *RATING3M.* Moreover, it correlates positively with *SIZE* and *PPE*, implying that larger firms often disclose more risks in their Form 10-K reports, likely due to their more complex operational environment. Furthermore, *RISKD_10K* correlates positively with *PROFIT*, suggesting that profitable firms are more comfortable discussing risk. Finally, in line with expectations, *RISKD_10K* exhibits a positive correlation with risk-related variables such *TLEV*, *VOL*, *BETA*, and *RMSE*.

[11] Risk-related disclosures can also result in disclosing firms experiencing adverse capital market outcomes, which can incentivize managers to reduce risk-related discussions (Campbell et al. 2014).

[Table 2.3]

2.6.2 The effect of risk-related narratives on rating stringency

Table 2.4 presents the first set of multivariate test results. In column [1], we present results from a model that does not account for the impact of risk-related narratives. The year indicator coefficients show an increasingly negative trend, suggesting a tightening of rating standards over time. Moreover, explanatory variables exhibit coefficient signs that are consistent with prior literature. Collectively, these findings are consistent with prior literature that reports evidence of increasing rating stringency over time (Blume et al. 1998; Alp 2013; Baghai et al. 2014). In column [2], we introduce *RISKD_10K* in the model as a base test of Hypothesis *H1*. The coefficient estimate of *RISKD_10K* is negative and statistically significant at the 1 percent level. This finding suggests a negative relationship between the intensity of risk-related discussions within Form 10-K reports and credit ratings. The direction of this correlation aligns with our main predictions and is intuitively understandable. For example, in the absence of issuer-supplied information, CRAs may consider a higher risk-discussion intensity as indicative of higher firm risk. Moreover, even when CRAs possess confidential issuer-supplied information from their management interactions, higher risk-discussion intensity could hold confirmatory value, a rating-relevant feature of public disclosures (Bozanic et al. 2023).

[Table 2.4]

Figure 2.2 plots the year indicator coefficients for columns [1] and [2] of Table 2.4, and shows that risk-related narrative disclosures moderate rating stringency by approximately 20 percent each fiscal year. Specifically, the year indicator coefficients in Model 2 (Table 2.4 column [2]), which accounts for narrative risk-related disclosures, are consistently lower than the respective year indicator coefficients of the baseline, Model 1 (Table 2.4 column [1]). Moreover, the plot lines in Figure 2.2 show a decrease in rating stringency after 2008.

[Figure 2.2]

2.6.3 The effect of risk-related narratives on rating stringency by risk category

The dictionary of Campbell et al. (2014) disaggregates risk into five subcategories. Consequently, we use this feature to examine how each risk subcategory affects rating stringency. Table 2.5 show that all risk subcategories exhibit a negative association with *RATING3M*. Moreover, in Figure 2.3 we show evidence of all risk subcategories reducing previously reported rating stringency. However, narrative disclosures about systematic risk reduce reported rating stringency more than those about idiosyncratic, legal, tax, and financial risks. The results are intuitively reasonable as systematic risks capture uncertainties about broader market conditions. Thus, narrative disclosures about systematic risk could supplement and enhance the private firm-specific information that CRAs have from interacting with management. Moreover, they could facilitate rating analysts in comparing the risk profiles of different firms.

[Table 2.5]

[Figure 2.3]

2.6.4 The effect of risk-related narratives on rating stringency by debt issuer type

Table 2.6 reports results for the investment-grade and speculative-grade firm subsamples, respectively. The literature on rating stringency suggests that CRAs can apply different rating standards across different types of issuers (e.g., Alp 2013; Baghai et al. 2014; Bonsall et al. 2018).

Moreover, research suggests that investment-grade and speculative-grade firms differ across several dimensions. Specifically, investment-grade firms are usually larger and bear a lower risk of default. However, defaults of investment-grade debt issuers can lead to legal and regulatory actions against CRAs (Dimitrov et al. 2015).

Table 2.6 columns [1] and [2] focus on investment-grade issuers, and provide evidence of rating stringency for such firms. Specifically, they show that rating stringency notably increases until 2008, and slows down afterwards. Regarding the effect of risk-related narratives on credit ratings, in column [2] of Table 2.6, the coefficient estimate of *RISKD_10K* is negative and statistically significant at the 1 percent level. Moreover, Figure 2.4, which plots the year indicator coefficients from Table 2.6 columns [1] and [2], suggests that accounting for risk-related narrative disclosures moderates rating stringency for investment-grade firms.

In columns [3] and [4] of Table 2.6, we present results for speculative-grade firms that suggest that they experience a decrease in rating stringency after 2008. Moreover, in Table 2.6 (column [4]), *RISKD_10K* displays a negative coefficient estimate that is statistically significant at the 1 percent level. Figure 2.5 plots the year indicator coefficients reported in Table 2.6 columns [3] and [4], and shows that risk-related narrative disclosures reduce reported stringency also for speculative-grade firms. However, this effect is weaker than what we document in columns [1] and [2] of Table 2.6 for investment-grade firms.

[Table 2.6]

[Figure 2.4]

[Figure 2.5]

2.6.5 The effect of risk-related narratives on rating stringency and Form 10-K report narrative disclosure properties

Prior research argues that users of financial information discount imprecise information in their analyses (Heinle and Smith 2017). Therefore, to further validate our inferences, we examine if the moderating effect of risk-related information on rating stringency is more pronounced when narrative information is more precise. To this end and, to test Hypothesis *H2a*, we use the specificity of the Form 10-K report narratives as a proxy for narrative disclosure precision, and partition the sample on whether *SPECIFICITY_10K* is above or below the sample median.

Table 2.7 presents results for the specificity subsample partitions. Columns [1] and [3] serve as the baseline specification, and do not account for narrative risk-related information. Columns [2] and [4] introduce narrative risk-related information in the analyses. *RISKD_10K* displays a negative and statistically significant coefficient estimate at the 1 percent level in both the high (Table 2.7 column [2]), and low (Table 2.7 column [4]) specificity subsamples. Figures 2.6 and 2.7 plot the year indicator coefficients reported in Table 2.7 for the high-specificity and low-specificity subsamples, respectively. A comparison between Figures 6 and 7 suggests that when we account for the intensity of risk-related narrative disclosures, rating stringency is reduced more for firms with more specific Form 10-K report narratives.[12]

[Table 2.7]

[Figure 2.6]

[Figure 2.7]

[12] We document similar findings when we use numerosity (i.e., quantitative narrative disclosure) as an alternative proxy for the precision of the Form 10-K report narratives (e.g., Campbell, Zheng, and Zhou 2021).

Finally, to test Hypothesis *H2b*, we examine if the moderating effect of risk-related disclosures is more pronounced for firms with less complex (i.e., more readable) Form 10-K report narratives. To this end, we use the Gunning Fog readability index (*GFOG_10K*) to partition the sample on whether the readability of a firm's Form 10-K report is above or below the sample median, and conduct the main tests again. Table 2.8 presents test results, which are consistent with our predictions. Specifically, in both readability subsamples, the association coefficient between *RISKD_10K* and *RATING3M* is negative and statistically significant. Moreover, Figure 2.8, which plots the year coefficients of the specifications we tabulate in Table 2.8 columns [1] and [2], shows a pronounced moderating effect on rating stringency in the high-readability subsample. In comparison, Figure 2.9, which plots the year coefficients of Table 2.8 columns [3] and [4], shows weaker evidence of a reduction in rating stringency in the low-readability subsample.

[Table 2.8]

[Figure 2.8]

[Figure 2.9]

2.6.6 The effect of uncertainty-related narratives on rating stringency

The Campbell et al. (2014) risk dictionary has several features that make it a good fit for our analyses. Nevertheless, despite its advantages, it is a predefined dictionary focusing on specific risks. Thus, to ameliorate construct validity concerns, and to validate our primary tests' conclusions, we conduct the main analyses again using an uncertainty-related narrative disclosure proxy based on the uncertainty dictionary of Loughran and McDonald (2011). The presence of uncertain words in public filings can proxy for risk information (Loughran and McDonald 2011). Moreover, Bonsall and Miller (2017) offer indicative evidence that uncertainty-related narrative disclosures affect the risk perceptions of CRAs. Furthermore, our primary proxy of risk-related disclosures assumes that risk disclosures should reduce uncertainty over factors that affect the creditworthiness of issuers. Therefore, incorporating a proxy of narrative uncertainty in our analyses is a suitable supplement to our primary tests.

Table 2.9 reports results when we use *UNCERTAINTY_10K* as an alternative proxy for risk-related narratives. To calculate *UNCERTAINTY_10K*, we follow Loughran and McDonald (2011), and divide the number of uncertainty-related words by the total number of words in the Form 10-K report. To ensure higher comparability across firms, we length-adjust the measure according to the methodology of Brown and Tucker (2011).[13] Column [1] focuses on the entire sample, whereas columns [2] and [3] focus on subsamples of investment-grade and speculative-grade debt issuers, respectively. The coefficient estimate of *UNCERTAINTY_10K* is negative and statistically significant at the 1 percent level across all specifications. Moreover, the magnitude of the coefficient of *UNCERTAINTY_10K* is higher for investment-grade firms. These findings suggest a negative relationship between uncertainty and firm creditworthiness. Moreover, these results are consistent with what we document in Table 2.4.

[Table 2.9]

Figure 2.10 plots the year indicator coefficients for Table 2.4 column [1] and Table 2.9 column [1], and visualizes evidence that uncertainty-related narratives moderate rating stringency in the sample. Figure 2.11 plots year indicator coefficients presented in Table 2.6 column [1] and those in Table 2.9 column [2], and shows a moderating effect for investment-grade firms. Finally, Figure 2.12, which plots the year indicator coefficients presented in Table 2.6 column [3] and Table

[13] We find similar findings when we measure *UNCERTAINTY_10K* similarly to *RISKD_10K*.

2.9 column [3] also provides evidence of uncertainty-related narratives reducing rating stringency for speculative-grade debt issuers. However, the moderating effect is less pronounced for speculative-grade firms than for investment-grade issuers. Overall, these findings are consistent with our primary results, and provide further evidence that soft information in the form of risk-related narrative disclosures reduces rating stringency.

[Figure 2.10]

[Figure 2.11]

[Figure 2.12]

2.6.7 Additional tests

Prior research suggests that changes in accounting quality over time explain the tightening of rating standards. Specifically, Jorion et al. (2009) document no rating stringency when they account for earnings management. Thus, we re-run the analyses after controlling for earnings management activities to account for this possibility. We measure discretionary accruals using the modified version of the Jones (1991) model, and also consider real activities management (Roychowdhury 2006). In both cases, results (untabulated) support the main findings.

2.7 Conclusion

We examine if risk-related narrative information affects the magnitude of the tightening of rating standards over time. To this end, we quantify risk-related narrative disclosure information in Form 10-K reports and show that it moderates the phenomenon, albeit not entirely. Further tests show this effect to be stronger when Form 10-K reports possess textual attributes that affect how users of financial statements contextualize firm risk. Specifically, we find the moderating effect of risk-related information to be more pronounced when the language of the Form 10-K report is more specific or readable. This study adds to the literature on the measurement of rating stringency and supplements recent research on how CRAs incorporate narrative disclosures from public filings in their ratings (Kraft 2015; Bozanic et al. 2023). Future research can further examine the incentives of CRAs to invest in information production from narrative disclosures, and how CRAs weigh soft information when determining credit ratings.

Appendix 2.A: Variable Definitions

Panel A: Quantitative Variables	
SIZE	The natural logarithm of total assets. [Source: Compustat].
INTCOV	Interest coverage ratio calculated as operating income before depreciation and amortization divided by net interest paid. [Source: Compustat].
PROFIT	Measure of firm profitability, defined as EBITDA divided by sales. [Source: Compustat].
VOL	Volatility of current and past four-year profitability (*PROFIT*). The variable is set to missing if fewer than two observations are available in any five-year rolling window. [Source: Compustat].
CASH	Cash divided by total assets. [Source: Compustat].
TLEV	Total liabilities divided by total assets. [Source: Compustat].
CONVD	Convertible debt divided by total assets. [Source: Compustat].
DEBT/EBITDA	Total liabilities divided by operating income before depreciation. [Source: Compustat].
NDEBT/EBITDA	Indicator variable equal to one if *DEBT/EBITDA* is negative, and zero otherwise. [Source: Compustat].
RENT	Rent expenses divided by total assets. [Source: Compustat].
PPE	Gross property, plant and equipment divided by total assets. [Source: Compustat].
CAPEX	Capital expenditures divided by total assets. [Source: Compustat].
BETA	Estimated as the firm's CAPM beta using market model regressions of firm daily stock returns on the CRSP value-weighted index return, over one calendar year for firms with at least 50 trading days. The regressions are adjusted for nonsynchronous trading effects using the Dimson (1979) procedure with one leading and one lagging value of the market return. As in Blume et al. (1998), *BETA* is scaled yearly by its sample average. [Source: CRSP].
RMSE	Estimated as the root mean squared error from market model regressions of firm daily stock returns on the CRSP value-weighted index return, over one calendar year for firms with at least 50 trading days. The regressions are adjusted for nonsynchronous trading effects using the Dimson (1979) procedure with one leading and one lagging value of the market return. As in Blume et al. (1998), *RMSE* is scaled yearly by its sample average. [Source: CRSP].

ICW	Indicator variable equal to 1 if the firm identified a SOX 404 weakness over the last three years, and 0 otherwise. [Source: Audit Analytics].
RESTATE	Indicator variable equal to 1 if the firm identified an accounting restatement over the last three years, and 0 otherwise. [Source: Audit Analytics].
FOLLOW	The natural logarithm of 1 plus the average number of analysts that follow the firm over the fiscal year date. [Source: IBES].
LCOVER	The natural logarithm of 1 plus the number of articles written about a firm during the six months ending one year before the fiscal year date. [Source: Ravenpack].
LAWSUIT	Indicator variable equal to 1 if the firm was the plaintiff in a federal class action lawsuit over the last three years, and 0 otherwise. [Source: Stanford Law School's Securities Class Action Clearinghouse].
Panel B: Narrative Disclosure Variables	
LFINANCIAL_10K	The natural logarithm of financial risk-related mentions, as defined by Campbell et al. (2014), in a Form 10-K report. [Source: Form 10-K reports].
LIDIOSYNCRATIC_10K	The natural logarithm of idiosyncratic risk mentions, as defined by Campbell et al. (2014), in a Form 10-K report. [Source: Form 10-K reports].
LSYSTEMATIC_10K	The natural logarithm of systematic risk mentions, as defined by Campbell et al. (2014), in a Form 10-K report. [Source: Form 10-K reports].
LLEGAL_10K	The natural logarithm of legal and regulatory risk mentions, as defined by Campbell et al. (2014), in a Form 10-K report. [Source: Form 10-K reports].
LTAX_10K	The natural logarithm of tax risk mentions, as defined by Campbell et al. (2014), in a Form 10-K report. [Source: Form 10-K reports].
RISKD_10K	This measure represents the intensity of risk-related discussions in Form 10-K reports. It is derived using principal component analysis on the correlated risk subcategories outlined by Campbell et al. (2014) (i.e., financial, idiosyncratic, systematic, legal, and tax). [Source: Form 10-K reports].
SPECIFICITY_10K	This measure quantifies the specificity of narrative disclosures within Form 10-K reports. It follows the construction method of Hope et al. (2016) and is adjusted for length as per Brown and Tucker (2011). [Source: Form 10-K reports].

GFOG_10K	This measure quantifies the readability of narrative disclosures within Form 10-K reports. It is calculated using the Gunning Fog index formula. [Source: Form 10-K reports].

Appendix 2.B: Risk-related Phrases by Risk Category

Risk Category	Phrase	Risk Category	Phrase
Financial	Anti-takeover (provision/provisions)	Financial	Penny stock
Financial	Bank Debt	Financial	Postretirement
Financial	Capital (expenditure/expenditures)	Financial	Rating
Financial	Chapter 11	Financial	Refinance
Financial	Chapter 7	Financial	Refinancing
Financial	Chapter 9	Financial	Reinsurance
Financial	Collateral	Financial	Renegotiation
Financial	Concentrated ownership	Financial	Reorganization
Financial	(Covenant/covenants)	Financial	Reserves
Financial	Credit(facility/facilities)	Financial	Revolver
Financial	Credit Rating	Financial	Sale of productive assets
Financial	Credit Risk	Financial	Stock market listing
Financial	Debt burden	Financial	Stock market drop
Financial	Decline in stock price	Financial	Stock price volatility
Financial	Default	Financial	Underfunded pensions
Financial	Defined benefit	Financial	Underwriting
Financial	Dilution	Financial	Volatility of operating results
Financial	Dividends	Financial	Volatility of revenues
Financial	Downgrade	Financial	Volatility of sales
Financial	Family	Financial	Working capital
Financial	Financial condition	Idiosyncratic	Acquisition
Financial	Financing costs	Idiosyncratic	Adequate staffing
Financial	Funded status	Idiosyncratic	Advertising
Financial	Liquid market	Idiosyncratic	Asset (impairment/impairments)
Financial	Improvements	Idiosyncratic	Asset securitization

Financial	Indebtedness	Idiosyncratic	Asset securitization
Financial	Insider sales	Idiosyncratic	Assimilation
Financial	Investment in equipment	Idiosyncratic	Backlog
Financial	Investment in plant	Idiosyncratic	Brand
Financial	(Lease/leases/leasing)	Idiosyncratic	Brand recognition
Financial	Lease (commitment/commitments)	Idiosyncratic	California power crisis
Financial	Leverage	Idiosyncratic	Certification
Financial	Leveraged (lease/leases)	Idiosyncratic	Clinical (trial/trials)
Financial	Limited Trading	Idiosyncratic	Commercialize
Financial	Liquidity	Idiosyncratic	Concentration
Financial	Loan	Idiosyncratic	Consolidation
Financial	Locked-in (lease/leases)	Idiosyncratic	Construction
Financial	Mandatory contribution	Idiosyncratic	(Contract/contracts)
Financial	Maturity	Idiosyncratic	(Copyright/copyrights)
Financial	Negative operating cash flow	Idiosyncratic	Corporate culture
Financial	New financing	Idiosyncratic	Cost control
Financial	Obligations	Idiosyncratic	Customer concentration
Financial	OPEB	Idiosyncratic	Customer service
Financial	O.P.E.B.	Idiosyncratic	Delivery
Financial	Operating losses	Idiosyncratic	Distribution
Idiosyncratic	(Distributor/distributors)	Idiosyncratic	Mortgage backed securities
Idiosyncratic	Downsizing	Idiosyncratic	Mortgage servicing rights
Idiosyncratic	Economies of scale	Idiosyncratic	MSR
Idiosyncratic	Embargo	Idiosyncratic	M.S.R.
Idiosyncratic	Enron	Idiosyncratic	Natural disasters
Idiosyncratic	Expand	Idiosyncratic	New Construction
Idiosyncratic	Expanding	Idiosyncratic	New product acceptance
Idiosyncratic	Expansion	Idiosyncratic	New product development
Idiosyncratic	(Export/exports)	Idiosyncratic	No current operations

Idiosyncratic	Facilities	Idiosyncratic	Online
Idiosyncratic	Franchise	Idiosyncratic	Orders
Idiosyncratic	Franchisee	Idiosyncratic	Patent
Idiosyncratic	Goodwill	Idiosyncratic	Personnel
Idiosyncratic	Goodwill (impairment/impairments)	Idiosyncratic	Preclinical
Idiosyncratic	Impairment	Idiosyncratic	Product
Idiosyncratic	Information technology	Idiosyncratic	Product development
Idiosyncratic	Innovation	Idiosyncratic	Product mix
Idiosyncratic	Insurance coverage	Idiosyncratic	Product performance Production
Idiosyncratic	Intangible	Idiosyncratic	Proprietary
Idiosyncratic	(Integrate/integrating/integration)	Idiosyncratic	Publicly
Idiosyncratic	Intellectual	Idiosyncratic	Redundancy
Idiosyncratic	Internal (control/controls)	Idiosyncratic	Reliance on key customer
Idiosyncratic	Invest	Idiosyncratic	Reliance on key customers
Idiosyncratic	Invest in (subsidiary/subsidiaries)	Idiosyncratic	Reliance on key supplier
Idiosyncratic	It	Idiosyncratic	Reliance on key suppliers
Idiosyncratic	I.T.	Idiosyncratic	Reporting controls
Idiosyncratic	Joint (venture/ventures)	Idiosyncratic	Research and development
Idiosyncratic	Keep and retain top management	Idiosyncratic	Restructuring
Idiosyncratic	Key personnel	Idiosyncratic	Restructuring implementation
Idiosyncratic	Labor (cost/costs)	Idiosyncratic	Sarbanes-Oxley
Idiosyncratic	Labor relations	Idiosyncratic	SARS
Idiosyncratic	Labor (union/unions)	Idiosyncratic	(Secret/secrets)
Idiosyncratic	(License/licenses)	Idiosyncratic	Security
Idiosyncratic	Limited operating history	Idiosyncratic	Shortages
Idiosyncratic	Maintenance	Idiosyncratic	Single customer
Idiosyncratic	Management retention	Idiosyncratic	Single supplier
Idiosyncratic	Market acceptance Marketing	Idiosyncratic	Software

Idiosyncratic	Material (weakness/weaknesses)	Idiosyncratic	Sole (supplier/suppliers)
Idiosyncratic	MBS	Idiosyncratic	SPE
Idiosyncratic	M.B.S.	Idiosyncratic	S.P.E.
Idiosyncratic	Merger	Idiosyncratic	Special purpose entity
Idiosyncratic	Strike	Legal/Regulatory	Fraud
Idiosyncratic	(Supplier/suppliers)	Legal/Regulatory	Government investigation
Idiosyncratic	Supply chain	Legal/Regulatory	Government policy
Idiosyncratic	(Synergy/synergies)	Legal/Regulatory	Governmental approval
Idiosyncratic	Systems	Legal/Regulatory	Hazardous
Idiosyncratic	(Tariff/tariffs)	Legal/Regulatory	IFRS
Idiosyncratic	Technological obsolescence	Legal/Regulatory	I.F.R.S
Idiosyncratic	Technologies	Legal/Regulatory	Infringe
Idiosyncratic	Technology	Legal/Regulatory	Injury
Idiosyncratic	Trade	Legal/Regulatory	Inquiries
Idiosyncratic	(Trademark/trademarks)	Legal/Regulatory	Inquiry
Idiosyncratic	Training	Legal/Regulatory	Intellectual property
Idiosyncratic	Union election	Legal/Regulatory	(Investigation/investigations)
Idiosyncratic	Variable interest entity	Legal/Regulatory	Legislation
Idiosyncratic	(Vendor/vendors)	Legal/Regulatory	Litigation
Idiosyncratic	VIE	Legal/Regulatory	Pay damages
Idiosyncratic	V.I.E.	Legal/Regulatory	(Penalty/penalties)
Idiosyncratic	Weather	Legal/Regulatory	Pending (lawsuit/lawsuits)
Idiosyncratic	Web security	Legal/Regulatory	Plaintiff
Idiosyncratic	(Website/websites)	Legal/Regulatory	Possibility of restatement
Legal/Regulatory	Adverse judgment	Legal/Regulatory	Possibility of restatements
Legal/Regulatory	Anti-trust	Legal/Regulatory	Potential (lawsuit/lawsuits)
Legal/Regulatory	Causality	Legal/Regulatory	Product liability
Legal/Regulatory	Charged	Legal/Regulatory	(Regulation/regulations)
Legal/Regulatory	Class action	Legal/Regulatory	Regulatory

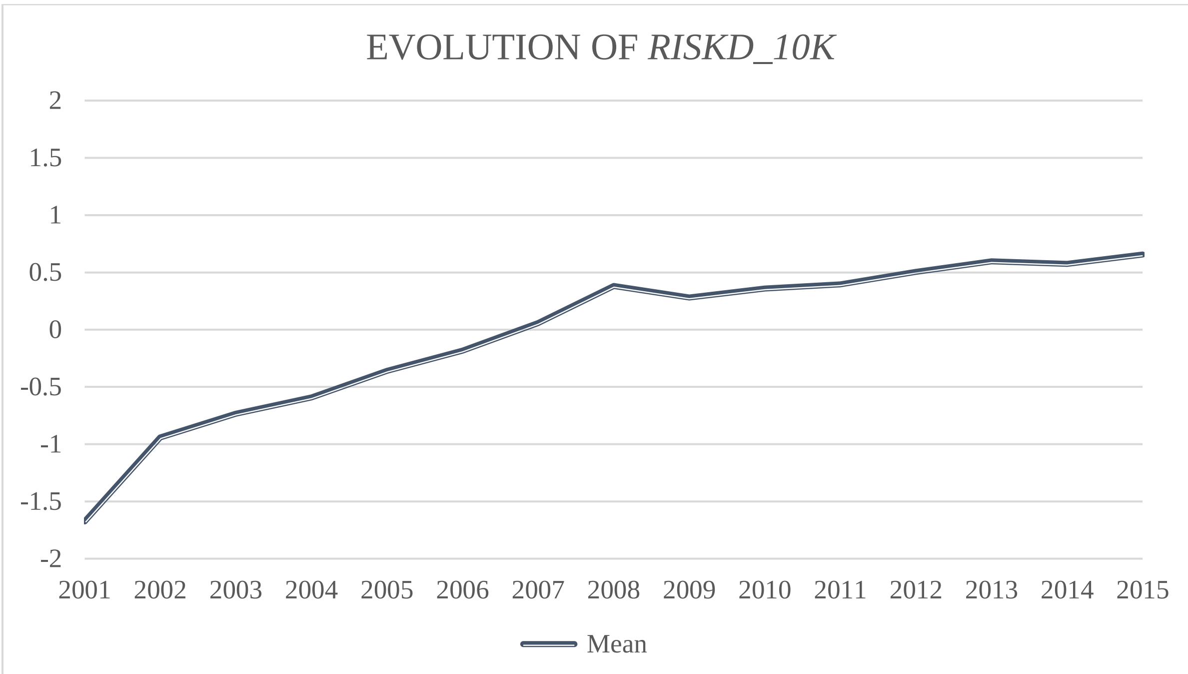
Legal/Regulatory	Compliance
Legal/Regulatory	Comply
Legal/Regulatory	(Conflict/conflicts) of interest
Legal/Regulatory	Contamination
Legal/Regulatory	Defendant
Legal/Regulatory	Deregulation
Legal/Regulatory	Effects of implementing new standard
Legal/Regulatory	Effects of implementing new standards
Legal/Regulatory	Effects of implementing new method
Legal/Regulatory	Effects of implementing new methods
Legal/Regulatory	Enforceability of judgments
Legal/Regulatory	Enforcement
Legal/Regulatory	Environmental
Legal/Regulatory	FDA approval
Legal/Regulatory	Federal
Legal/Regulatory	Fines
Systematic	Capacity
Systematic	Coal
Systematic	(Commodity/commodities)
Systematic	Competition
Systematic	(Competitor/competitors)
Systematic	Complement
Systematic	Concentration
Systematic	Consumer confidence
Systematic	Consumer spending
Systematic	Consumption
Systematic	Currency collapse
Systematic	Currency (Fluctuation/fluctuations)
Systematic	Cyclical
Legal/Regulatory	Regulatory approval
Legal/Regulatory	Regulatory change
Legal/Regulatory	Regulatory compliance
Legal/Regulatory	Regulatory enforcement
Legal/Regulatory	Regulatory environment
Legal/Regulatory	Related (party/parties)
Legal/Regulatory	Remediation
Legal/Regulatory	(Restatement/restatements)
Legal/Regulatory	Safety
Legal/Regulatory	Superfund
Legal/Regulatory	Uncertainty regarding accounting estimates
Systematic	Afghanistan
Systematic	Aggregate demand
Systematic	Asian crisis
Systematic	Business conditions
Systematic	Call
Systematic	Gold
Systematic	Growth (rate/rates)
Systematic	Hedge
Systematic	Hedging
Systematic	Housing
Systematic	Housing starts
Systematic	Industry (condition/conditions)
Systematic	Industry environment
Systematic	Inflation
Systematic	Iraq
Systematic	(Market/markets)
Systematic	Market demand
Systematic	Market supply

Systematic	Demand	Systematic	Marketplace
Systematic	(Derivatives/derivatives)	Systematic	Materials
Systematic	Discounting	Systematic	(Medal/medals)
Systematic	(Economic/economics)	Systematic	Middle East
Systematic	Economic (condition/conditions)	Systematic	Mineral/minerals
Systematic	Economic (downturn/downturns)	Systematic	Mining
Systematic	Economic growth	Systematic	Monetary policy
Systematic	Economic uncertainties	Systematic	Mortgage
Systematic	Economy	Systematic	Natural gas
Systematic	Electricity	Systematic	Obsolescence
Systematic	Energy	Systematic	Oil
Systematic	EU	Systematic	Operating environment
Systematic	E.U.	Systematic	Option
Systematic	Euro	Systematic	Ore
Systematic	European Union	Systematic	Overstocked
Systematic	Exchange (rate/rates)	Systematic	Peso
Systematic	Financial crisis	Systematic	Petroleum
Systematic	Fiscal policy	Systematic	Political climate
Systematic	Foreign currency	Systematic	Political instability
Systematic	Foreign exchange	Systematic	Pound
Systematic	(Forward/forwards)	Systematic	Price pressure
Systematic	Fuel	Systematic	Prices
Systematic	Future	Systematic	Pricing Power
Systematic	Gas	Systematic	Raw (material/materials)
Systematic	Gasoline	Systematic	Real
Systematic	GDP	Systematic	Real estate investment trust
Systematic	G.D.P.	Systematic	Recession
Systematic	GNP	Systematic	REIT
Systematic	G.N.P.	Systematic	R.E.I.T.
Systematic	General business risks	Systematic	Renmenbi
Systematic	General conditions	Systematic	RMB

Systematic	General economic conditions	Systematic	Ruble
Systematic	Rupee	Tax	Permanently reinvested
Systematic	Saving	Tax	PRE
Systematic	Seasonal	Tax	Pre(tax/−tax)
Systematic	September (11/11th)	Tax	Provision for income (tax/taxes)
Systematic	Short	Tax	Rate difference
Systematic	Silver	Tax	Repatriate
Systematic	Steel	Tax	Repatriated
Systematic	(Substitute/substitutes)	Tax	Repatriation
Systematic	Swap	Tax	Settle
Systematic	Terrorism	Tax	Settled
Systematic	U.S. Dollar	Tax	Settlement
Systematic	Underlying	Tax	Settles
Systematic	Unsalable inventory	Tax	State (tax/taxes)
Systematic	War	Tax	Statutory
Systematic	Yen	Tax	Tax (authority/authorities)
Systematic	Yuan	Tax	Tax (liability/liabilities)
Tax	Aggressive tax (position/positions)	Tax	Tax (penalty/penalties)
Tax	Apportion	Tax	(tax/taxes)
Tax	Apportioned	Tax	Tax audit
Tax	Apportions	Tax	Tax basis
Tax	Assessment (audit/tax)	Tax	Tax credit
Tax	Back taxes	Tax	Tax expense
Tax	Deductible	Tax	Tax plan
Tax	Deferred tax (asset/assets)	Tax	Tax planning
Tax	Deferred tax (liability/liabilities)	Tax	Tax position
Tax	DTA	Tax	Tax provision
Tax	DTL	Tax	Tax(law/laws)
Tax	Effective tax	Tax	Tax strategy
Tax	FIN 48	Tax	Taxable

Tax	Foreign Tax	Tax	Taxable income
Tax	Haven	Tax	Transfer pricing
Tax	Havens	Tax	Trapped cash
Tax	I.R.S.	Tax	Uncertain tax (position/positions)
Tax	Income shift	Tax	Undistributed foreign earnings
Tax	Indefinitely reinvested	Tax	Unrecognized tax benefit
Tax	Internal Revenue Service	Tax	Unrepatriate
Tax	Interpretation Number 48	Tax	Unrepatriated
Tax	Interpretation No. 48	Tax	Unrepatriation
Tax	IRS	Tax	UTB
Tax	IRS audit	Tax	Valuation Allowance
Tax	IRS judgment	Tax	Loss (carryforward/carryforwards)
Tax	Jurisdiction	Tax	Nondeductible
Tax	Loss (carryback/carryback s)		

Appendix 2.C: Evolution of *RISKD_10K* over time



This figure plots the mean values by year, from 2001 to 2015, for the variable *RISKD_10K*. The underlying variable is the natural logarithm of the Form 10-K report number of risk-related mentions of the five subcategories of risk, as defined by Campbell et al. (2014). Because the five risk subcategories are highly correlated, *RISKD_10K* is the latent risk factor that we get if we use principal component analysis on them.

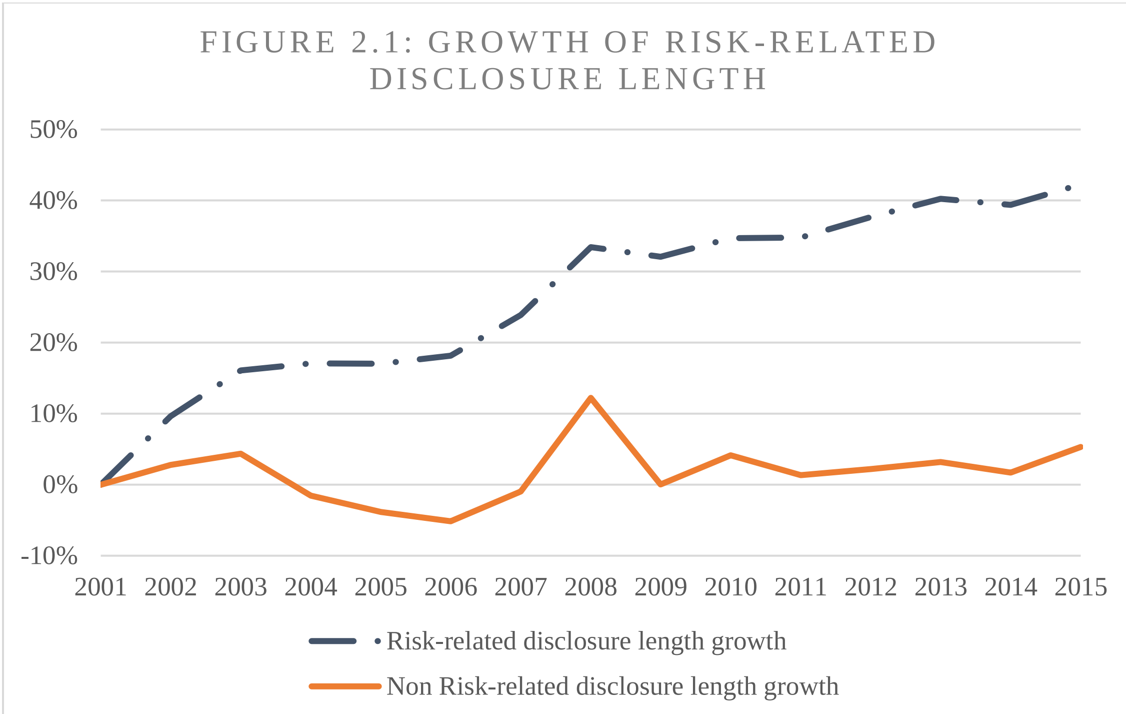


Figure 2.1: This figure compares the percentage growth of the risk-related disclosures length and the non-risk-related Form 10-K report disclosures length, from 2001 to 2015. Risk-related disclosures capture the number of quadgrams referencing at least one entry in the Campbell et al. (2014) dictionary. We calculate non-risk-related disclosures by subtracting risk-related disclosure quadgrams from total Form 10-K report disclosure quadgrams.

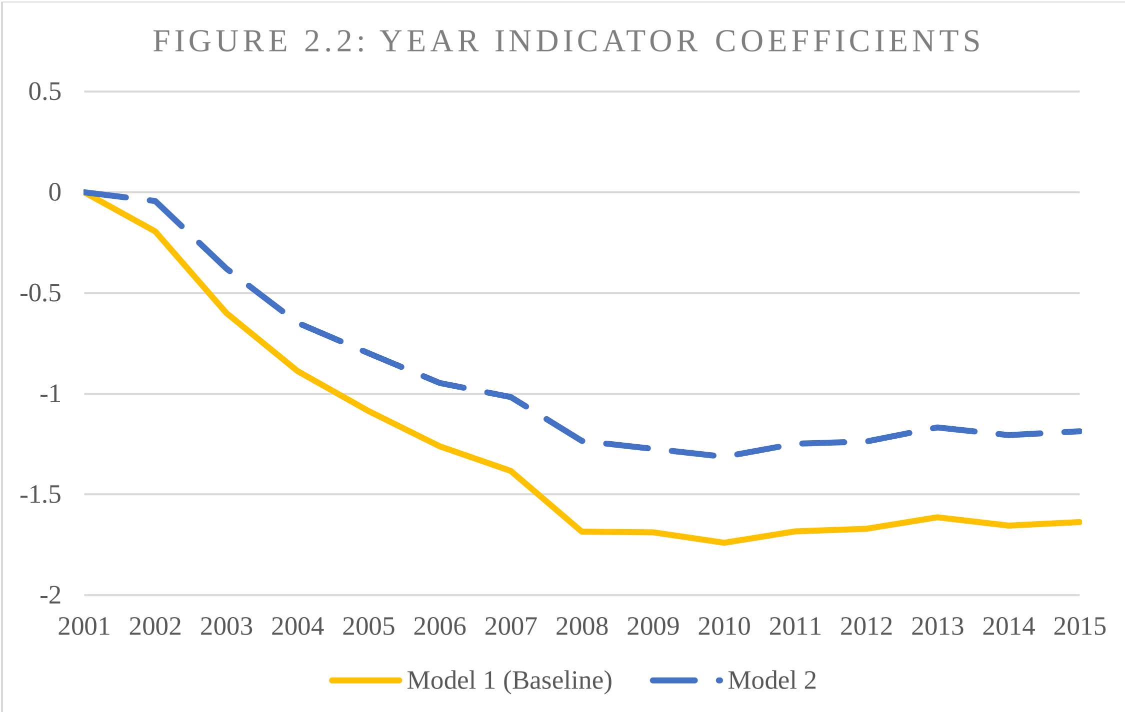


Figure 2.2: This figure plots the year indicator coefficients from Table 2.4, from 2001 to 2015. Model 1 serves as the baseline model, and corresponds to Table 2.4 column [1]. Model 2 controls for the effect of risk-related narrative disclosures, and corresponds to Table 2.4 column [2].

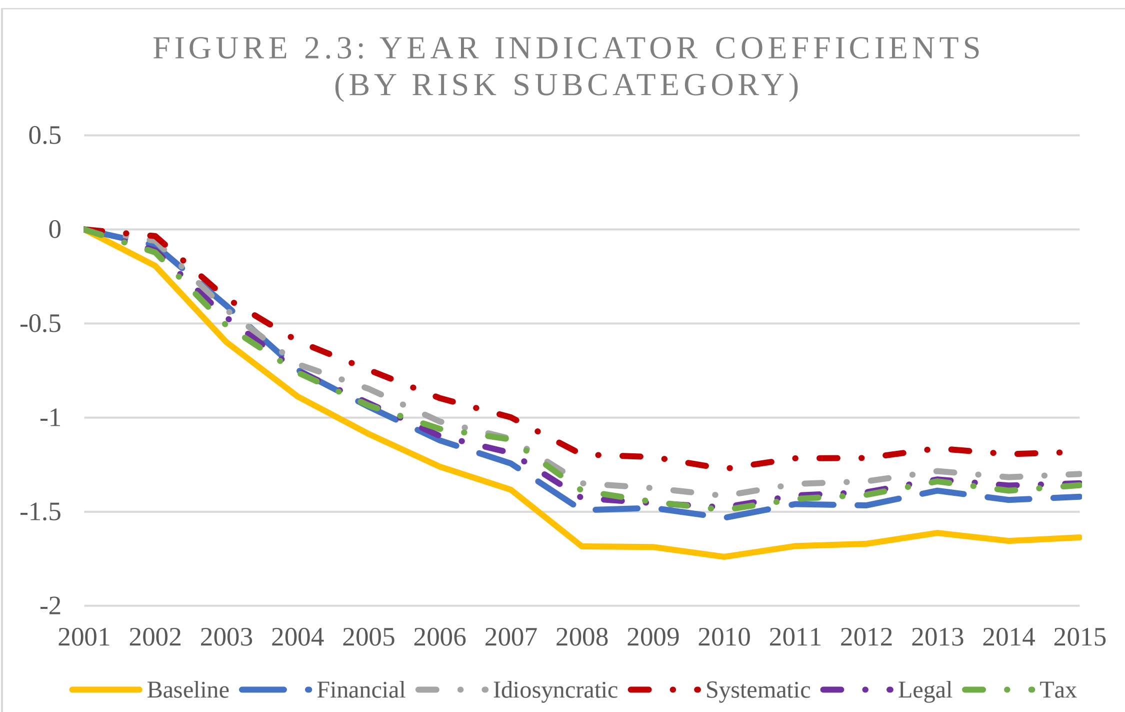


Figure 2.3: This figure plots the year indicator coefficients from Table 2.4 column [1] (Baseline), and Table 2.5 columns [1] to [5], which control for the effect of risk-related narrative disclosures by risk subcategory, from 2001 to 2015.

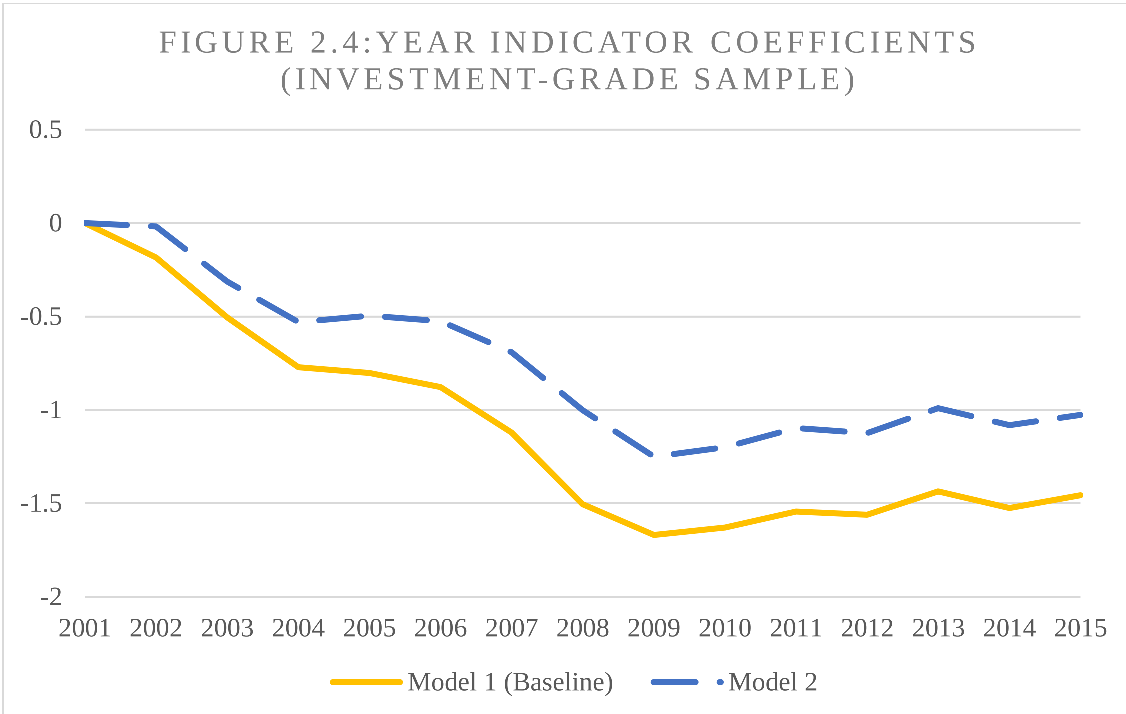


Figure 2.4: This figure concentrates on investment-grade debt issuers, and plots the year indicator coefficients from Table 2.6 columns [1] and [2], from 2001 to 2015. Model 1 serves as the baseline, and corresponds to Table 2.6 column [1]. Model 2 accounts for the effect of risk-related narrative disclosures, and corresponds to Table 2.6 column [2].

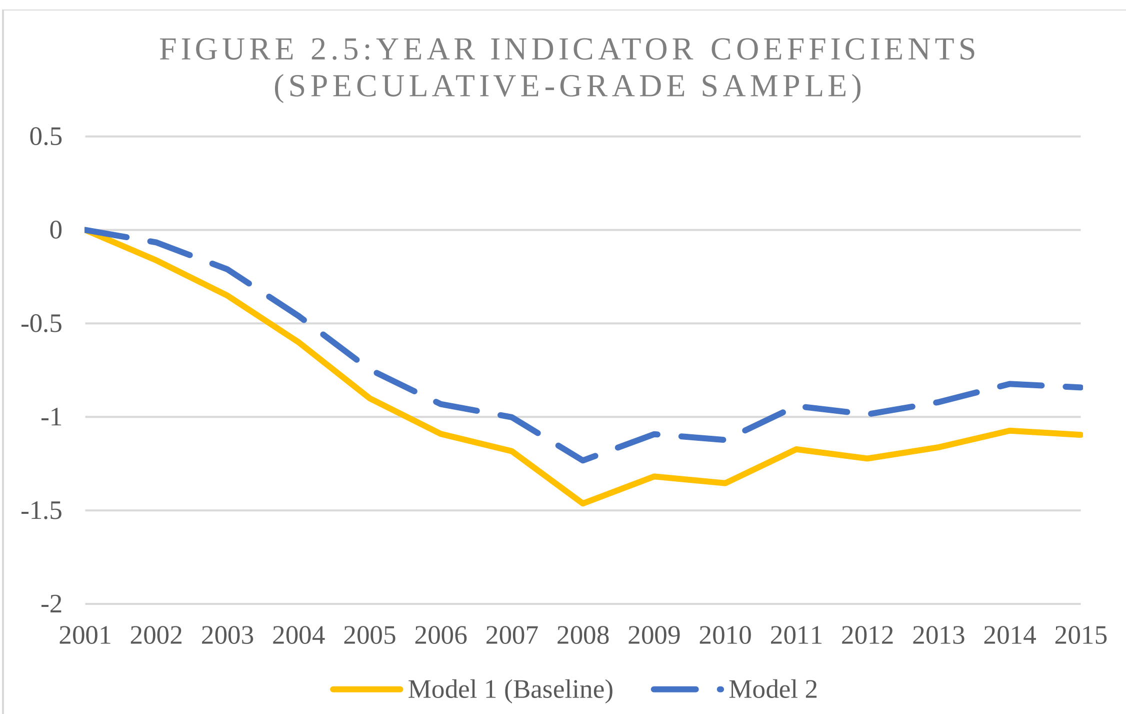


Figure 2.5: This figure concentrates on speculative-grade debt issuers, and plots the year indicator coefficients from Table 2.6 columns [3] and [4], from 2001 to 2015. Model 1 serves as the baseline, and corresponds to Table 2.6 column [3]. Model 2 accounts for the effect of risk-related narrative disclosures, and corresponds to Table 2.6 column [4].

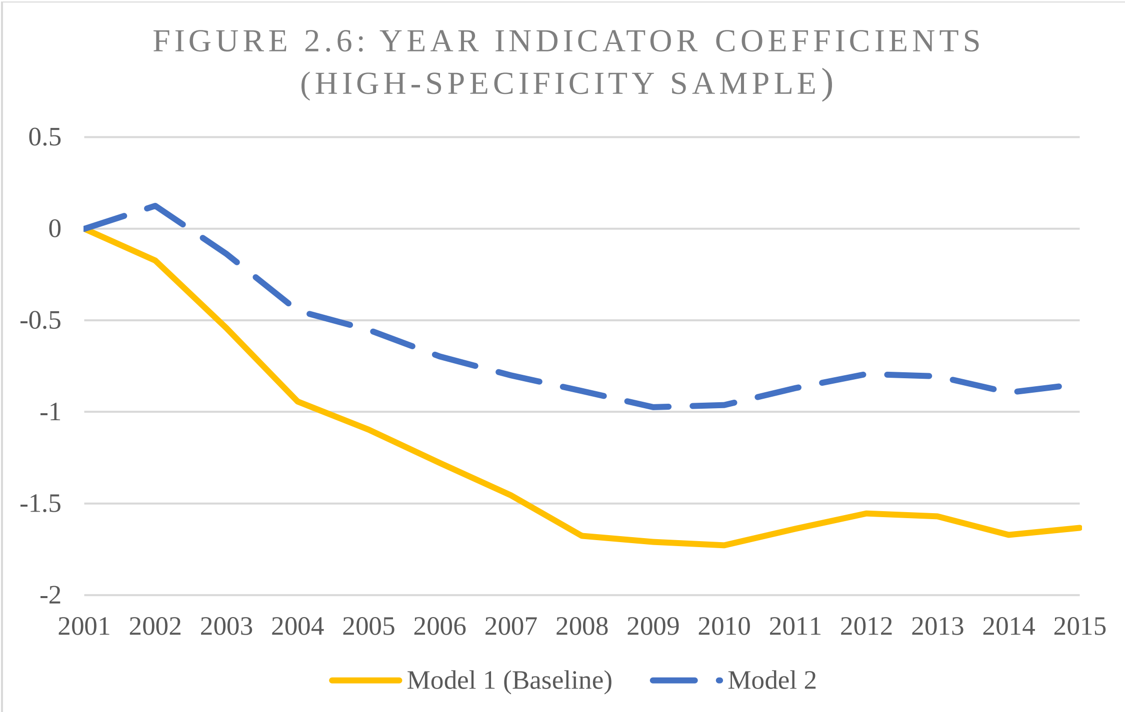


Figure 2.6: This figure concentrates on high-specificity observations, and plots the year indicator coefficients from Table 2.7 columns [1] and [2], from 2001 to 2015. Model 1 serves as the baseline, and corresponds to Table 2.7 column [1]. Model 2 accounts for the effect of risk-related narrative disclosures, and corresponds to Table 2.7 column [2].

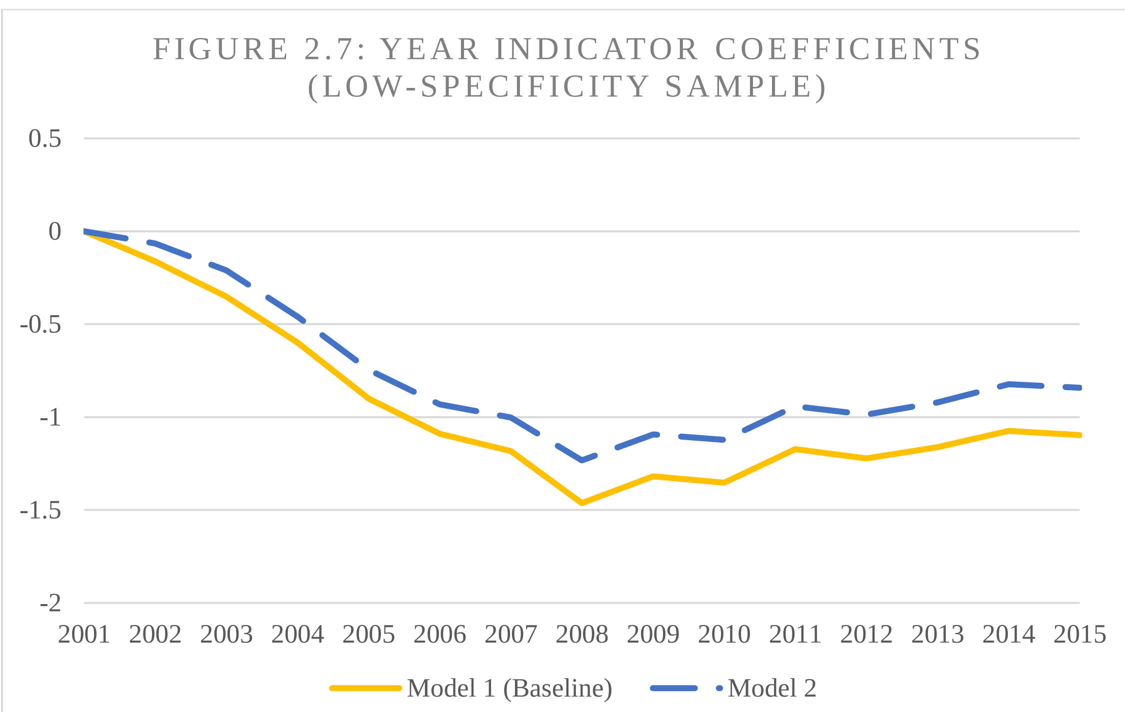


Figure 2.7: This figure concentrates on low-specificity observations, and plots the year indicator coefficients from Table 2.7 columns [3] and [4], from 2001 to 2015. Model 1 serves as the baseline, and corresponds to Table 2.7 column [3]. Model 2 accounts for the effect of risk-related narrative disclosures, and corresponds to Table 2.7 column [4].

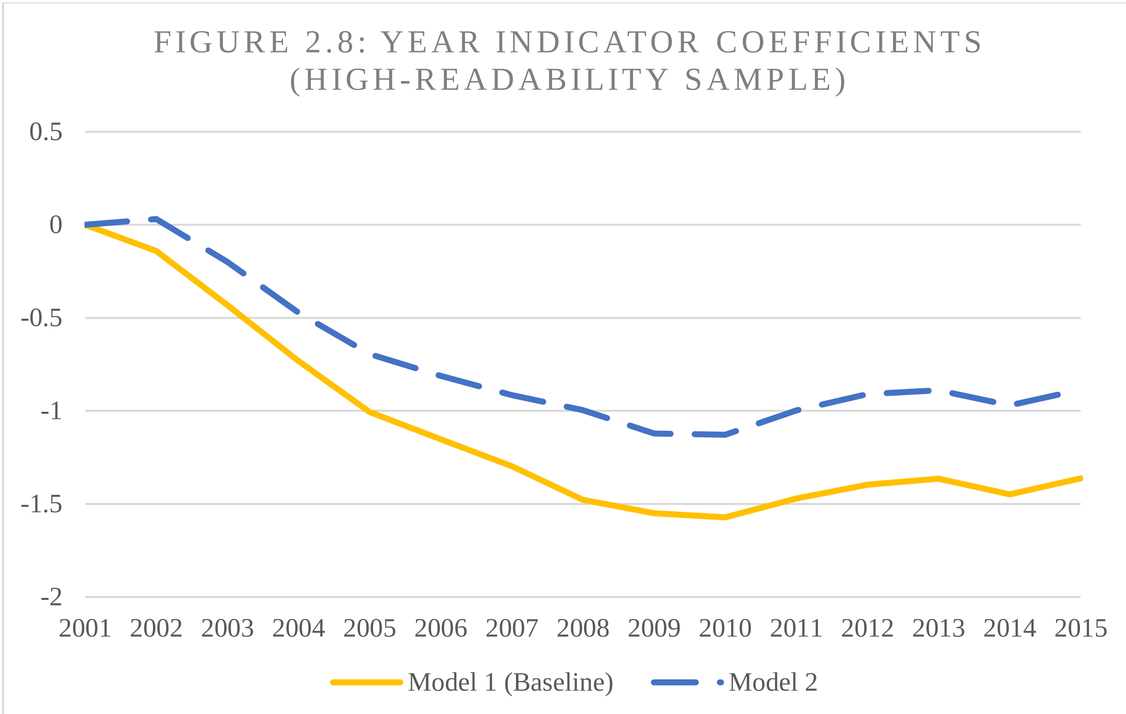


Figure 2.8: This figure concentrates on high-readability observations, and plots the year indicator coefficients from Table 2.8 columns [1] and [2], from 2001 to 2015. Model 1 serves as the baseline, and corresponds to Table 2.8 column [1]. Model 2 accounts for the effect of risk-related narrative disclosures, and corresponds to Table 2.8 column [2].

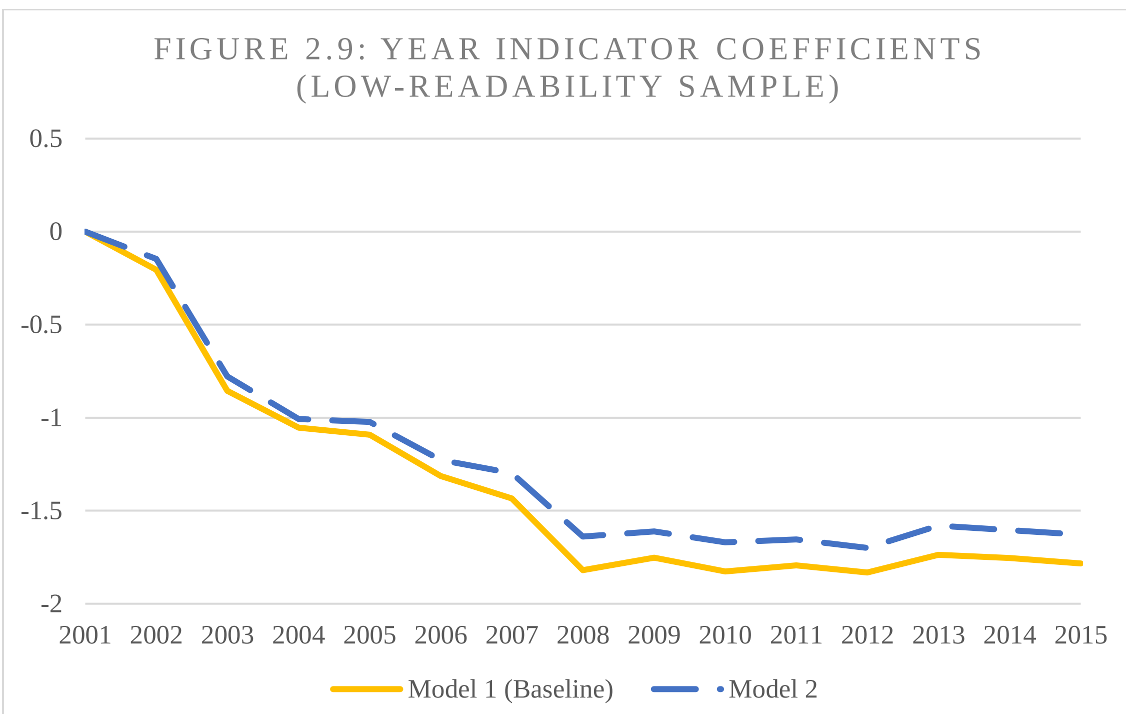


Figure 2.9: This figure concentrates on low-readability observations, and plots the year indicator coefficients from Table 2.8 columns [3] and [4], from 2001 to 2015. Model 1 serves as the baseline, and corresponds to Table 2.8 column [3]. Model 2 accounts for the effect of risk-related narrative disclosures, and corresponds to Table 2.8 column [4].

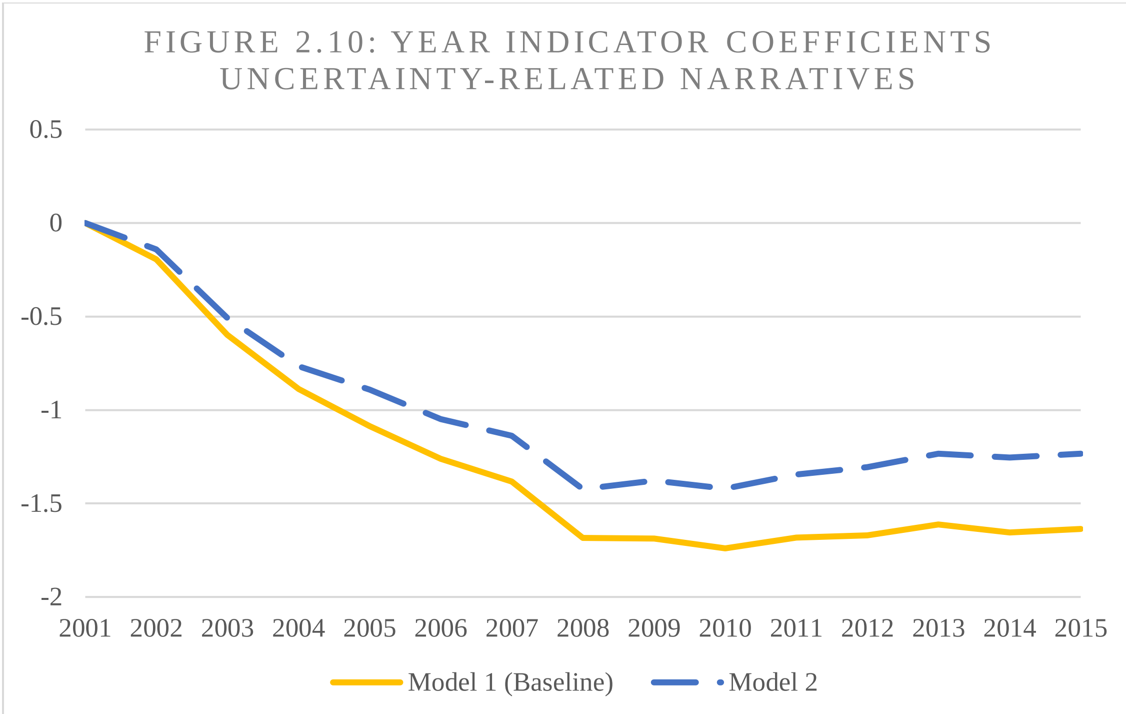


Figure 2.10: This figure plots the year indicator coefficients from Table 2.4 column [1] and Table 2.9 column [1], from 2001 to 2015. Model 1 serves as the baseline model, and corresponds to Table 2.4 column [1]. Model 2 controls for the effect of uncertainty-related narrative disclosures, and corresponds to Table 2.9 column [1].

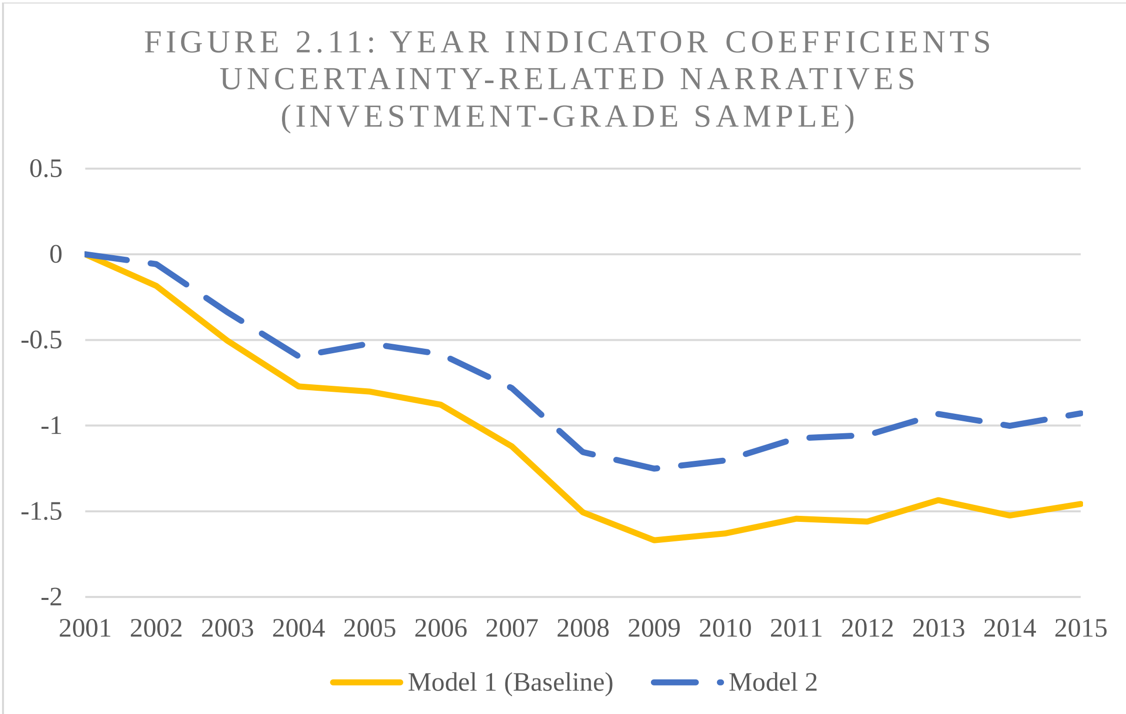


Figure 2.11: This figure concentrates on investment-grade debt issuers, and plots the year indicator coefficients from Table 2.6 column [1] and Table 2.9 column [2], from 2001 to 2015. Model 1 serves as the baseline, and corresponds to Table 2.6 column [1]. Model 2 accounts for the effect of uncertainty-related narrative disclosures, and corresponds to Table 2.9 column [2].

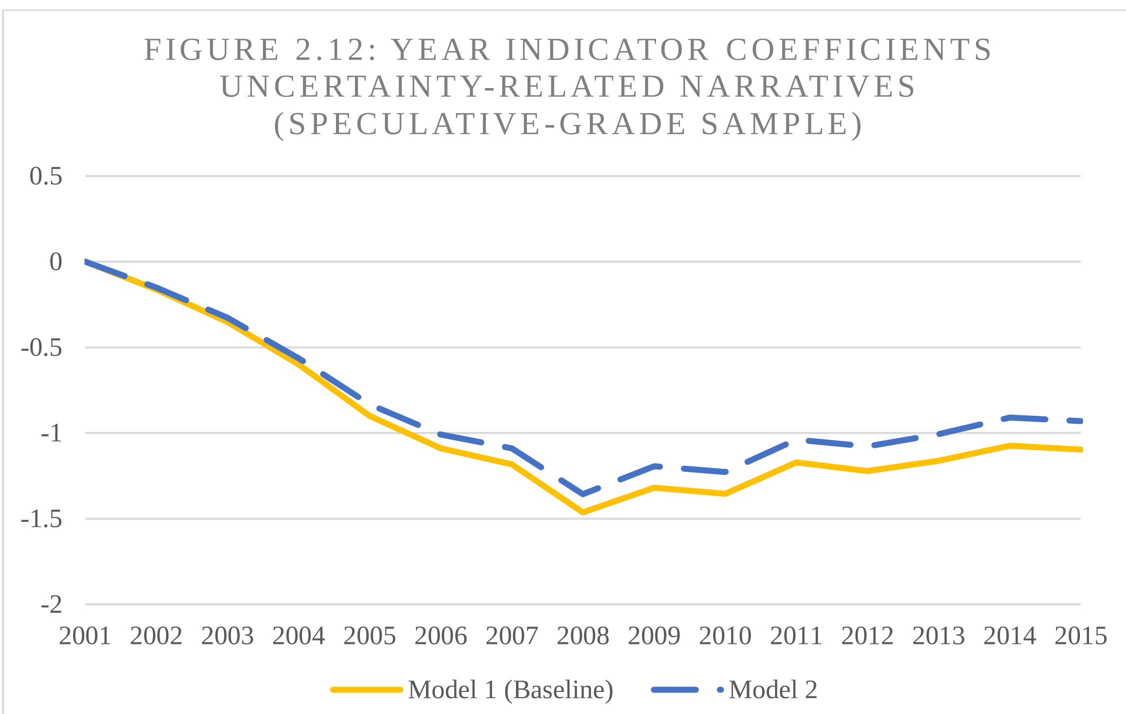


Figure 2.12: This figure concentrates on speculative-grade debt issuers, and plots the year indicator coefficients from Table 2.6 column [3] and Table 2.9 column [3], from 2001 to 2015. Model 1 serves as the baseline, and corresponds

to Table 2.6 column [3]. Model 2 accounts for the effect of uncertainty-related narrative disclosures, and corresponds to Table 2.9 column [3].

Table 2.1

Number of Observations by Year and S&P Rating Category

	Speculative-grade					Investment-grade				
Year	**C**	**CC**	**CCC**	**B**	**BB**	**BBB**	**A**	**AA**	**AAA**	**Total**
2001	0	3	11	101	138	135	74	11	4	477
2002	0	1	31	149	224	221	117	16	4	763
2003	0	1	18	166	253	224	119	16	5	802
2004	0	3	10	161	251	231	113	15	4	788
2005	0	1	18	156	237	234	114	13	4	777
2006	0	1	13	163	244	230	103	14	6	774
2007	0	0	10	172	235	225	96	14	5	757
2008	0	6	31	176	217	223	87	13	5	758
2009	0	1	20	192	201	230	82	15	4	745
2010	0	2	9	186	218	237	84	12	4	752
2011	0	1	8	181	233	246	95	9	4	777
2012	0	0	11	180	226	253	94	10	4	778
2013	0	0	9	165	240	256	103	13	4	790
2014	0	0	13	189	256	258	101	15	4	836
2015	0	4	25	163	259	247	89	15	3	805
Total	0	24	237	2,500	3,432	3,450	1,471	201	64	11,379

This table presents the sample composition by year and long-term issuer S&P credit rating. For ease of presentation, we pool all the "+" and "–" ratings with the middle rating. For example, the AA rating category contains firms with ratings equal to AA+, AA, and AA−. Ratings right (left) of the BBB rating category are considered as investment (speculative) grade.

Table 2.2

Descriptive Statistics

Variable	N	Mean	Sd	P25	P50	P75
RATING3M	11,379	11.076	3.279	9.000	11.000	13.000
RISKD_10K	11,379	0.002	1.894	-1.143	-0.019	1.098
SIZE	11,379	8.265	1.368	7.311	8.148	9.153
INTCOV	11,379	12.313	18.784	3.326	6.105	12.419
PROFIT	11,379	0.186	0.148	0.096	0.158	0.253
VOL	11,379	0.047	0.098	0.012	0.021	0.041
CASH	11,379	0.094	0.103	0.020	0.058	0.131
TLEV	11,379	0.351	0.194	0.217	0.323	0.450
CONVD	11,379	0.022	0.061	0.000	0.000	0.000
DEBT/EBITDA	11,379	3.187	3.887	1.392	2.550	4.294
NDEBT/EBITDA	11,379	0.028	0.166	0.000	0.000	0.000
RENT	11,379	0.018	0.027	0.005	0.010	0.019
PPE	11,379	0.619	0.405	0.274	0.570	0.914
CAPEX	11,379	0.056	0.057	0.021	0.039	0.068
BETA	11,379	0.997	0.532	0.629	0.922	1.271
RMSE	11,379	0.993	0.518	0.627	0.866	1.206
ICW	11,379	0.070	0.255	0.000	0.000	0.000
RESTATE	11,379	0.281	0.449	0.000	0.000	1.000
FOLLOW	11,379	2.110	0.912	1.609	2.303	2.773
LCOVER	11,379	3.874	2.062	3.664	4.564	5.130
LAWSUIT	11,379	0.347	0.476	0.000	0.000	1.000
SPECIFICITY_10K	11,379	0.060	0.014	0.051	0.060	0.070
GFOG_10K	11,379	18.799	1.674	18.081	18.921	19.739
UNCERTAINTY_10K	11,379	0.012	0.003	0.010	0.012	0.014

This table displays descriptive statistics for our sample, which includes non-financial public U.S. firms with a long-term issuer credit rating from S&P, and non-missing narrative disclosure and control variable data. All continuous variables are winsorized at the top and bottom one percentile. To mitigate the impact of outliers, *BETA* and *RMSE* are winsorized prior to their standardization. Appendix 2.A summarizes all variable definitions in more detail.

Table 2.3

Variable Correlations

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)	(21)	(22)
RATING3M	1.000																					
RISKD_10K	-0.043	1.000																				
SIZE	0.599	0.330	1.000																			
INTCOV	0.369	-0.131	0.143	1.000																		
PROFIT	0.202	0.127	0.187	0.107	1.000																	
VOL	-0.259	0.102	-0.083	-0.081	-0.052	1.000																
CASH	-0.009	-0.052	-0.040	0.281	-0.112	0.129	1.000															
TLEV	-0.489	0.080	-0.270	-0.451	0.063	0.145	-0.209	1.000														
CONVD	-0.216	-0.047	-0.161	-0.063	-0.128	0.188	0.298	0.074	1.000													
DEBT/EBITDA	-0.307	0.114	-0.077	-0.276	0.012	-0.039	-0.137	0.408	0.045	1.000												
NDEBT/EBIT.	-0.205	0.034	-0.088	-0.087	-0.395	0.486	0.144	0.093	0.174	-0.432	1.000											
RENT	-0.174	-0.181	-0.214	0.052	-0.230	-0.100	0.071	0.006	0.021	-0.038	-0.014	1.000										
PPE	-0.049	0.108	0.006	-0.114	0.229	0.196	-0.290	0.187	-0.115	0.020	0.034	0.036	1.000									
CAPEX	-0.057	0.091	0.009	0.005	0.344	0.332	-0.169	0.081	-0.037	-0.076	0.094	0.011	0.628	1.000								
BETA	-0.331	0.022	-0.118	-0.060	-0.159	0.190	0.165	0.053	0.200	0.070	0.184	0.029	-0.003	0.062	1.000							
RMSE	-0.670	0.005	-0.412	-0.178	-0.208	0.274	0.082	0.357	0.167	0.219	0.250	0.148	0.057	0.065	0.453	1.000						
ICW	-0.161	0.070	-0.087	-0.062	-0.074	0.017	0.018	0.041	0.024	0.052	0.007	0.052	-0.027	-0.019	0.059	0.121	1.000					
RESTATE	-0.173	0.046	-0.084	-0.089	-0.071	0.013	0.005	0.087	0.062	0.084	0.014	0.062	-0.040	-0.047	0.075	0.109	0.298	1.000				
FOLLOW	0.414	0.090	0.505	0.227	0.163	-0.005	0.134	-0.254	0.023	-0.174	-0.023	-0.066	-0.055	0.075	-0.036	-0.296	-0.117	-0.089	1.000			
LCOVER	0.253	0.052	0.252	0.125	0.040	-0.089	0.092	-0.142	-0.022	-0.090	-0.042	-0.008	0.002	-0.024	-0.057	-0.192	-0.032	-0.057	0.250	1.000		

LAWSUIT	-0.111	-0.121	-0.146	-0.033	-0.049	0.069	0.025	0.071	0.063	0.045	0.045	0.096	-0.068	-0.009	0.016	0.103	-0.049	-0.018	-0.062	-0.103	1.000	
YEAR	-0.016	0.304	0.200	0.029	0.082	0.005	0.035	0.024	-0.152	0.001	-0.014	-0.068	0.025	0.049	0.000	0.000	0.006	-0.013	0.131	0.129	-0.345	-0.016

This table displays Pearson correlation coefficients for the main test variables. For ease of presentation, in the first row of tabulated data, numbers in parentheses denote variables according to the order they are presented in column [1]. Thus, *(1)* corresponds to *RATING3M*, whereas *(22)* corresponds to *YEAR*. The sample includes non-financial public U.S. firms with a long-term issuer credit rating from S&P, and non-missing narrative disclosure and control variable data. All continuous variables are winsorized at the top and bottom one percentile. Appendix 2.A summarizes all variable definitions in more detail.

Table 2.4

Rating Stringency & Risk-related Narrative Disclosures

	(1) *RATING3M*	(2) *RATING3M*
RISKD_10K		-0.252***
		(-11.5)
SIZE	0.875***	1.028***
	(16.8)	(19.0)
INTCOV	0.021***	0.020***
	(6.2)	(6.1)
PROFIT	0.403	0.390
	(1.0)	(0.9)
VOL	-2.502***	-2.433***
	(-5.6)	(-5.4)
CASH	-0.119	0.105
	(-0.3)	(0.2)
TLEV	-2.198***	-2.095***
	(-7.2)	(-7.0)
CONVD	-2.979***	-3.055***
	(-4.9)	(-5.1)
DEBT/EBITDA	-0.169***	-0.164***
	(-12.0)	(-11.8)
NDEBT/EBITDA	-2.582***	-2.500***
	(-7.6)	(-7.2)
RENT	-5.866***	-5.420**
	(-2.7)	(-2.5)
PPE	0.195	0.208
	(1.3)	(1.4)
CAPEX	0.755	0.652
	(0.8)	(0.7)
BETA	-0.347***	-0.346***
	(-6.2)	(-6.2)
RMSE	-2.244***	-2.172***
	(-25.9)	(-25.6)
ICW	-0.519***	-0.440***
	(-4.7)	(-4.0)
RESTATE	-0.287***	-0.243***
	(-4.2)	(-3.5)
FOLLOW	0.246***	0.234***
	(4.1)	(3.9)
LCOVER	0.068***	0.063***
	(3.2)	(3.0)
LAWSUIT	-0.377***	-0.318***
	(-6.2)	(-5.2)

2002	-0.194**	-0.043
	(-2.6)	(-0.5)
2003	-0.599***	-0.378***
	(-6.6)	(-3.9)
2004	-0.888***	-0.648***
	(-8.8)	(-6.1)
2005	-1.087***	-0.799***
	(-9.9)	(-6.9)
2006	-1.261***	-0.946***
	(-11.1)	(-7.8)
2007	-1.383***	-1.017***
	(-11.8)	(-8.1)
2008	-1.685***	-1.234***
	(-14.3)	(-9.6)
2009	-1.688***	-1.274***
	(-14.2)	(-10.0)
2010	-1.740***	-1.313***
	(-14.6)	(-10.3)
2011	-1.683***	-1.248***
	(-14.0)	(-9.7)
2012	-1.670***	-1.237***
	(-13.7)	(-9.5)
2013	-1.613***	-1.167***
	(-13.2)	(-8.9)
2014	-1.655***	-1.206***
	(-13.3)	(-9.1)
2015	-1.637***	-1.186***
	(-12.7)	(-8.7)
Industry Dummies (SIC2)	Yes	Yes
Pseudo R^2	0.267	0.275
N	11,379	11,379

This table reports results from estimating an ordered logistic regression where we model S&P long-term issuer credit ratings as a function of firm characteristics, and industry and year indicator variables. Year indicator coefficients capture rating stringency. Variables of interest are highlighted in gray; t-statistics are presented in parentheses. ***, **, and * denote significance at the 1 percent, 5 percent, and 10 percent levels, respectively. All continuous variables are winsorized at the top and bottom one percentile. Appendix 2.A summarizes all variable definitions in more detail.

Table 2.5

Rating Stringency & Risk-related Narrative Disclosures
Risk-related Categories Disaggregation

	(1)	(2)	(3)	(4)	(5)
	RATING3M	*RATING3M*	*RATING3M*	*RATING3M*	*RATING3M*
LFINANCIAL_10K	-0.741***				
	(-14.3)				
LIDIOSYNCRATIC_10K		-0.788***			
		(-9.4)			
LSYSTEMATIC_10K			-0.994***		
			(-8.4)		
LLEGAL_10K				-0.522***	
				(-8.8)	
LTAX_10K					-0.448***
					(-7.0)
SIZE	0.988***	0.994***	1.016***	0.964***	0.960***
	(19.0)	(18.0)	(18.3)	(18.3)	(17.6)
INTCOV	0.020***	0.021***	0.020***	0.020***	0.020***
	(6.0)	(6.3)	(6.0)	(6.4)	(6.2)
PROFIT	0.557	0.264	0.384	0.331	0.434
	(1.4)	(0.6)	(0.9)	(0.8)	(1.0)
VOL	-2.354***	-2.455***	-2.381***	-2.438***	-2.551***
	(-5.3)	(-5.4)	(-5.3)	(-5.4)	(-5.7)
CASH	-0.283	0.150	-0.006	0.005	0.163
	(-0.7)	(0.4)	(-0.0)	(0.0)	(0.4)
TLEV	-1.945***	-2.071***	-2.181***	-2.116***	-2.237***
	(-6.5)	(-6.8)	(-7.2)	(-7.1)	(-7.5)
CONVD	-3.207***	-2.767***	-3.011***	-3.082***	-3.083***
	(-5.3)	(-4.7)	(-4.9)	(-5.1)	(-5.0)
DEBT/EBITDA	-0.161***	-0.167***	-0.161***	-0.169***	-0.166***
	(-11.8)	(-12.0)	(-11.6)	(-12.1)	(-11.9)
NDEBT/EBITDA	-2.442***	-2.581***	-2.444***	-2.592***	-2.535***
	(-7.0)	(-7.5)	(-7.1)	(-7.5)	(-7.3)
RENT	-4.605**	-5.474**	-6.172***	-6.162***	-5.410**
	(-2.2)	(-2.5)	(-2.9)	(-2.8)	(-2.5)
PPE	0.253*	0.023	0.302**	0.219	0.236
	(1.7)	(0.2)	(2.1)	(1.5)	(1.6)
CAPEX	1.092	0.420	1.037	0.782	0.416
	(1.2)	(0.5)	(1.2)	(0.9)	(0.5)
BETA	-0.320***	-0.358***	-0.326***	-0.360***	-0.354***
	(-5.7)	(-6.4)	(-5.7)	(-6.4)	(-6.3)
RMSE	-2.155***	-2.165***	-2.211***	-2.202***	-2.220***
	(-25.4)	(-25.5)	(-25.9)	(-25.8)	(-25.8)
ICW	-0.480***	-0.448***	-0.475***	-0.460***	-0.466***
	(-4.4)	(-4.1)	(-4.3)	(-4.1)	(-4.2)
RESTATE	-0.240***	-0.254***	-0.260***	-0.255***	-0.266***

	(-3.5)	(-3.7)	(-3.8)	(-3.7)	(-3.9)
FOLLOW	0.217***	0.260***	0.232***	0.239***	0.237***
	(3.7)	(4.4)	(3.9)	(4.0)	(3.9)
LCOVER	0.063***	0.064***	0.067***	0.065***	0.063***
	(3.0)	(3.0)	(3.1)	(3.0)	(3.0)
LAWSUIT	-0.324***	-0.317***	-0.342***	-0.326***	-0.360***
	(-5.3)	(-5.2)	(-5.6)	(-5.3)	(-5.9)
2002	-0.084	-0.061	-0.036	-0.112	-0.122
	(-1.0)	(-0.8)	(-0.4)	(-1.4)	(-1.6)
2003	-0.404***	-0.427***	-0.366***	-0.467***	-0.510***
	(-4.1)	(-4.5)	(-3.8)	(-5.0)	(-5.5)
2004	-0.746***	-0.716***	-0.594***	-0.753***	-0.761***
	(-7.0)	(-6.8)	(-5.5)	(-7.2)	(-7.3)
2005	-0.943***	-0.847***	-0.747***	-0.924***	-0.936***
	(-8.2)	(-7.4)	(-6.3)	(-8.1)	(-8.3)
2006	-1.121***	-1.020***	-0.896***	-1.098***	-1.060***
	(-9.4)	(-8.6)	(-7.3)	(-9.3)	(-9.0)
2007	-1.243***	-1.113***	-0.998***	-1.188***	-1.116***
	(-10.1)	(-9.1)	(-7.9)	(-9.7)	(-9.0)
2008	-1.492***	-1.349***	-1.196***	-1.427***	-1.389***
	(-12.0)	(-10.8)	(-9.1)	(-11.5)	(-11.0)
2009	-1.481***	-1.374***	-1.209***	-1.455***	-1.448***
	(-12.0)	(-11.0)	(-9.2)	(-11.7)	(-11.5)
2010	-1.533***	-1.416***	-1.273***	-1.477***	-1.491***
	(-12.4)	(-11.3)	(-9.7)	(-11.8)	(-11.9)
2011	-1.460***	-1.353***	-1.216***	-1.413***	-1.433***
	(-11.7)	(-10.8)	(-9.3)	(-11.2)	(-11.3)
2012	-1.466***	-1.339***	-1.215***	-1.397***	-1.411***
	(-11.6)	(-10.5)	(-9.2)	(-10.9)	(-11.0)
2013	-1.389***	-1.284***	-1.163***	-1.328***	-1.339***
	(-10.9)	(-10.0)	(-8.8)	(-10.3)	(-10.3)
2014	-1.437***	-1.316***	-1.195***	-1.361***	-1.389***
	(-11.1)	(-10.1)	(-8.9)	(-10.4)	(-10.6)
2015	-1.421***	-1.300***	-1.182***	-1.349***	-1.359***
	(-10.6)	(-9.7)	(-8.5)	(-10.0)	(-10.1)
Industry (SIC2)	Yes	Yes	Yes	Yes	Yes
Pseudo R^2	0.278	0.273	0.273	0.272	0.270
N	11,379	11,379	11,379	11,379	11,379

This table reports results from estimating an ordered logistic regression where we model S&P long-term issuer credit ratings as a function of firm characteristics, and industry and year indicator variables. Year indicator coefficients capture rating stringency. Variables of interest are highlighted in gray; t-statistics are presented in parentheses. ***, **, and * denote significance at the 1 percent, 5 percent, and 10 percent levels, respectively. All continuous variables are winsorized at the top and bottom one percentile. Appendix 2.A summarizes all variable definitions in more detail.

Table 2.6

Rating Stringency & Risk-related Narrative Disclosures

	Investment-grade Sample		**Speculative-grade Sample**	
	(1)	(2)	(3)	(4)
	RATING3M	*RATING3M*	*RATING3M*	*RATING3M*
RISKD_10K		-0.287***		-0.122***
		(-6.9)		(-5.6)
SIZE	0.761***	0.957***	0.556***	0.631***
	(8.7)	(10.4)	(9.2)	(10.2)
INTCOV	0.028***	0.026***	0.011***	0.011***
	(5.8)	(5.8)	(2.7)	(2.6)
PROFIT	0.745	0.652	0.529	0.556
	(0.9)	(0.8)	(1.2)	(1.2)
VOL	-7.351***	-6.727***	-1.494***	-1.485***
	(-3.2)	(-3.2)	(-3.9)	(-3.9)
CASH	1.681**	2.187***	-1.522***	-1.473***
	(2.5)	(3.1)	(-3.3)	(-3.2)
TLEV	1.210	1.036	-1.964***	-1.913***
	(1.6)	(1.4)	(-6.5)	(-6.3)
CONVD	-1.696	-1.724	-2.001***	-2.043***
	(-0.9)	(-0.9)	(-3.3)	(-3.4)
DEBT/EBITDA	-0.352***	-0.317***	-0.136***	-0.134***
	(-4.6)	(-4.2)	(-10.8)	(-10.7)
NDEBT/EBITDA	-1.288	-1.075	-2.527***	-2.480***
	(-1.1)	(-1.0)	(-7.5)	(-7.3)
RENT	-13.545**	-10.642**	-3.129	-3.098
	(-2.6)	(-2.0)	(-1.4)	(-1.4)
PPE	0.185	0.327	-0.159	-0.178
	(0.5)	(1.0)	(-1.0)	(-1.2)
CAPEX	1.371	0.200	1.285	1.390
	(0.7)	(0.1)	(1.3)	(1.4)
BETA	-0.505***	-0.577***	-0.124**	-0.115**
	(-4.1)	(-4.8)	(-2.2)	(-2.0)
RMSE	-2.594***	-2.400***	-1.670***	-1.653***
	(-10.5)	(-9.9)	(-21.1)	(-21.1)
ICW	-0.362*	-0.214	-0.315***	-0.276**
	(-1.7)	(-1.0)	(-2.7)	(-2.4)
RESTATE	-0.369***	-0.313***	-0.136	-0.125
	(-3.2)	(-2.6)	(-1.6)	(-1.5)
FOLLOW	0.032	0.032	0.333***	0.328***
	(0.3)	(0.3)	(5.6)	(5.5)
LCOVER	0.028	0.021	0.020	0.020
	(0.7)	(0.5)	(0.9)	(0.8)
LAWSUIT	-0.048	-0.016	-0.378***	-0.349***
	(-0.4)	(-0.1)	(-5.3)	(-4.9)

2002	-0.184	-0.018	-0.162	-0.066
	(-1.5)	(-0.1)	(-1.4)	(-0.5)
2003	-0.505***	-0.312**	-0.351***	-0.211
	(-3.5)	(-2.1)	(-2.6)	(-1.5)
2004	-0.771***	-0.529***	-0.600***	-0.460***
	(-4.6)	(-3.0)	(-4.2)	(-3.1)
2005	-0.802***	-0.495***	-0.900***	-0.746***
	(-4.4)	(-2.6)	(-5.7)	(-4.6)
2006	-0.877***	-0.525***	-1.090***	-0.931***
	(-4.6)	(-2.6)	(-6.9)	(-5.7)
2007	-1.120***	-0.691***	-1.183***	-1.002***
	(-5.7)	(-3.3)	(-7.3)	(-6.0)
2008	-1.505***	-1.000***	-1.463***	-1.233***
	(-7.9)	(-4.8)	(-8.8)	(-7.0)
2009	-1.669***	-1.250***	-1.319***	-1.093***
	(-8.5)	(-5.8)	(-8.0)	(-6.3)
2010	-1.630***	-1.200***	-1.354***	-1.123***
	(-8.2)	(-5.6)	(-8.2)	(-6.5)
2011	-1.543***	-1.096***	-1.172***	-0.942***
	(-7.8)	(-5.2)	(-7.0)	(-5.4)
2012	-1.560***	-1.124***	-1.222***	-0.986***
	(-7.8)	(-5.3)	(-7.3)	(-5.7)
2013	-1.435***	-0.990***	-1.163***	-0.921***
	(-6.9)	(-4.5)	(-7.0)	(-5.3)
2014	-1.525***	-1.081***	-1.074***	-0.823***
	(-7.3)	(-4.9)	(-6.1)	(-4.5)
2015	-1.457***	-1.026***	-1.096***	-0.842***
	(-6.8)	(-4.5)	(-6.3)	(-4.6)
Industry (SIC2)	Yes	Yes	Yes	Yes
Pseudo R^2	0.165	0.178	0.221	0.223
N	5,186	5,186	6,193	6,193

This table reports results from estimating an ordered logistic regression where we model S&P long-term issuer credit ratings as a function of firm characteristics, and industry and year indicator variables. Year indicator coefficients capture rating stringency. Variables of interest are highlighted in gray; t-statistics are presented in parentheses. ***, **, and * denote significance at the 1 percent, 5 percent, and 10 percent levels, respectively. All continuous variables are winsorized at the top and bottom one percentile. Appendix 2.A summarizes all variable definitions in more detail.

Table 2.7

Rating Stringency & Risk-related Narrative Disclosures

	High-specificity Sample		**Low-specificity Sample**	
	(1)	(2)	(3)	(4)
	RATING3M	*RATING3M*	*RATING3M*	*RATING3M*
RISKD_10K		-0.319***		-0.221***
		(-9.1)		(-8.8)
SIZE	0.735***	0.947***	1.092***	1.218***
	(11.8)	(14.2)	(16.6)	(17.7)
INTCOV	0.020***	0.018***	0.023***	0.022***
	(5.2)	(5.0)	(5.5)	(5.5)
PROFIT	0.481	0.386	0.149	0.198
	(0.9)	(0.7)	(0.3)	(0.4)
VOL	-3.173***	-3.173***	-2.004***	-1.893***
	(-4.8)	(-4.8)	(-3.6)	(-3.5)
CASH	-0.537	-0.246	0.002	0.180
	(-0.9)	(-0.4)	(0.0)	(0.4)
TLEV	-2.283***	-2.150***	-2.095***	-2.011***
	(-5.7)	(-5.5)	(-5.5)	(-5.4)
CONVD	-2.485***	-2.506***	-3.607***	-3.701***
	(-3.1)	(-3.2)	(-4.6)	(-4.8)
DEBT/EBITDA	-0.165***	-0.155***	-0.181***	-0.177***
	(-8.8)	(-8.5)	(-9.0)	(-9.1)
NDEBT/EBITDA	-2.336***	-2.191***	-3.001***	-2.962***
	(-5.3)	(-4.9)	(-5.9)	(-5.8)
RENT	-5.137*	-4.774*	-7.333***	-6.704**
	(-1.9)	(-1.7)	(-2.6)	(-2.5)
PPE	0.003	0.039	0.443**	0.459**
	(0.0)	(0.2)	(2.3)	(2.4)
CAPEX	1.871	1.653	-0.299	-0.421
	(1.6)	(1.4)	(-0.3)	(-0.4)
BETA	-0.307***	-0.309***	-0.378***	-0.370***
	(-4.2)	(-4.1)	(-4.9)	(-4.8)
RMSE	-2.388***	-2.294***	-2.086***	-2.022***
	(-20.8)	(-20.5)	(-17.8)	(-17.5)
ICW	-0.429***	-0.324**	-0.582***	-0.505***
	(-3.1)	(-2.3)	(-3.6)	(-3.1)
RESTATE	-0.277***	-0.196**	-0.292***	-0.272***
	(-3.2)	(-2.2)	(-3.2)	(-3.0)
FOLLOW	0.287***	0.298***	0.204**	0.180**
	(4.1)	(4.2)	(2.5)	(2.3)
LCOVER	0.059**	0.053**	0.072**	0.069**
	(2.5)	(2.1)	(2.4)	(2.4)
LAWSUIT	-0.380***	-0.305***	-0.383***	-0.328***
	(-4.5)	(-3.6)	(-4.8)	(-4.1)

2002	-0.174	0.125	-0.197	-0.121
	(-1.4)	(1.0)	(-1.5)	(-0.9)
2003	-0.541***	-0.137	-0.683***	-0.563***
	(-4.1)	(-1.0)	(-4.7)	(-3.8)
2004	-0.943***	-0.448***	-0.816***	-0.738***
	(-6.5)	(-2.8)	(-5.1)	(-4.5)
2005	-1.097***	-0.553***	-1.102***	-0.978***
	(-7.0)	(-3.2)	(-6.7)	(-5.8)
2006	-1.279***	-0.697***	-1.274***	-1.113***
	(-8.0)	(-3.9)	(-7.3)	(-6.2)
2007	-1.455***	-0.800***	-1.315***	-1.121***
	(-9.0)	(-4.4)	(-7.2)	(-6.0)
2008	-1.676***	-0.885***	-1.754***	-1.510***
	(-10.2)	(-4.6)	(-10.1)	(-8.4)
2009	-1.710***	-0.974***	-1.670***	-1.443***
	(-10.7)	(-5.3)	(-9.4)	(-7.9)
2010	-1.728***	-0.963***	-1.809***	-1.587***
	(-10.8)	(-5.2)	(-10.3)	(-8.9)
2011	-1.638***	-0.870***	-1.825***	-1.590***
	(-9.7)	(-4.6)	(-10.8)	(-9.1)
2012	-1.554***	-0.793***	-1.861***	-1.626***
	(-9.0)	(-4.1)	(-10.7)	(-9.1)
2013	-1.570***	-0.806***	-1.750***	-1.498***
	(-9.1)	(-4.2)	(-10.0)	(-8.3)
2014	-1.671***	-0.895***	-1.748***	-1.493***
	(-9.6)	(-4.6)	(-10.0)	(-8.3)
2015	-1.632***	-0.848***	-1.775***	-1.519***
	(-9.1)	(-4.2)	(-9.9)	(-8.2)
Industry (SIC2)	Yes	Yes	Yes	Yes
Pseudo R^2	0.263	0.273	0.281	0.288
N	5,689	5,689	5,690	5,690

This table reports results from estimating an ordered logistic regression where we model S&P long-term credit ratings as a function of firm characteristics, and industry and year indicator variables. Year indicator coefficients capture rating stringency. Variables of interest are highlighted in gray; t-statistics are presented in parentheses. ***, **, and * denote significance at the 1 percent, 5 percent, and 10 percent levels, respectively. All continuous variables are winsorized at the top and bottom one percentile. Appendix 2.A summarizes all variable definitions in more detail.

Table 2.8

Rating Stringency & Risk-related Narrative Disclosures

	High-readability Sample		**Low-readability Sample**	
	(1)	(2)	(3)	(4)
	RATING3M	*RATING3M*	*RATING3M*	*RATING3M*
RISKD_10K		-0.266***		-0.246***
		(-9.0)		(-8.3)
SIZE	1.005***	1.176***	0.770***	0.914***
	(15.8)	(17.5)	(12.9)	(14.5)
INTCOV	0.020***	0.019***	0.021***	0.020***
	(4.3)	(4.2)	(5.8)	(5.7)
PROFIT	0.501	0.398	0.533	0.618
	(0.9)	(0.7)	(1.1)	(1.3)
VOL	-3.631***	-3.574***	-2.069***	-1.985***
	(-5.2)	(-5.1)	(-4.1)	(-3.9)
CASH	0.577	0.826	-0.492	-0.410
	(1.1)	(1.5)	(-0.9)	(-0.8)
TLEV	-2.508***	-2.480***	-1.989***	-1.792***
	(-5.9)	(-6.1)	(-5.8)	(-5.2)
CONVD	-2.430***	-2.534***	-3.475***	-3.665***
	(-2.9)	(-3.0)	(-4.9)	(-5.2)
DEBT/EBITDA	-0.165***	-0.159***	-0.164***	-0.160***
	(-8.4)	(-8.1)	(-9.5)	(-9.7)
NDEBT/EBITDA	-2.287***	-2.180***	-2.624***	-2.534***
	(-5.0)	(-4.6)	(-6.0)	(-5.8)
RENT	-7.243***	-7.072***	-4.041	-3.321
	(-2.7)	(-2.7)	(-1.5)	(-1.2)
PPE	0.272	0.299	0.061	0.066
	(1.5)	(1.6)	(0.4)	(0.4)
CAPEX	2.121*	2.049	-0.483	-0.745
	(1.7)	(1.6)	(-0.5)	(-0.7)
BETA	-0.414***	-0.421***	-0.332***	-0.332***
	(-5.5)	(-5.5)	(-4.6)	(-4.5)
RMSE	-2.538***	-2.422***	-2.016***	-1.986***
	(-19.9)	(-19.1)	(-19.6)	(-19.7)
ICW	-0.724***	-0.620***	-0.359***	-0.297**
	(-4.7)	(-4.0)	(-2.8)	(-2.3)
RESTATE	-0.318***	-0.272***	-0.280***	-0.236***
	(-3.6)	(-3.1)	(-3.3)	(-2.7)
FOLLOW	0.217***	0.202***	0.287***	0.272***
	(2.8)	(2.7)	(4.1)	(3.9)
LCOVER	0.055**	0.049*	0.074***	0.070***
	(2.0)	(1.8)	(3.0)	(2.9)
LAWSUIT	-0.278***	-0.220**	-0.474***	-0.422***
	(-3.2)	(-2.5)	(-6.2)	(-5.5)

2002	-0.140	0.031	-0.205	-0.146
	(-1.4)	(0.3)	(-1.1)	(-0.7)
2003	-0.432***	-0.200	-0.856***	-0.778***
	(-3.6)	(-1.6)	(-4.3)	(-3.9)
2004	-0.732***	-0.472***	-1.053***	-1.008***
	(-5.4)	(-3.3)	(-5.2)	(-5.0)
2005	-1.006***	-0.694***	-1.091***	-1.023***
	(-6.8)	(-4.5)	(-5.3)	(-4.9)
2006	-1.153***	-0.812***	-1.313***	-1.228***
	(-7.5)	(-5.1)	(-6.3)	(-5.7)
2007	-1.297***	-0.915***	-1.434***	-1.298***
	(-8.3)	(-5.5)	(-6.7)	(-6.0)
2008	-1.478***	-0.996***	-1.820***	-1.639***
	(-9.1)	(-5.6)	(-8.6)	(-7.6)
2009	-1.550***	-1.121***	-1.752***	-1.611***
	(-9.4)	(-6.4)	(-8.3)	(-7.5)
2010	-1.572***	-1.128***	-1.826***	-1.670***
	(-9.5)	(-6.4)	(-8.7)	(-7.8)
2011	-1.471***	-0.997***	-1.794***	-1.655***
	(-8.9)	(-5.6)	(-8.7)	(-7.9)
2012	-1.397***	-0.910***	-1.832***	-1.700***
	(-8.3)	(-5.1)	(-8.8)	(-8.1)
2013	-1.365***	-0.889***	-1.737***	-1.581***
	(-8.1)	(-4.9)	(-8.2)	(-7.5)
2014	-1.449***	-0.970***	-1.755***	-1.605***
	(-8.5)	(-5.3)	(-8.3)	(-7.5)
2015	-1.363***	-0.885***	-1.783***	-1.629***
	(-7.7)	(-4.7)	(-8.4)	(-7.6)
Industry (SIC2)	Yes	Yes	Yes	Yes
Pseudo R^2	0.284	0.293	0.260	0.267
N	5,690	5,690	5,689	5,689

This table reports results from estimating an ordered logistic regression where we model S&P long-term issuer credit ratings as a function of firm characteristics, and industry and year indicator variables. Year indicator coefficients capture rating stringency. Variables of interest are highlighted in gray; t-statistics are presented in parentheses. ***, **, and * denote significance at the 1 percent, 5 percent, and 10 percent levels, respectively. All continuous variables are winsorized at the top and bottom one percentile. Appendix 2.A summarizes all variable definitions in more detail.

Table 2.9

Rating Stringency & Uncertainty-related Narrative Disclosures

	Full Sample	**Investment-grade Sample**	**Speculative-grade Sample**
	(1)	(2)	(3)
	RATING3M	*RATING3M*	*RATING3M*
UNCERTAINTY_10K	-99.687***	-139.550***	-42.330**
	(-6.1)	(-4.9)	(-2.2)
SIZE	0.882***	0.801***	0.557***
	(17.1)	(9.2)	(9.2)
INTCOV	0.021***	0.028***	0.012***
	(6.4)	(5.9)	(2.9)
PROFIT	0.466	0.786	0.549
	(1.1)	(1.0)	(1.2)
VOL	-2.431***	-7.257***	-1.471***
	(-5.4)	(-3.5)	(-3.8)
CASH	0.062	2.153***	-1.481***
	(0.1)	(3.1)	(-3.2)
TLEV	-2.201***	1.239*	-1.960***
	(-7.3)	(1.7)	(-6.5)
CONVD	-2.773***	-1.533	-1.924***
	(-4.5)	(-0.8)	(-3.2)
DEBT/EBITDA	-0.170***	-0.365***	-0.136***
	(-12.0)	(-4.8)	(-10.8)
NDEBT/EBITDA	-2.591***	-1.590	-2.526***
	(-7.6)	(-1.3)	(-7.5)
RENT	-5.837***	-13.230**	-3.111
	(-2.6)	(-2.5)	(-1.4)
PPE	0.121	0.137	-0.197
	(0.8)	(0.4)	(-1.3)
CAPEX	1.060	1.473	1.405
	(1.2)	(0.7)	(1.5)
BETA	-0.335***	-0.524***	-0.118**
	(-5.9)	(-4.2)	(-2.1)
RMSE	-2.223***	-2.506***	-1.666***
	(-25.6)	(-10.2)	(-21.0)
ICW	-0.555***	-0.380*	-0.333***
	(-5.0)	(-1.7)	(-2.8)
RESTATE	-0.280***	-0.355***	-0.138
	(-4.1)	(-3.1)	(-1.6)
FOLLOW	0.259***	0.036	0.341***
	(4.3)	(0.3)	(5.7)
LCOVER	0.066***	0.017	0.022
	(3.1)	(0.4)	(0.9)
LAWSUIT	-0.346***	-0.028	-0.367***

	(-5.7)	(-0.3)	(-5.2)
2002	-0.141*	-0.058	-0.152
	(-1.8)	(-0.5)	(-1.3)
2003	-0.507***	-0.338**	-0.327**
	(-5.5)	(-2.3)	(-2.4)
2004	-0.767***	-0.596***	-0.564***
	(-7.5)	(-3.5)	(-4.0)
2005	-0.892***	-0.521***	-0.834***
	(-7.9)	(-2.7)	(-5.2)
2006	-1.048***	-0.582***	-1.009***
	(-8.9)	(-2.9)	(-6.3)
2007	-1.138***	-0.780***	-1.089***
	(-9.3)	(-3.8)	(-6.5)
2008	-1.423***	-1.154***	-1.357***
	(-11.5)	(-5.6)	(-7.9)
2009	-1.378***	-1.251***	-1.194***
	(-10.8)	(-5.7)	(-6.9)
2010	-1.421***	-1.203***	-1.227***
	(-11.0)	(-5.5)	(-7.1)
2011	-1.345***	-1.074***	-1.039***
	(-10.3)	(-4.8)	(-5.9)
2012	-1.306***	-1.055***	-1.078***
	(-9.8)	(-4.6)	(-6.1)
2013	-1.234***	-0.932***	-1.007***
	(-9.2)	(-4.0)	(-5.7)
2014	-1.255***	-1.001***	-0.910***
	(-9.0)	(-4.3)	(-4.8)
2015	-1.233***	-0.929***	-0.930***
	(-8.6)	(-3.9)	(-4.9)
Industry Dummies (SIC2)	Yes	Yes	Yes
Pseudo R^2	0.269	0.170	0.221
N	11,379	5,186	6,193

This table reports results from estimating an ordered logistic regression where we model S&P long-term issuer credit ratings as a function of firm characteristics, and industry and year indicator variables. Year indicator coefficients capture rating stringency. Variables of interest are highlighted in gray; t-statistics are presented in parentheses. ***, **, and * denote significance at the 1 percent, 5 percent, and 10 percent levels, respectively. All continuous variables are winsorized at the top and bottom one percentile. Appendix 2.A summarizes all variable definitions in more detail.

Chapter 3: Context matters: The role of fair value footnote narratives

3.1 Chapter 3 summary

This study examines whether the narrative component of fair value footnotes, which should help users contextualize quantitative fair value information, affects investor uncertainty. Although footnote disclosures about fair values should reduce fair value measurement uncertainty, financial statement users have questioned the effectiveness of these disclosures in conveying meaningful information. The study's findings suggest that fair value narratives can help investors' understanding of the measurement process of opaque fair values. However, they also suggest that boilerplate fair value footnote narratives can increase investor uncertainty about opaque fair values. Moreover, results suggest that fair value narratives are incrementally informative to investors relative to the volume of tabulated fair value footnote disclosures. Overall, this study sheds new light on the role of narrative information in the fair value footnotes, and informs accounting standard setters and financial statement preparers on how to make fair value measurement more understandable to investors.

3.2 Introduction

Fair value measurement standards (i.e., International Financial Reporting Standard [IFRS] 13, and Statement of Financial Accounting Standards [SFAS] 157) set a framework for measuring fair values and ranks fair value measurement inputs into three levels according to their inherent opacity: Level 1, which are observable inputs from quoted prices in active markets; Level 2, which are inputs from quoted prices of identical items in inactive markets, comparable items in active markets, or other market-corroborated information; and Level 3, which are unobservable, firm-generated inputs. The subjectivity in the choice and use of fair value measurement inputs have caused financial statement users (hereafter, users) to demand more information about the fair value measurement process. In response, the FASB and the IASB have mandated that additional disclosures about reporting firms' fair value measurement processes appear in the notes (i.e., footnotes) to the financial statements. These disclosures, which can be several pages long, contain a narrative and a quantitative (i.e., tabulated) component.

We investigate the effect of the narrative component of the fair value footnotes on investor uncertainty. According to accounting standard setters, fair value footnote narratives (hereafter, fair value narratives) "should provide additional information that helps users of financial statements evaluate the disclosed quantitative information" (FASB 2011, par. 820-10-55-104). However, although users recognize that fair value narratives can contain valuable information, they also observe that these disclosures are not always meaningful. Consequently, they have demanded more quantitative fair value footnote disclosures (FASB 2018 BC38-41). Nevertheless, financial statement preparers and practitioners have opposed such a change, citing concerns about increased preparation and auditing costs of fair value disclosures (FASB 2018 BC42-46).

If fair value narratives increase fair value measurement transparency, they should reduce investor uncertainty about opaque fair values. However, such a prediction is not always warranted. First, prior research shows that investors find that footnote disclosures are costly to process and understand (Michels 2017).[14] Second, both the FASB and IASB note that footnote disclosures have become less informative over time, and contain a lot of irrelevant information (IASB 2013; FASB 2014). These concerns are particularly salient for fair value narratives, which are unstructured, add substantial volume to the fair value footnote, and are costlier to process than tabulated fair value footnote disclosures. Thus, if fair value narratives are uninformative or detracting, investors can discount or rationally ignore them, and allocate their limited attention to quantitative fair value disclosures.[15]

For our first set of tests, we examine if fair value narratives affect investor uncertainty. We show that longer fair value narratives, which should contain a greater quantity of information, are associated with reduced investor uncertainty for Level 3, and to a lesser degree Level 2, fair values. Moreover, we do not find such a result for Level 1 fair values, which use reliable market-based inputs. Additionally, when we account for inter-investor variation in disclosure processing costs, we find that longer fair value narratives are associated with reduced uncertainty for sophisticated investors, but not for retail investors. These results suggest that although fair value narratives can inform investors, they do not uniformly assist all investor types in understanding the measurement process of opaque fair values.

[14] Following the collapse of Silicon Valley Bank (SVB) in March 2023, the financial press expressed concern that users often overlook fair value footnote information (Foley 2023; Bissessur and Bouwens 2023).
[15] Users can rationally disregard disclosures that are not cost-beneficial to use (e.g., Grossman and Stiglitz 1980; Blankespoor, DeHaan, Wertz, and Zhu 2019).

To better understand the link between fair value narratives and investor uncertainty, we also examine if textual properties that capture the information quality of fair value narratives affect investor uncertainty for opaque fair values. Consistent with the notion that financial disclosure should not benefit users if it does not communicate new or useful information (Hoogervorst 2013), we do not find a reduction in investor uncertainty when fair value narratives contain less firm-specific information. Instead, we document an increase in investor uncertainty towards Level 3 fair values when fair value narratives are boilerplate. This result is not entirely unexpected, as theory suggests that accounting information can also lead to increased user uncertainty (e.g., Kim and Verrecchia 1994; McNichols and Trueman 1994; Johnstone 2016). Nevertheless, it validates users' concerns about boilerplatedness reducing the meaningfulness of fair value footnotes (FASB 2018).

In further tests, we show that our findings do not result from a mechanical relationship between the narrative and quantitative components of the fair value footnotes. Specifically, we find that fair value narratives affect investor uncertainty about opaque values even when we control for the volume of the quantitative disclosures tabulated in the fair value footnotes. Consequently, our findings suggest that investors do not discount fair value narratives relative to quantitative fair value disclosures when contextualizing the measurement process of opaque fair values.

Our results contribute to several research streams. By showing that fair value narratives can affect investors' understanding of the measurement process for opaque fair values, we add to the debate on the informativeness of fair value footnotes (Bens, Cheng, and Neamtiu 2016; Chung, Goh, Ng, and Yong 2017), and extend the literature on fair value reporting that predominately focuses on quantitative disclosures (e.g., Song, Thomas, and Yi 2010; Riedl and Serafeim 2011; Magnan, Menini, and Parbonetti 2015; Goh, Li, Ng, and Yong 2015). Furthermore, by demonstrating that the textual properties of fair value narratives can differentially affect investor uncertainty, we add to the emerging literature that examines the narrative components of financial statement notes (e.g., McMullin 2016; Mauritz, Nienhaus, and Oehler 2023; Ahn et al. 2022), and contribute to the literature that investigates how users contextualize financial information (Brown and Tucker 2011; Lang and Stice-Lawrence 2015; Hope et al. 2016; Cazier et al. 2021).

Our findings also have policy implications. In recent years, the FASB and the IASB have taken steps to improve the quality of fair value footnotes (FASB 2018; IASB 2021). These initiatives reflect a broader commitment by accounting standard setters to ensuring clarity, consistency, and meaningfulness in financial statement footnote disclosures. Nevertheless, there is little empirical evidence to inform standard setters on how to improve footnote disclosures. Thus, our findings can assist them in making such disclosures more meaningful to users. For example, instead of introducing new quantitative footnote disclosures, accounting standards could prescribe textual properties that reduce the boilerplatedness of footnote disclosure narratives.

The rest of the study is organized as follows. Section 3.3 provides the hypothesis development. Section 3.4 outlines the sample selection process. Section 3.5 describes our research design, and the construction of the main variables of interest. Section 3.6 presents the empirical results. Section 3.7 concludes.

3.3 Institutional background and hypothesis development

SFAS 157, which became effective for fiscal years beginning after November 15, 2007, defines *fair value* as “the price that would be received to sell an asset or paid to transfer a liability in an orderly transaction between market participants at the measurement date.” The standard also introduced a three-level hierarchy for categorizing fair values into different levels according to their inherent opacity.[16] Prior literature suggests that investors view Level 3 fair values, which are subject to moral hazard and estimation error concerns, with greater scepticism than Level 1 and 2 fair values (e.g., Song et al. 2010), and documents a positive association between the opacity of fair values and investor uncertainty (Riedl and Serafeim 2011). Prior research also shows that following the introduction of the fair value hierarchy, firms reporting more opaque fair values provided additional voluntary disclosures in their fair value footnotes (Chung et al. 2017). To improve the reliability and transparency of Level 3 fair values, Accounting Standards Update (ASU) 2011-04, mandated firms to provide narrative fair value footnote disclosures about the unobservable inputs and valuation techniques used to estimate these fair values.

Prior literature suggests that longer narratives are more informative (Lang and Stice-Lawrence 2015). Moreover, using more words to provide context to quantitative footnote disclosures can reduce the likelihood of a firm receiving a comment letter over disclosure deficiencies by regulators (Ahn et al. 2022). Consistent with these findings, fair value narratives appear to increase in length following the issuance to firms of comment letters that identify fair value reporting deficiencies (Bens et al. 2016), and this increase is greater when firm auditors possess fair value expertise (Ahn, Hoitash, and Hoitash 2020).

Theory suggests that increased disclosure can increase transparency and benefit disclosing firms (Diamond and Verrecchia 1991; Leuz and Verrecchia 2000; Verrecchia 2001). Moreover, prior research argues that supplemental information about the fair value measurement process can

[16] SFAS 157, which has been recodified to Accounting Standard Codification 820 (ASC 820), and IFRS 13 are products of the convergence process between the International Accounting Standards Board (IASB) and the Financial Accounting Standards Board (FASB). Therefore, they are very similar in their main principles and objectives.

make fair values more transparent (Laux and Leuz 2009; Riedl and Serafeim 2011; Barron, Chung, and Yong 2016). Furthermore, by increasing the quantity of information available to users regarding the fair value measurement process, fair value footnote disclosures should improve fair value measurement transparency (Riedl and Serafeim 2011). Thus, for our first hypothesis, we posit that longer fair value narratives, which should contain a greater quantity of information about the fair value measurement process, reduce investor uncertainty about opaque fair values.

H1: Investor uncertainty associated with opaque fair values is reduced for firms that provide longer fair value narratives.

The expectation that longer fair value narratives reduce investor uncertainty depends on them possessing more information, and even then, is not fully warranted. For starters, the benefits of expanded disclosures can be small in rich information environments, such as the U.S. (Leuz and Verrecchia 2000). Furthermore, longer financial narratives take longer to read, and impose a greater cognitive load on the reader (e.g., Li 2008; Loughran and McDonald 2014; Bochkay, Brown, Leone, and Tucker 2022). Moreover, narrative disclosures constitute soft information, which is difficult to process and verify (Liberti and Petersen 2019). Therefore, although longer fair value narratives can provide more information to users, they may also increase disclosure processing costs for them.

Different user types face different barriers to disclosure processing. Specifically, the financial expertise and resources of sophisticated investors allow them to efficiently process longer disclosures. In contrast, less sophisticated users, like retail investors, face higher disclosure processing costs, which can adversely affect their trading behavior (e.g., Miller 2010; Lawrence, 2013; Blankespoor, DeHaan, and Marinovic 2020). Thus, as an extension to our first hypothesis, we posit that longer fair value narratives reduce investor uncertainty about opaque fair values when they are less costly to process.

H1b: Investor uncertainty associated with opaque fair values is reduced more for firms that provide longer fair value narratives, when these are less costly to process.

Ceteris paribus, financial narratives' usefulness to investors depends on how much firm-specific information they contain, and how costly they are to process (Blankespoor et al. 2020). A narrative disclosure property that inhibits the usefulness of financial disclosure is boilerplatedness, where financial narratives are so standardized across firms that they become uninformative to users (FASB 2012; Hoogervost 2013; Lang and Stice-Lawrence 2015; Cazier and Pfeiffer 2017). Boilerplate financial narratives can also increase disclosure processing costs if they hinder the reader from distinguishing relevant from irrelevant information (Blankespoor et al. 2020). Consequently, users have expressed concerns about how the prevalence of boilerplate information in fair value footnotes reduces their quality (FASB 2018).[17]

Overall, we should not expect fair value narratives to benefit investors when they are uninformative. Thus, for our second hypothesis, we focus on the quality of the fair value narratives, and posit that they should not lead to reduced investor uncertainty about opaque fair values when they are standardized.

H2a: Investor uncertainty associated with opaque fair values is not reduced for firms that provide more standardized fair value narratives.

[17] Prior research shows that narratives in Form 10-K reports that discuss fair value also exhibit high levels of boilerplatedness (Dyer et al. 2017).

Although prior literature considers standardized text as boilerplate, standardization can help users more easily compare footnote information across firms (McMullin 2016; Mauritz et al. 2023). However, even if disclosures are not standardized, they can still be boilerplate if they are inherently non-specific (Cazier et al. 2021). More specific financial narratives are more understandable and verifiable ex-post, and can improve the reader's understanding of firm-specific risks (Hope et al. 2016). Moreover, according to accounting standard setters, understandability and verifiability are qualitative characteristics that enhance the reliability of accounting information (FASB 2010; IASB 2018). Thus, as an extension of our second hypothesis, we posit that fair value narratives that use more specific language should reduce investor uncertainty for opaque fair values.

H2b: Investor uncertainty associated with opaque fair values is reduced for firms that provide more specific fair value narratives.

3.4 Sample selection

We use standardized eXtensible Business Reporting Language (XBRL) tags to harvest fair value footnote data. As a result, our sample starts in 2011, the year XBRL tags became widely available, and ends in 2019 to avoid confounding effects associated with the COVID-19 pandemic. We focus on Form 10-K reports because they offer the most comprehensive set of fair value disclosures, and reduce investor uncertainty more than Form 10-Q reports (Bens et al. 2016; Barron et al. 2016). The technical appendix discusses how we collect Form 10-K report footnote data in more detail. Moreover, we focus on U.S. banks and insurance firms as they hold relatively more Level 2 and 3 fair values than firms in other industries (Chung et al. 2017). Because the FASB requires additional narrative disclosures regarding the measurement of Level 3 fair values, we further restrict our sample to firms with non-missing Level 3 fair values. Finally, we drop sample observations with no available data in Compustat and the Center for Research in Security Prices (CRSP).

Our sample consists of 2,064 firm-year observations (1,560 bank-year and 504 insurance-year observations). Table 3.1: Panel A details the sample selection process, whereas Table 3.1: Panel B decomposes the sample by fiscal year and financial sector (i.e., banks or insurance firms).

[Table 3.1]

3.5 Research design and variable measurement

Our research design follows the framework of Riedl and Serafeim (2011). They examine if firms with greater exposure to opaque financial assets exhibit higher investor uncertainty. To this end, they disaggregate assets into their fair value (Level 1, Level 2, and Level 3) and non-fair value components. Subsequently, they derive the leverage-adjusted beta for each firm with respect to the decomposition of their assets through algebraic manipulations of the balance sheet identity (Assets = Liabilities + Equity). Appendix 3.A provides the complete decomposition of the model.

To test our hypotheses, we extend the framework of Riedl and Serafeim (2011) so that it accounts for the disclosure properties of the fair value narratives, and estimate the following regression model:

$$\begin{aligned}\mathrm{Beta\_adj}_{i,t} = {} & a_1\mathrm{FVF\_Property}_{i,t} + \mathrm{FVF\_Property}_{i,t} * (a_2\mathrm{FVA1}_{i,t} + a_3\mathrm{FVA2}_{i,t} + a_4\mathrm{FVA3}_{i,t}) \\ & + a_5\mathrm{FVA1}_{i,t} + a_6\mathrm{FVA2}_{i,t} + a_7\mathrm{FVA3}_{i,t} + a_8\mathrm{NFVA}_{i,t} + a_9\mathrm{LEV}_{i,t} \\ & + e_{i,t} \qquad (3)\end{aligned}$$

The dependent variable is *Beta_adj*, and serves as a proxy for investor uncertainty in the spirit of Lambert, Leuz, and Verrecchia (2007), who theoretically demonstrate that a firm's Capital Asset Pricing Model (CAPM) beta is a function of information uncertainty. Specifically, they show that high-quality disclosures about a firm's future cash flows reduce assessed covariances with the cash flows of other firms. Consequently, this leads to a decreased cost of capital for the disclosing firm. Consistent with Riedl and Serafeim (2011), we measure *Beta_adj* as the equity beta from the single-factor CAPM model. Moreover, we use weekly stock and market returns to ameliorate concerns regarding the effects of stock return volatility in the estimation process (Hou and Moskowitz 2005; Rield and Serafeim 2011). Similar to Chung et al. (2017), we use an estimation window of one fiscal year.

An inherent limitation of using the CAPM beta as a proxy of investor uncertainty is that it does not separate information uncertainty from other risk types (e.g., fundamental risk) that can systematically vary across fair value hierarchy levels (Riedl and Serafeim 2011). To address this concern, we decompose beta into its two components, the correlation of the firm's stock return with the market return, and the ratio of the standard deviation of the firm's stock return to the standard deviation of the market return:

$$\text{CAPM beta} = corr_{i,m}\frac{std_i}{std_m} \quad (4)$$

From the two components of the single-factor CAPM beta, $corr_{i,m}$ more likely captures investor uncertainty, whereas $\frac{std_i}{std_m}$ can also capture elements of fundamental risk. This assumption stems from finance theory (e.g., Morck, Yeung, and Yu 2000; Durnev, Morck, Yeung, and Zarowin 2003; Jin and Myers 2006), which argues that in the absence of firm-specific information market participants value firms using available systematic information. As a result, the stock return of more opaque firms will exhibit a higher correlation with the market return. Thus, to ensure a better identification of investor uncertainty, we use the leverage-adjusted correlation (*Corr_adj*) as an alternative dependent variable in our tests.

Depending on the hypothesis we examine, *FVF_Property* captures two textual constructs: length, and boilerplatedness. We measure *FV_LogLength,* a proxy for the quantity of information fair value narratives provide to users, as the natural logarithm of the number of words in the firm's fair value narratives. Regarding our proxies for boilerplatedness, we rely on the framework of Lang and Stice-Lawrence (2015).[18] Their proxy assumes that standardized phrases carry little firm-specific information. Specifically, to assess the prevalence of boilerplate language in annual reports, they identify common four-gram (i.e., four-word sequence), and calculate the percentage of words in sentences that include at least one of these common phrases. To better capture the nuances of the input disclosures, we use a variation of the measure of Lang and Stice-Lawrence (2015). Specifically, we follow Mauritz et al. (2023), and define a sentence as standardized if it includes an eight-gram found in at least 10 percent of the sample observations for a given fiscal year.

The following example illustrates how we identify standardized sentences. In 2013, the eight-gram "in an orderly transaction between market participants" appears in at least 10 percent of the sample's fair value narratives. Thus, the following sentence was labelled as boilerplate:

[18] In accounting research, most narrative disclosure boilerplatedness proxies rely on the work of Lang and Stice-Lawrence (2015).

Fair value is defined as the price at which an asset could be exchanged ***in an orderly transaction between market participants*** *at the balance sheet date.*

The measure of Mauritz et al. (2023) provides a better fit for our analyses for two reasons. First, it is based on a study that investigates footnote disclosures. Second, it identifies standardized disclosures on an annual basis. Therefore, it suffers less from forward-looking bias and captures changes in language over time. Moreover, it is not affected by the language of firms that do not enter our analyses. As an alternative proxy for boilerplatedness, we also use the specificity of the fair value narratives (*FV_Specificity*), which we measure as the proportion of specific references in the fair value narratives. To identify specific references, we follow prior literature (e.g., Hope et al. 2016; Cazier et al. 2021), and use Stanford's NER algorithm. We use the seven-class Stanford NER model to identify references to seven mutually exclusive categories: date, location, money, organization, percent, person, and time. Chapter 2 provides additional information on how researchers can measure narrative disclosure specificity following Hope et al. (2016).

Prior literature argues that textual measures of boilerplatedness are unsuitable for comparisons across firms due to their mechanical relation to disclosure length (Lang and Stice-Lawrence 2015). To alleviate this concern, we follow the methodology of Brown and Tucker (2011), and length-adjust *FV_Standard* and *FV_Specificity*. Specifically, we regress them on the first five polynomials of fair value narrative word count, and subsequently subtract the fitted measure from the raw measure. Moreover, this adjustment is important for our second hypothesis, which focuses on fair value narratives' quality rather than quantity. Thus, adjusting *FV_Standard* and *FV_Specificity* for the effect of fair value narrative length ensures a more accurate identification of the constructs under investigation.

The independent variables of the model include firm assets decomposed into Level 1 fair values (*FVA1*), Level 2 fair values (*FVA2*), Level 3 fair values (*FVA3*), assets not measured at fair value (*NFVA*), and the firm's debt financing (*LEV*), all scaled by total assets. Consistent with Riedl and Serafeim (2011), we decompose only financial assets since exposures across the fair value hierarchy categories are substantially greater for assets than financial liabilities. Moreover, experimental evidence suggests that investors perceive asset fair values as more relevant than the fair values of financial liabilities (Koonce, Nelson, and Shakespeare 2011), thus providing further support for this research design choice.

Because of the opacity and inherent complexity of Level 2 and Level 3 fair values, we focus on the interaction terms between *FVA2*, *FVA3*, and *FVF_Property*. Specifically, if the textual properties of fair value narratives help to reduce (increase) investor uncertainty associated with fair values of differing opacity for investors, the coefficient of the interaction terms between *FVF_Property* and *FVA2*, *FVA3* should exhibit a negative (positive) sign. Given that Level 1 fair values use observable quotes from active and liquid markets as inputs, they should be fully transparent to investors. Therefore, we make no predictions regarding the interaction term between *FVF_Property* and *FVA1*. Moreover, the framework of Riedl and Serafeim (2011) assumes that the firm's equity beta is the aggregate beta for the individual firm's portfolio of assets. Thus, we predict that α_5 through α_8 in equation (3) will have a positive sign. Additionally, since a_9 proxies for the beta of the firm's debt, we predict that it will exhibit a negative sign.

In all multivariate analyses, we cluster standard errors at the firm level. Moreover, to directly measure the implied betas of different asset levels, we estimate our models without an intercept.[19] Furthermore, to deal with the effect of outliers, we follow Song et al. (2010), and drop observations where the studentized regression residuals exceed 2. As a result, we end up with a different number of observations for each of our model specifications.[20]

3.6 Results

3.6.1 Descriptive statistics

Table 3.2 reports sample descriptive statistics for our main variables. The means of the proportion of Level 1 (*FVA1*), Level 2 (*FVA2*), and Level 3 (*FVA3*) assets to total assets are 0.03, 0.25, and 0.04, respectively. Evidently, Level 2 fair values are our sample's most prominent fair value hierarchy class. Moreover, the proportion of non-fair value assets to total assets (*NVFA*) has a mean of 0.69. Furthermore, firm leverage (*LEV*) displays a mean value of 0.85.

[Table 3.2]

Table 3.3 presents Pearson correlations for our main variables. *Beta_adj* exhibits a positive correlation coefficient with all fair value hierarchy asset classes (*FVA1*, *FVA2*, and *FVA3*). *Corr_adj* also exhibits a positive correlation with *FVA1* and *FVA2*, and a negative correlation, albeit of a magnitude that is close to zero, with *FVA3*. *FV_LogLength* correlates negatively with both *Beta_adj* and *Corr_adj.* Moreover, it correlates positively with *FVA1,* and negatively with *FVA2* and *FVA3*. *FV_Standard* displays a negative correlation with *Beta_adj* and *Corr_adj,* as well as with *FVA1*, *FVA2*, and *FVA3*. Regarding *FV_Specificity,* it correlates positively with *Beta_adj* and *Corr_adj*. Furthermore, it correlates positively with *FVA1* and *FVA2*, and negatively

[19] We document similar findings when we estimate equation (3) with an intercept.
[20] Winsorizing continuous variables at the top and bottom one percentile does not affect the conclusions of our analyses.

with *FVA3*. Also, the correlation between *FV_Standard* and *FV_Specificity* is negative and equal to -0.14. Thus, although these two variables capture elements of disclosure boilerplatedness, the descriptive evidence we present suggests that they can also represent distinct textual properties.

[Table 3.3]

3.6.2 The effect of fair value narrative length on investor uncertainty

Table 3.4 reports results from estimating equation (3), where we extend the framework of Riedl and Serafeim (2011) to examine if the quantity of the information found in the fair value narratives affects investor uncertainty regarding opaque fair values. *Beta_adj* (columns [1] and [2]) and *Corr_adj* (columns [3] and [4]) are our main proxies for investor uncertainty. In addition, *FV_LogLength* proxies for the information quantity of the fair value narratives. Columns [1] and [3] present results with no fixed effects, whereas columns [2] and [4] control for year and financial-sector (i.e., banks or insurance firms) fixed effects. The interaction term *FVA3*FV_LogLength* displays a negative and statistically significant coefficient estimate across all specifications. Moreover, apart from column [2], *FVA2*FV_LogLength* also displays a negative and significant coefficient estimate. Thus, consistent with our first hypothesis, we find evidence that longer fair value narratives reduce investor uncertainty for opaque fair values. Furthermore, we do not find statistically significant results regarding *FVA1*FV_LogLength*. This result is not surprising as Level 1 estimates are considered more reliable and transparent by users than Level 2 and Level 3 fair values.

[Table 3.4]

For our first hypothesis, the length of the fair value narratives proxies for their information quantity. However, financial narrative length can increase the cognitive load on the reader, and capture elements of disclosure complexity or obfuscation (e.g., Loughran and McDonald 2014; Bochkay et al. 2022). To better understand the underlying dynamics behind our findings, and to decouple the effect of the fair value narratives' information quantity from that of narrative complexity, we rely on the variation in disclosure processing costs between retail (i.e., individual) and sophisticated investors. Prior research argues that investors are subject to processing and capacity constraints that can affect how they contextualize financial information (Blankespoor et al. 2020). Specifically, the expertise and resources of sophisticated investors should allow them to process longer disclosures more efficiently than retail investors.

Table 3.5 presents results from tests examining if sophisticated investors, who should find longer narrative disclosures less costly to process, benefit more from longer fair value narratives relative to retail investors. The dependent variables are *Beta_adj* (Table 3.5 Panel A), and *Corr_adj* (Table 3.5 Panel B). In columns [1] and [2] of both Panels, we partition our sample into high and low retail investor trading observations, respectively. Specifically, we follow Boehmer, Jones, Zhang, and Zhang (2021), and use NYSE Trade and Quote (TAQ) data to identify trades by retail investors over the fiscal year following the filing date of the Form 10-K report. Moreover, to ameliorate endogeneity concerns, in columns [3] and [4] we also present test results after implementing propensity score matching to ensure that any differences in observable dimensions across the subsamples are close to random (Rosenbaum and Rubin 1983). To obtain propensity scores, we estimate a logit regression of an indicator variable set to 1 for firms that experience high retail trading (i.e., above the median) over the fiscal year following the filing of the Form 10-K report, and 0 otherwise. Moreover, we match observations on year, financial-sector, and the equation (3) variables, without replacement, and use a caliper distance in propensity scores of 0.01.

In columns [1] and [2] of Table 3.5, where we present results without propensity score matching, we find that, for both subsamples, longer fair value narratives reduce investor uncertainty for opaque fair values. However, in both Panels A and B, F-test results do not support the existence of meaningful differences between the two subsamples. In columns [3] and [4], where we implement propensity score matching, the interaction terms *FVA2*FV_LogLength* (in Table 3.5 Panel A) and *FVA3*FV_LogLength* (in Table 3.5 Panels A and B) display negative and statistically significant coefficient estimates for low-retail trading observations, at the 10 and 1 percent levels, respectively. Moreover, regarding this finding, F-tests suggest the existence of a statistically significant variation between the two subsamples. Across both Panels, we do not document evidence that longer fair value narratives affect retail investor uncertainty about opaque fair values. These findings are consistent with more resources or lower marginal disclosure processing costs allowing sophisticated investors to integrate more complex financial narratives better than retail investors (Blankespoor et al. 2020).

[Table 3.5]

3.6.3 The effect of fair value narrative boilerplatedness on investor uncertainty

In Table 3.6, we examine if more standardized fair value narratives affect investors' understanding of the measurement process associated with opaque fair values. According to our second hypothesis, boilerplate fair value narratives, which provide less firm-specific information to investors (Hoogervorst 2013; Lang and Stice-Lawrence 2015; Cazier and Pfeiffer 2017), should not reduce fair value measurement uncertainty. In our analyses, *FV_Standard* captures the standardization of the fair value footnote narratives. *Beta_adj* (columns [1] and [2]) and *Corr_adj* (columns [3] and [4]) are our main proxies for investor uncertainty. Columns [1] and [3] report results without fixed effects. Columns [2] and [4] include year and financial-sector fixed effects. Importantly for our research question, the interaction between *FVA3* and *FV_Standard* displays a positive coefficient estimate across all specifications. Moreover, we document no significant result for *FVA1*FV_Standard,* whereas for *FVA2*FV_Standard*, we find weak statistical evidence of a negative association in column [3]. Collectively, these results suggest that more standardized fair value narratives, which contain less firm-specific information, increase investor uncertainty for the opaquest fair values. Therefore, these findings support users' demands for actions that reduce the boilerplatedness of fair value footnotes by standard setters (FASB 2018).

[Table 3.6]

In Table 3.7, we investigate if more specific fair value narratives reduce investor uncertainty. Although standardized text is generally considered less informative, its use can result in more comparable footnotes across firms (McMullin 2016; Mauritz et al. 2023). Nevertheless, narrative disclosures can be boilerplate if they are inherently non-specific (Cazier et al. 2021). Thus, we employ *FV_Specificity* as an inverse boilerplatedness proxy. In columns [1] and [2], the dependent variable is *Beta_adj*. In columns [3] and [4], the dependent variable is *Corr_adj*. Columns [1] and [3] report results without fixed effects, while columns [2] and [4] include year and financial-sector fixed effects. Consistent with the argument that more specific narratives enhance the reliability of accounting information (Hope et al. 2016), our results suggest that more specific fair value narratives reduce investor uncertainty for Level 3 fair values. Specifically, the interaction term *FVA3*FV_Specificity,* which captures whether more specific (i.e., less boilerplate) fair value narratives improve investors' understanding of the measurement process of Level 3 fair values, displays a consistently negative coefficient estimate across all specifications. Moreover, we document no statistically significant interaction terms for *FVA1*FV_Specificity* and *FVA2*FV_Specificity*.

[Table 3.7]

3.6.4 Controlling for the effect of tabulated fair value footnote disclosures

Our primary test results suggest that fair value narratives can affect investor uncertainty regarding the fair value measurement process. However, fair value footnotes also contain a quantitative component that typically presents data, such as fair value amounts and quantitative inputs, in a structured format. Ultimately, these two fair value footnote components are linked. Specifically, accounting standard setters emphasize the importance of fair value narratives in helping users evaluate the disclosed quantitative information about fair values (FASB 2011, par. 820-10-55-104).

In Table 3.8, we account for the effect of tabulated fair value footnote disclosures on investor uncertainty about opaque fair values. We do so to mitigate potential confounding effects arising from the relationship between the quantitative and narrative components of the fair value footnotes. To this end, we incorporate in our analyses *FV_LogNum,* which captures the volume of quantitative (i.e., tabulated) disclosures in the fair value footnotes, and its interaction terms with *FVA1*, *FVA2*, and *FVA3*. Tabulated disclosures in the fair value footnotes also cover information about financial assets and liabilities not measured at fair value. Thus, we consider *FV_LogNum* an appropriate control for the total quantity of quantitative disclosures in the fair value footnote. Importantly for our research question, this analysis allows us to evaluate whether fair value narratives are incrementally informative to investors relative to quantitative fair value footnote disclosures.[21]

To calculate the fair value footnote tabulated disclosures volume, we use footnote data from xbrlresearch.com, and the Division of Economic and Risk Analysis (DERA) library. Specifically, the Ahn et al. (2020) data, which are publicly available at xbrlresearch.com, exclude tables, whereas the DERA Financial Statement and Notes" dataset contains these disclosures. Thus, to measure the volume of tabulated content in the fair value footnotes, we subtract the number of numbers found in the xbrlresearch.com fair value footnote narrative dataset from the number of numbers found in the corresponding DERA dataset. While it is possible to measure this variable programmatically, this multi-source method is faster to implement and more replicable. Moreover, this approach underscores how combining public datasets can help economize the time and resources required to research narrative disclosures.

Panel A of Table 3.8 presents results where the dependent variable is *Beta_adj*. In column [1], the interaction term *FVA3*FV_LogLength* displays a negative and statistically significant coefficient estimate, while interaction terms involving *FV_LogNum* do not exhibit significance. This finding suggests that longer fair value narratives are incrementally informative to investors relative to the volume of tabulated fair value footnote disclosures. In column [2] of Table 3.8, we report results where both *FV_LogNum* and *FV_Standard*, as well as their interaction terms with *FVA1*, *FVA2*, and *FVA3*, are part of our model. In this specification, *FVA2*FV_LogNum* and *FVA3*FV_LogNum* exhibit negative coefficients that are statistically significant at the 5 and 10 percent levels, respectively. Moreover, the interaction term between *FV_Standard* and *FVA3*

[21] The technical appendix provides more information on the datasets used to calculate fair value footnote tabulated disclosures volume.

displays a positive and significant coefficient at the 1 percent level. Finally, in column [3], the interaction terms *FVA2*FV_LogNum* and *FVA3*FV_LogNum* have a negative and significant coefficient. Furthermore, *FVA2*FV_Specificity* displays a positive and weakly statistically significant coefficient, whereas *FVA3*FV_Specificity* is negative and significant at the 1 percent level.

In Table 3.8 Panel B, we use *Corr_adj* as our dependent variable. Results exhibit a similar pattern to Panel A. In column [1], we document no significant interaction term involving *FV_LogNum*. However, we find a negative and significant coefficient for *FVA2*FV_LogLength* and *FVA3*FV_LogLength*. In column [2], *FVA2*FV_LogNum* and *FVA3*FV_LogNum* exhibit a negative, and statistically significant coefficient. Moreover, the coefficient of *FVA3*FV_Standard* is positive and significant at the 10 percent level. In addition, *FVA2*FV_Standard* shows a negative and weakly significant coefficient estimate. Therefore, although we find evidence of an effect associated with standardization, these are weaker than the evidence of Panel A (column [2]). Finally, in column [3], *FVA3*FV_Specificity, FVA2*FV_LogNum* and *FVA3*FV_LogNum* have a negative and statistically significant coefficient.

[Table 3.8]

Overall, Table 3.8 results support our main findings. Moreover, the interaction terms involving fair value narrative properties (i.e., length, standardization, and specificity) exhibit consistently larger coefficient magnitudes than those involving *FV_LogNum*. Thus, our findings suggest that fair value narratives provide investors with additional information about the measurement process of opaque fair values, which goes beyond what quantitative fair value footnote disclosures already convey.

3.6.5 Additional tests

Our analyses yield similar results regardless of whether we use *Beta_adj* or *Corr_adj* as the dependent variable. Thus, we posit that information uncertainty is more likely to drive our findings than some other fundamental risk. Nevertheless, to further assess the robustness of our main results, we recalculate *Beta_adj* and *Corr_adj* using daily returns instead of weekly returns, and conduct our tests again. We also calculate both variables using equal-weighted market returns instead of value-weighted returns. In both cases, we find results (untabulated) supporting our main findings.

To mitigate concerns related to the construct validity of our textual variables, we also use alternative specifications for *FV_Standard* and *FV_Specificity*. In our primary analyses, we label a sentence as standardized if it contains an eight-word sequence found in at least 10 percent of all fair value narratives within a fiscal year. We document similar results when we gradually raise this threshold to 40 percent. We also confirm the robustness of our main results when we measure *FV_Standard* in the spirit of Lang and Stice-Lawrence (2015).

Finally, we find results supporting our main findings when we measure specificity at the sentence level using FinBERT, a state-of-the-art large language model (Huang, Wang, and Yang 2023). BERT (Bidirectional Encoder Representations from Transformers) models are powerful NLP tools that researchers can also train for NER. While BERT is resource-intensive tool to use, and opaque relative to simpler NLP algorithms, it can consider context from both directions (left-to-right and right-to-left), enabling the extraction of nuanced, context-dependent information from narrative disclosures. Therefore, it can be a good tool for researchers aiming for precise and customizable entity recognition.

Although there are several BERT models available, we use the FinBERT model of Huang et al. (2023) since it is pre-trained on financial texts such as public filings, analyst reports, and earnings conference call transcripts. Subsequently, we fine-tune (i.e., adapt) FinBERT for NER using the 2003 Conference on Computational Natural Language Learning (CoNLL-2003) shared task dataset, which focused on recognizing English named entities. Afterwards, we identify the number of sentences in the fair value narratives that contain named entities, and scale this figure by the number of sentences in the fair value narratives. For this analysis, focusing on the sentence level stems from both conceptual and practical considerations. Specifically, a sentence is the smallest unit of text that can convey an idea (Ivers 1991). Moreover, by conducting the analysis at the sentence level, we can expedite the NER process, and save computational resources.

3.7 Conclusion

We examine the narrative components of fair value footnotes in Form 10-K reports, and show that they can affect investors' understanding of the measurement process of opaque fair values. Specifically, we show that longer fair value narratives are associated with reduced investor uncertainty for Level 3, and to a lesser degree Level 2, fair values. However, we document no such effect for Level 1 asset fair values, consistent with investors considering them more reliable. We also show that longer fair value narratives reduce uncertainty around Level 3 fair values for sophisticated, but not retail, investors. Moreover, we document increased investor uncertainty associated with Level 3 fair value asset estimates when fair value narratives are boilerplate. Finally, we show that fair value narratives offer incremental information to investors relative to quantitative fair value footnote disclosures.

Our study is subject to certain trade-offs and limitations that also present paths for future research. First, we use a single XBRL tag to identify fair value footnotes. Although this approach allows us to identify and systematically extract fair value footnote data, firms can freely choose XBRL tags for their fair value footnotes. Subsequent studies can build upon our findings by investigating whether firms opportunistically choose XBRL tags when labeling footnote disclosure components. Second, we focus on the quantity and quality of information in fair value narratives. We do not, however, examine for any potential effects linked to their actual content or formatting. Third, we concentrate on equity investors as the primary users of financial statement information. However, other user groups, such as regulators and debtholders, have distinct informational needs and perspectives. Examining how these stakeholders perceive and utilize fair value narratives can prove a fruitful avenue for future research.

Appendix 3.A: Beta derivation according to Rield and Serafeim (2011)

Assuming a firm financed by debt and equity, in the absence of taxes, and according to the balance sheet identity:

$$\mathrm{A} = \mathrm{L} + \mathrm{E}$$

Where:

A = firm total assets,

L = total liabilities, and

E = equity.

Decomposing firm total assets according to the fair value hierarchy results in the following equation:

$$\mathrm{A1} + \mathrm{A2} + \mathrm{A3} + \mathrm{OA} = \mathrm{L} + \mathrm{E}$$

Where:

A1, A2, A3 = Fair value of assets designated as Level 1, 2 and 3, and

OA = Assets not measured at fair value.

By scaling the equation terms using the firm's total assets, we can compute the firm's weighted-average beta (βE) in the following manner:

$$\left(\beta\mathrm{A1} * \frac{\mathrm{A1}}{\mathrm{TA}}\right) + \left(\beta\mathrm{A2} * \frac{\mathrm{A2}}{\mathrm{TA}}\right) + \left(\beta\mathrm{A3} * \frac{\mathrm{A3}}{\mathrm{TA}}\right) + \left(\beta\mathrm{OA} * \frac{\mathrm{OA}}{\mathrm{TA}}\right) = \beta\mathrm{L} * \frac{\mathrm{L}}{\mathrm{TA}} + \beta\mathrm{E} * \frac{\mathrm{E}}{\mathrm{TA}}$$

Where:

βA1, *βA2*, *βA3*, *βOA* = Betas of fair value asset at Levels 1, 2, 3, and assets not measured at fair value, respectively.

TA = total assets,

βL = beta corresponding to total liabilities, and

βE = beta corresponding to the firm's equity.

Finally, we rearrange the equation terms to solve for the leverage-adjusted (i.e., equity) beta for each firm with respect to the decomposition of their assets.

$$\beta E * \frac{E}{TA} = \left(\beta A1 * \frac{A1}{TA}\right) + \left(\beta A2 * \frac{A2}{TA}\right) + \left(\beta A3 * \frac{A3}{TA}\right) + \left(\beta OA * \frac{OA}{TA}\right) - \beta L * \frac{L}{TA}$$

Appendix 3.B: Variable Definitions

Beta_adj	The coefficient from a regression of firm-specific weekly returns on value-weighted stock market returns, over the fiscal year following the Form 10-K report filing date, multiplied by the ratio of common equity to total assets. [Source: Filing dates from EDGAR, and market data from CRSP].
Corr_adj	The correlation, over the fiscal year following the Form 10-K report filing date, between firm-specific weekly returns and value-weighted stock market returns, multiplied by the ratio of common equity to total assets. [Source: Filing dates from EDGAR, and market data from CRSP].
FV_LogLength	The natural logarithm of the number of words in the firm's fair value narratives (excluding tables). [Source: Footnote data from Ahn et al. (2020)].
FV_Standard	The number of words in standardized sentences in the firm's fair value narratives, scaled by the number of words found in the firm's fair value narratives (excluding tables). We define a sentence as standardized if it contains an eight-gram that occurs in at least 10 percent of the sample narratives in a fiscal year. Furthermore, in our analyses, we length-adjust the measure according to Brown and Tucker (2011). [Source: Footnote data from Ahn et al. (2020)].
FV_Specificity	The proportion of specific references in the firm's fair value narratives (excluding tables). We construct the measure similar to Hope et al. (2016). Furthermore, in our analyses, we length-adjust the measure according to Brown and Tucker (2011). [Source: Footnote data from Ahn et al. (2020)].
FV_LogNum	The natural logarithm of the number of tabulated numbers in the firm's fair value footnotes. [Source: Footnote data from Ahn et al. (2020) and DERA].
FVA1	Fair value assets based on Level 1 inputs, scaled by total assets. [Source: Compustat].
FVA2	Fair value assets based on Level 2 inputs, scaled by total assets. [Source: Compustat].
FVA3	Fair value assets based on Level 3 inputs, scaled by total assets. [Source: Compustat].
NFVA	Assets not measured at fair value, scaled by total assets. [Source: Compustat].
LEV	Total liabilities, scaled by total assets. [Source: Compustat].

Table 3.1

Sample Selection & Composition

Panel A: Sample selection process

Firm-year observations with non-missing Central Index Key (CIK) in the "Compustat Fundamentals Annual" database (2011 – 2019)	47,288
Non-banking & non-insurance firms	(41,396)
Firm-year observations with missing Level 1, Level 2, and Level 3 fair values	(384)
Firm-year observations with missing/zero Level 3 fair value assets	(2,499)
Firm-year observations with missing CRSP data	(525)
Firm-year observations with missing fair value footnote data	(420)
Total sample observations	**2,064**

Panel B: Sample composition by fiscal year and financial sector

Fiscal year	**Banking firms**	**Insurance firms**	**N**
2011	151	52	203
2012	185	61	246
2013	186	63	249
2014	190	62	252
2015	186	58	244
2016	172	58	230
2017	167	51	218
2018	168	50	218
2019	155	49	204
Total	**1,560**	**504**	**2,064**

This table presents the sample selection process, and the sample composition. Panel A details the sample selection process. We restrict the sample to U.S. banks and insurance firms as they hold proportionately more assets and liabilities measured at fair value than firms in other industries. We identify banks and insurance firms using the Fama and French 48-industry classification. We restrict the sample to firms with reported Level 3 asset fair values that file Form 10-K reports and have available data in the intersection of Compustat and CRSP. Fair value footnotes are identified based on the standardized XBRL TextBlock tag "us-gaap:FairValueDisclosuresTextBlock." Panel B presents the sample composition by fiscal year (between 2011 and 2019), and financial sector (banks or insurance firms).

Table 3.2

Descriptive Statistics

Variable	N	Mean	Sd	P1	P25	P50	P75	P99
Beta_adj	2,064	0.133	0.127	-0.038	0.066	0.112	0.165	0.676
Corr_adj	2,064	0.068	0.057	-0.015	0.035	0.060	0.086	0.279
FV_LogLength	2,064	7.379	0.597	5.717	7.041	7.453	7.755	8.468
FV_LogNum	2,064	5.410	0.712	3.584	5.011	5.378	5.751	7.492
FV_Standard	2,064	0.183	0.103	0.000	0.110	0.169	0.244	0.470
FV_Specificity	2,064	0.006	0.008	0.000	0.001	0.004	0.009	0.036
FVA1	2,064	0.030	0.064	0.000	0.000	0.002	0.032	0.311
FVA2	2,064	0.246	0.198	0.000	0.111	0.182	0.328	0.789
FVA3	2,064	0.037	0.136	0.000	0.001	0.003	0.011	0.862
NFVA	2,064	0.692	0.248	0.080	0.561	0.795	0.871	0.993
LEV	2,064	0.849	0.105	0.431	0.848	0.882	0.903	0.967

This table presents descriptive statistics for the main variables used in our analyses. We restrict the sample to U.S. banks and insurance firms as they hold proportionately more assets and liabilities measured at fair value than firms in other industries. We identify Banks and insurance firms using the Fama and French 48-industry classification. We restrict the sample to firms with reported Level 3 asset fair values that file Form 10-K reports and have available data in the intersection of Compustat and CRSP. *Beta_adj* is the single-factor CAPM beta multiplied by the ratio of common equity to total assets. *Corr_adj* is the correlation between firm-specific weekly returns and value-weighted market returns multiplied by the ratio of common equity to total assets. *FV_LogLength* is the natural logarithm of the number of words in the firm's fair value narratives. *FV_Standard* is the number of words in standardized (i.e., boilerplate) sentences in the firm's fair value narratives, scaled by the number of fair value narrative words. *FV_Specificity* is the proportion of specific references in the firm's fair value narratives. *FVA1* (*FVA2*) [*FVA3*] are assets reported at Levels 1 (2) [3], scaled by total assets. *NFVA* are assets not reported at fair value, scaled by total assets. *LEV* is the firm's total liabilities, scaled by total assets. Appendix 3.B summarizes all variable definitions in more detail.

Table 3.3

Variable Correlations

	Beta_adj	*Corr_adj*	*FV_LogL.*	*FV_LogN.*	*FV_Stan.*	*FV_Spec.*	*FVA1*	*FVA2*	*FVA3*	*NFVA*	*LEV*
Beta_adj	1.000										
Corr_adj	0.781	1.000									
FV_LogLength	-0.119	-0.139	1.000								
FV_LogNum	-0.039	-0.013	0.619	1.000							
FV_Standard	-0.213	-0.272	-0.336	-0.398	1.000						
FV_Specificity	0.090	0.133	-0.096	0.012	-0.142	1.000					
FVA1	0.182	0.270	0.029	0.200	-0.298	0.053	1.000				
FVA2	0.148	0.265	-0.071	0.250	-0.310	0.107	0.369	1.000			
FVA3	0.125	-0.002	-0.081	-0.062	-0.010	-0.003	0.024	-0.143	1.000		
NFVA	-0.232	-0.281	0.122	-0.163	0.309	-0.089	-0.546	-0.776	-0.442	1.000	
LEV	-0.611	-0.703	0.366	0.258	0.130	-0.116	-0.317	-0.258	-0.123	0.365	1.000

This table displays Pearson correlation coefficients for the main variables used in our analyses. *Beta_adj* is the single-factor CAPM beta multiplied by the ratio of common equity to total assets. *Corr_adj* is the correlation between firm-specific weekly returns and value-weighted market returns multiplied by the ratio of common equity to total assets. *FV_LogLength* is the natural logarithm of the number of words in the firm's fair value narratives. *FV_Standard* is the number of words in standardized (i.e., boilerplate) sentences in the firm's fair value narratives, scaled by the number of fair value narrative words. *FV_Specificity* is the proportion of specific references in the firm's fair value narratives. *FVA1* (*FVA2*) [*FVA3*] are assets reported at Levels 1 (2) [3], scaled by total assets. *NFVA* are assets not reported at fair value, scaled by total assets. *LEV* is the firm's total liabilities, scaled by total assets. No variable outlier adjustments have taken place. Appendix 3.B summarizes all variable definitions in more detail.

Table 3.4

The Effect of Fair Value Narrative Length on Investor Uncertainty

	(1) *Beta_adj*	(2) *Beta_adj*	(3) *Corr_adj*	(4) *Corr_adj*
FV_LogLength	0.057***	0.046***	0.030***	0.029***
	(7.7)	(6.7)	(8.2)	(10.4)
*FVA1*FV_LogLength*	-0.027	-0.034	0.006	0.000
	(-0.4)	(-0.4)	(0.2)	(0.0)
*FVA2*FV_LogLength*	-0.069***	-0.033	-0.041***	-0.031***
	(-2.6)	(-1.5)	(-3.2)	(-2.7)
*FVA3*FV_LogLength*	-0.092***	-0.097***	-0.048***	-0.048***
	(-5.1)	(-5.9)	(-5.5)	(-7.0)
FVA1	0.378	0.327	0.035	0.030
	(0.6)	(0.5)	(0.1)	(0.1)
FVA2	0.714***	0.398**	0.416***	0.313***
	(3.7)	(2.4)	(4.5)	(3.5)
FVA3	0.888***	0.938***	0.411***	0.412***
	(7.6)	(8.4)	(8.4)	(9.2)
NFVA	0.191***	0.208***	0.087***	0.090***
	(2.7)	(3.4)	(2.6)	(3.5)
LEV	-0.577***	-0.501***	-0.296***	-0.278***
	(-8.0)	(-7.6)	(-10.0)	(-9.8)
Fiscal year fixed effects	No	Yes	No	Yes
Sector fixed effects	No	Yes	No	Yes
N	2,016	2,014	2,023	2,023
Adj R^2	0.772	0.785	0.805	0.822

This table presents results from regressions examining the effect of the fair value narratives' length on investor uncertainty. In columns [1] and [2], the dependent variable is *Beta_adj,* the single-factor CAPM beta multiplied by the ratio of common equity to total assets. In columns [3] and [4], the dependent variable is *Corr_adj*, the correlation between firm-specific weekly returns and value-weighted market returns multiplied by the ratio of common equity to total assets. *FV_LogLength* is the natural logarithm of the number of words in the firm's fair value narratives. *FVA1* (*FVA2*) [*FVA3*] are assets reported at Levels 1 (2) [3], scaled by total assets. *NFVA* are assets not reported at fair value, scaled by total assets. *LEV* is the firm's total liabilities, scaled by total assets. In each model, we drop observations with a residual higher than 2. Standard errors are clustered at the firm level. t-statistics are indicated (in parentheses) below the coefficients. ***, **, and * denote significance at the 1 percent, 5 percent, and 10 percent levels, respectively. Appendix 3.B summarizes all variable definitions in more detail.

Table 3.5

The Effect of Fair Value Narrative Length on Investor Uncertainty

Panel A: Dependent variable: *Beta_adj*

	High retail trading	Low retail trading	High retail trading	Low retail trading
	(1)	(2)	(3)	(4)
FV_LogLength	0.049***	0.043***	0.006	0.061***
	(4.4)	(3.1)	(0.6)	(5.0)
*FVA1*FV_LogLength*	-0.093	0.023	-0.086	-0.218
	(-1.3)	(0.1)	(-1.1)	(-0.7)
*FVA2*FV_LogLength*	-0.096***	-0.020	0.011	-0.087*
	(-3.2)	(-0.3)	(0.4)	(-1.9)
*FVA3*FV_LogLength*	-0.073***	-0.151***	-0.009	-0.156***
	(-3.0)	(-4.0)	(-0.2)	(-3.3)
FVA1	0.877	-0.263	1.339***	1.222
	(1.6)	(-0.1)	(2.7)	(0.6)
FVA2	0.919***	0.254	0.808***	0.541*
	(3.9)	(0.6)	(5.5)	(1.7)
FVA3	0.807***	1.244***	0.903***	1.082***
	(4.5)	(5.0)	(3.4)	(3.5)
NFVA	0.240***	0.128	0.872***	-0.094
	(3.0)	(0.9)	(7.7)	(-0.6)
LEV	-0.544***	-0.410***	-0.909***	-0.315***
	(-5.1)	(-4.6)	(-10.0)	(-3.0)
Propensity score match	No	No	Yes	Yes
Fiscal year fixed effects	Yes	Yes	Yes	Yes
Sector fixed effects	Yes	Yes	Yes	Yes
N	949	956	532	535
Adj R^2	0.872	0.702	0.914	0.698
F-test	Prob > chi2 = 0.225		Prob > chi2 = 0.038	

Panel B: Dependent variable: *Corr_adj*

	High retail trading	Low retail trading	High retail trading	Low retail trading
	(1)	(2)	(3)	(4)
FV_LogLength	0.033***	0.016**	0.012***	0.030***
	(8.5)	(2.5)	(3.4)	(4.1)
*FVA1*FV_LogLength*	-0.104***	-0.099	-0.089	-0.123
	(-2.9)	(-0.7)	(-1.5)	(-0.7)
*FVA2*FV_LogLength*	-0.059***	0.018	-0.007	-0.039
	(-6.4)	(0.7)	(-0.8)	(-1.5)
*FVA3*FV_LogLength*	-0.026**	-0.049***	0.019	-0.066***
	(-2.3)	(-4.0)	(1.0)	(-4.0)
FVA1	0.893***	0.737	1.050**	0.745
	(3.1)	(0.8)	(2.3)	(0.7)
FVA2	0.537***	0.021	0.406***	0.291*
	(7.9)	(0.1)	(7.1)	(1.8)

FVA3	0.239***	0.490***	0.150	0.475***
	(2.8)	(6.3)	(1.3)	(3.9)
NFVA	0.095***	0.148**	0.337***	0.003
	(2.9)	(2.5)	(8.8)	(0.0)
LEV	-0.306***	-0.247***	-0.401***	-0.201***
	(-7.3)	(-6.9)	(-16.7)	(-4.6)
Propensity score match	No	No	Yes	Yes
Fiscal year fixed effects	Yes	Yes	Yes	Yes
Sector fixed effects	Yes	Yes	Yes	Yes
N	956	954	535	536
Adj R^2	0.908	0.754	0.942	0.734
F-test	Prob > chi2 = 0.137		Prob > chi2 = 0.001	

This table presents results from regressions examining the effect of the fair value narratives' length on investor uncertainty. In columns [1] and [3] ([2] and [4]), the sample consists of observations that are characterized by retail investor trading that is below (above) the sample median. We identify the number of trades by retail investors, over the fiscal year following the filing date of the Form 10-K report. We use propensity-score matching to ensure that subsample observations are otherwise similar with respect to their observable dimensions. In Panel A, the dependent variable is *Beta_adj*, which is the single-factor CAPM beta multiplied by the ratio of common equity to total assets. In Panel B, the dependent variable is *Corr_adj*, which is the correlation between firm-specific weekly returns and value-weighted market returns multiplied by the ratio of common equity to total assets. *FV_LogLength* is the natural logarithm of the number of words in the firm's fair value narratives. FVA1 (FVA2) [FVA3] are assets reported at Levels 1 (2) [3], scaled by total assets. *NFVA* are assets not reported at fair value, scaled by total assets. *LEV* is the firm's total liabilities, scaled by total assets. In each model, we drop observations with a residual higher than 2. Standard errors are clustered at the firm level. t-statistics are indicated (in parentheses) below the coefficients. ***, **, and * denote significance at the 1 percent, 5 percent, and 10 percent levels, respectively. Appendix 3.B summarizes all variable definitions in more detail.

Table 3.6

The Effect of Fair Value Narrative Standardization on Investor Uncertainty

	(1) *Beta_adj*	(2) *Beta_adj*	(3) *Corr_adj*	(4) *Corr_adj*
FV_Standard	-0.130**	-0.132**	-0.026	-0.021
	(-2.1)	(-2.1)	(-0.8)	(-0.7)
*FVA1*FV_Standard*	-0.535	-0.776	-0.298	-0.463
	(-0.7)	(-1.0)	(-0.7)	(-1.0)
*FVA2*FV_Standard*	-0.051	0.068	-0.274*	-0.183
	(-0.2)	(0.3)	(-1.9)	(-1.3)
*FVA3*FV_Standard*	0.546***	0.607***	0.206***	0.208***
	(3.7)	(3.9)	(3.6)	(3.4)
FVA1	0.484***	0.281***	0.243***	0.166***
	(5.0)	(3.1)	(5.8)	(3.3)
FVA2	0.482***	0.359***	0.252***	0.209***
	(7.7)	(6.1)	(8.2)	(6.2)
FVA3	0.525***	0.477***	0.228***	0.219***
	(8.8)	(8.8)	(8.7)	(8.2)
NFVA	0.501***	0.450***	0.255***	0.248***
	(8.0)	(8.3)	(9.0)	(8.9)
LEV	-0.445***	-0.393***	-0.225***	-0.214***
	(-6.4)	(-6.5)	(-7.0)	(-7.0)
Fiscal year fixed effects	No	Yes	No	Yes
Sector fixed effects	No	Yes	No	Yes
N	2,014	2,016	2,024	2,028
Adj R^2	0.753	0.772	0.790	0.806

This table presents results from regressions examining the effect of the fair value narratives' standardization on investor uncertainty. In columns [1] and [2], the dependent variable is *Beta_adj,* the single-factor CAPM beta multiplied by the ratio of common equity to total assets. In columns [3] and [4], the dependent variable is *Corr_adj*, the correlation between firm-specific weekly returns and value-weighted market returns multiplied by the ratio of common equity to total assets. *FV_Standard* is the number of words in standardized (i.e., boilerplate) sentences in the firm's fair value narratives, scaled by the number of fair value narrative words. To control for the mechanical relationship between *FV_Standard* and fair value narrative length, we length-adjust the measure according to Brown and Tucker (2011). *FVA1* (*FVA2*) [*FVA3*] are assets reported at Levels 1 (2) [3], scaled by total assets. *NFVA* are assets not reported at fair value, scaled by total assets. *LEV* is the firm's total liabilities, scaled by total assets. In each model, we drop observations with a residual higher than 2. Standard errors are clustered at the firm level. t-statistics are indicated (in parentheses) below the coefficients. ***, **, and * denote significance at the 1 percent, 5 percent, and 10 percent levels, respectively. Appendix 3.B summarizes all variable definitions in more detail.

Table 3.7

The Effect of Fair Value Narrative Specificity on Investor Uncertainty

	(1) *Beta_adj*	(2) *Beta_adj*	(3) *Corr_adj*	(4) *Corr_adj*
FV_Specificity	-0.229	-0.393	-0.031	-0.238
	(-0.3)	(-0.4)	(-0.1)	(-0.6)
*FVA1*FV_Specificity*	-3.984	-7.871	4.822	1.972
	(-0.4)	(-0.8)	(0.8)	(0.4)
*FVA2*FV_Specificity*	2.739	4.113	0.528	1.748
	(1.0)	(1.5)	(0.4)	(1.3)
*FVA3*FV_Specificity*	-7.241***	-9.136***	-3.117***	-3.135***
	(-3.7)	(-5.8)	(-4.6)	(-4.6)
FVA1	0.537***	0.337***	0.274***	0.183***
	(7.7)	(4.7)	(7.7)	(4.1)
FVA2	0.503***	0.367***	0.277***	0.215***
	(8.8)	(6.3)	(9.1)	(6.3)
FVA3	0.516***	0.469***	0.237***	0.219***
	(8.8)	(8.8)	(9.1)	(8.4)
NFVA	0.503***	0.463***	0.260***	0.251***
	(8.5)	(9.0)	(9.1)	(9.3)
LEV	-0.454***	-0.408***	-0.236***	-0.220***
	(-6.9)	(-7.2)	(-7.3)	(-7.3)
Fiscal year fixed effects	No	Yes	No	Yes
Sector fixed effects	No	Yes	No	Yes
N	2,011	2,016	2,020	2,025
Adj R^2	0.747	0.771	0.778	0.802

This table presents results from regressions examining the effect of the fair value narratives' specificity on investor uncertainty. In columns [1] and [2], the dependent variable is *Beta_adj,* the single-factor CAPM beta multiplied by the ratio of common equity to total assets. In columns [3] and [4], the dependent variable is *Corr_adj*, the correlation between firm-specific weekly returns and value-weighted market returns multiplied by the ratio of common equity to total assets. *FV_Specificity* is the proportion of specific references in the firm's fair value narratives. To control for the mechanical relationship between *FV_Specificity* and fair value narrative length, we length-adjust the measure according to Brown and Tucker (2011). *FVA1* (*FVA2*) [*FVA3*] are assets reported at Levels 1 (2) [3], scaled by total assets. *NFVA* are assets not reported at fair value, scaled by total assets. *LEV* is the firm's total liabilities, scaled by total assets. In each model, we drop observations with a residual higher than 2. Standard errors are clustered at the firm level. t-statistics are indicated (in parentheses) below the coefficients. ***, **, and * denote significance at the 1 percent, 5 percent, and 10 percent levels, respectively. Appendix 3.B summarizes all variable definitions in more detail.

Table 3.8

The Effect of Fair Value Narratives on Investor Uncertainty
Controlling for the Volume of Tabulated Fair Value Footnote Disclosures

Panel A: Dependent variable: *Beta_adj*

	(1)	(2)	(3)
FV_LogNum	0.031***	0.046***	0.049***
	(3.0)	(6.8)	(7.1)
FV_LogLength	0.027***		
	(2.9)		
FV_Standard		-0.089*	
		(-1.7)	
FV_Specificity			-0.437
			(-0.5)
*FVA1*FV_LogNum*	0.045	-0.054	-0.055
	(0.3)	(-0.8)	(-0.9)
*FVA2*FV_LogNum*	-0.021	-0.046**	-0.052***
	(-0.9)	(-2.4)	(-3.0)
*FVA3*FV_LogNum*	-0.008	-0.048*	-0.041**
	(-0.2)	(-1.8)	(-2.1)
*FVA1*FV_LogLength*	-0.120		
	(-0.8)		
*FVA2*FV_LogLength*	-0.024		
	(-0.9)		
*FVA3*FV_LogLength*	-0.105**		
	(-2.2)		
*FVA1*FV_Standard*		-0.614	
		(-0.7)	
*FVA2*FV_Standard*		0.000	
		(0.0)	
*FVA3*FV_Standard*		0.649***	
		(3.0)	
*FVA1*FV_Specificity*			-8.213
			(-0.9)
*FVA2*FV_Specificity*			4.455*
			(1.7)
*FVA3*FV_Specificity*			-9.685***
			(-4.8)
FVA1	0.680	0.394	0.433
	(1.1)	(0.9)	(1.2)
FVA2	0.400**	0.431***	0.457***
	(2.5)	(3.7)	(4.3)
FVA3	1.018***	0.547***	0.487***
	(6.1)	(4.5)	(5.2)
NFVA	0.190***	0.273***	0.272***
	(3.2)	(4.5)	(4.9)
LEV	-0.512***	-0.460***	-0.478***
	(-7.6)	(-7.3)	(-8.3)
Fiscal year fixed effects	Yes	Yes	Yes
Sector fixed effects	Yes	Yes	Yes

N	2,018	2,018	2,016
Adj R^2	0.789	0.788	0.790

Panel B: Dependent variable: *Corr_adj*			
	(1)	(2)	(3)
FV_LogNum	0.021***	0.027***	0.029***
	(4.5)	(8.7)	(9.3)
FV_LogLength	0.013***		
	(3.2)		
FV_Standard		0.002	
		(0.1)	
FV_Specificity			-0.268
			(-0.7)
*FVA1*FV_LogNum*	0.017	-0.008	-0.018
	(0.2)	(-0.2)	(-0.5)
*FVA2*FV_LogNum*	-0.015	-0.037***	-0.041***
	(-1.3)	(-3.1)	(-4.4)
*FVA3*FV_LogNum*	0.003	-0.032***	-0.025***
	(0.3)	(-4.3)	(-3.7)
*FVA1*FV_LogLength*	-0.032		
	(-0.4)		
*FVA2*FV_LogLength*	-0.023*		
	(-1.7)		
*FVA3*FV_LogLength*	-0.058***		
	(-4.7)		
*FVA1*FV_Standard*		-0.382	
		(-0.8)	
*FVA2*FV_Standard*		-0.226*	
		(-1.7)	
*FVA3*FV_Standard*		0.131*	
		(1.9)	
*FVA1*FV_Specificity*			2.330
			(0.5)
*FVA2*FV_Specificity*			1.934
			(1.6)
*FVA3*FV_Specificity*			-3.291***
			(-4.6)
FVA1	0.167	0.106	0.176
	(0.5)	(0.4)	(0.8)
FVA2	0.322***	0.310***	0.333***
	(3.6)	(4.4)	(5.8)
FVA3	0.465***	0.284***	0.240***
	(10.0)	(7.1)	(7.9)
NFVA	0.085***	0.146***	0.141***
	(3.3)	(5.2)	(5.3)
LEV	-0.285***	-0.256***	-0.262***
	(-9.6)	(-8.5)	(-9.6)
Fiscal year fixed effects	Yes	Yes	Yes
Sector fixed effects	Yes	Yes	Yes
N	2,023	2,028	2,024

Adj R^2	0.826	0.826	0.824

This table presents results from regressions examining the effect of the fair value footnote components (narrative and quantitative) on investor uncertainty. In Panel A, the dependent variable is *Beta_adj,* the single-factor CAPM beta multiplied by the ratio of common equity to total assets. In Panel B, the dependent variable is *Corr_adj*, the correlation between firm-specific weekly returns and value-weighted market returns multiplied by the ratio of common equity to total assets. *FV_LogNum* is the natural logarithm of the number of tabulated numbers in the firm's fair value footnote. *FV_LogLength* is the natural logarithm of the number of words in the firm's fair value narratives. *FV_Standard* is the number of words in standardized (i.e., boilerplate) sentences in the firm's fair value narratives, scaled by the number of fair value narrative words. *FV_Specificity* is the proportion of specific references in the firm's fair value narratives. To control for their mechanical relationship with fair value narrative length, we length-adjust *FV_Standard* and *FV_Specificity* according to Brown and Tucker (2011). *FVA1* (*FVA2*) [*FVA3*] are assets reported at Levels 1 (2) [3], scaled by total assets. *NFVA* are assets not reported at fair value, scaled by total assets. *LEV* is the firm's total liabilities, scaled by total assets. In each model, we drop observations with a residual higher than 2. Standard errors are clustered at the firm level. t-statistics are indicated (in parentheses) below the coefficients. ***, **, and * denote significance at the 1 percent, 5 percent, and 10 percent levels, respectively. Appendix 3.B summarizes all variable definitions in more detail.

Chapter 4: Thesis conclusion

Narrative disclosures do more than relay information to the firm's external information environment; they provide a context that allows users to place financial data within a broader narrative. This thesis contains two thematically linked essays that further our understanding of the role of narrative disclosures in financial reporting. Specifically, it examines narrative disclosures in Form 10-K reports, and asserts that these disclosures are not mere adjuncts to quantitative information. Moreover, this thesis underscores the importance of narrative disclosures in communicating risk and uncertainty in financial reporting, and how they can add to empirical accounting research studies.

The first essay, "*Tightening rating standards: The effect of narrative risk-related disclosures*," which constitutes Chapter 2 of this thesis, builds on recent research that explores the integration of narrative disclosures from public filings into credit ratings (Kraft 2015; Bozanic et al. 2023), and examines whether soft information in Form 10-K reports explains why CRAs appear to assign stricter ratings to debt issuers over time. The study's findings suggest that risk-related narrative disclosures moderate rating stringency. Further test results show that this effect is stronger when textual attributes of Form 10-K report narratives facilitate users' comprehension of financial information.

Chapter 2 adds to the literature on rating stringency, and supplements research on the determinants of credit ratings (e.g., Bozanic et al. 2023). Moreover, it contributes to the literature that employs textual analysis to examine risk information within public filings (e.g., Loughran and McDonald 2011; Campbell et al. 2014; Campbell et al. 2019). Future research can build upon these contributions, and explore the factors compelling CRAs to invest in information acquisition and synthesis from narrative disclosures. Furthermore, future research can also examine how CRAs contextualize qualitative information when determining credit ratings. In sum, this essay furthers our understanding of the role of Form 10-K report narrative disclosures within financial reporting and credit assessment, and provides several opportunities for further research pursuits.

The second essay, "*Context matters: The role of fair value footnote narratives*," which comprises Chapter 3 of this thesis, examines whether narrative disclosures in the notes to the financial statement that explain fair value measurement can affect investor uncertainty about opaque fair values. This study underscores the multifaceted role of Form 10-K report footnote disclosure narratives in enhancing users' comprehension of financial information. Moreover, unlike prior research, which focused mainly on quantitative fair value disclosures, this study explores the often-neglected narrative component of the fair value footnotes. The study's findings suggest that longer fair value narratives reduce investor uncertainty about complex and opaque fair values. However, this result applies predominantly to sophisticated investors. The study also shows that when fair value narratives are standardized and non-specific, investor uncertainty about opaque fair values increases. Further test results show that fair value narratives are incrementally informative to investors relative to tabulated fair value footnote disclosures.

Chapter 3 shows that fair value narratives can affect investors' perceptions of opaque fair values, and provide them with incremental insights compared to tabulated fair value footnote disclosures. Thus, this study contributes to the discourse about the informativeness of fair value footnote disclosures (Bens et al. 2016; Chung et al. 2017), and adds to the fair value reporting literature, which predominantly focuses on numerical disclosures (e.g., Song et al. 2010; Riedl and Serafeim 2011; Magnan et al. 2015; Goh et al. 2015). Furthermore, as accounting standard-setting bodies, such as the FASB and IASB, work to improve the quality of footnote disclosures in public filings (FASB 2018; IASB 2021), the insights from this study can contribute to making fair value footnotes more meaningful to users. This study also paves the way for future research to investigate the content and formatting of fair value narratives, and how different user groups interpret and utilize them.

The technical appendix, "*A guide on extracting, processing, and operationalizing narrative disclosure data*," explains how researchers can extract, clean, store, and quantify narrative disclosure information from Form 10-K reports, and highlights the associated challenges. Moreover, in addition to increasing the transparency concerning the data and textual constructs used in this thesis, the technical appendix serves as a practical guide for researchers interested in using narrative disclosure data from Form 10-K reports in their studies.

In conclusion, this thesis explores narrative disclosures in Form 10-K reports. These disclosures constitute the majority of information firms provide, and offer invaluable insights into a firm's financial health, risk factors, and overall performance. Through a comprehensive exploration of narrative disclosures in Form 10-K reports, and a discussion of how they can enrich empirical accounting research, this thesis contributes to the accounting literature, and underscores the important role these disclosures play in financial reporting.

Technical appendix: A guide on extracting, processing, and operationalizing narrative disclosure data

Narrative disclosures are integral to financial reporting and a rich information source for financial statement users. Specifically, these disclosures often provide insights that quantitative data alone cannot convey, and allow firms to communicate more abstract information about their performance, risks, and outlook. Moreover, they comprise about 80 percent of an annual report (Lo et al. 2017), and provide users with financial and non-financial information. However, they also constitute soft information and carry nuanced and context-dependent details that are difficult to quantify (Liberti and Petersen 2019). Overall, quantifying soft information has been a fundamental challenge for researchers working with narrative disclosures. To address this challenge, accounting researchers rely on natural language processing (NLP) techniques, and interdisciplinary approaches that borrow from linguistics, psychology, and computer science.

Extracting information from narrative disclosures in annual reports poses several challenges. First, as narrative disclosures are unstructured, identifying and extracting relevant narratives from annual reports requires a combination of specialized NLP techniques and manual review. Second, narrative disclosures come in varying lengths, structures, styles, and formats. Thus, storing, quantifying, and analyzing these disclosures requires substantial computational resources. Third, these disclosures often discuss multidimensional constructs and complex topics (e.g., strategy, risk). Therefore, operationalizing these disclosures into research variables, while ensuring construct validity, poses a significant challenge to researchers.

Given the difficulties involved in working with narrative disclosures, researchers initially defaulted to using hard information like financial statements and ratios. However, technological advancements have since made extracting and processing textual data easier (Bochkay, Brown, Leone, and Tucker 2023). Specifically, modern computers allow faster data processing speeds, while big data technologies and cloud computing services make storing large text volumes easier. Moreover, innovations in computational linguistics, and regulatory initiatives that improve transparency and accessibility of business information, like XBRL, have simplified the integration of narrative disclosure data in empirical research. Furthermore, open-source libraries and application programming interface (API) services have democratized access to textual analysis tools.

In this thesis, in addition to downloading data directly from EDGAR, I also capitalize on additional information sources that distil EDGAR annual report information into easier-to-use formats. Specifically, I leverage three data sources: the Software Repository for Accounting and Finance, which provides clean Form 10-K report filing data; xbrlresearch.com, which uses XBRL to construct a database of the narrative component of the most prevalent financial statement notes of Form 10-K reports; and the Division of Economic and Risk Analysis (DERA), which contains aggregated data from public filings.

These resources, some of which are thoughtfully compiled and shared by the academic community, significantly streamline the process of working with narrative disclosure data from Form 10-K reports. Also, they enable the extraction of narrative and tabulated disclosure insights from Form 10-K report footnotes. Ultimately, these resources allow researchers to save considerable time and computing power. Furthermore, as they are publicly available, and have undergone quality assurance by experienced users and academics, these resources offer a great starting point for researchers looking to use Form 10-K report narrative disclosure data in their studies.

Extracting and storing narrative disclosure data from Form 10-K reports

Prior literature acknowledges the many challenges of working with narrative disclosure data (e.g., Loughran and McDonald 2016; Bae, Yu Hung, and van Lent 2023). However, most studies focus on common NLP challenges like computational power limitations, storage constraints, and the coding intricacies of algorithmic text processing, and pay less attention to the equally important and resource-consuming task of identifying and collecting narrative disclosure data.

Although issues relating to textual data collection and handling have historically been a significant barrier to entry for those interested in working with narrative disclosures, recent technological advances provide researchers with the hardware and software infrastructure to collect and process textual data more efficiently. These innovations allow researchers to focus on questions that they could not otherwise investigate, and have contributed to increasing textual analysis publications over time (Bochkay et al. 2023). However, easier access to tools necessary for textual analysis has highlighted the importance of high-quality textual data as inputs. Moreover, it introduces a need for a more thorough discussion of the challenges of identifying, collecting, and storing such input data (Loughran and McDonald 2016).

Electronic Data Gathering, Analysis, and Retrieval (EDGAR)

Form 10-K reports are a key component of the regulatory framework that governs public firms in the U.S., and help to promote transparency by disclosing financial and operational information to investors and the public. Moreover, firms must file these reports with the U.S. SEC, typically 60 to 90 days after a firm’s fiscal year-end. Subsequently, the

SEC's Electronic Data Gathering, Analysis, and Retrieval (EDGAR) system makes these reports publicly available.

EDGAR is an invaluable data source for accounting researchers interested in working with narrative disclosures. However, doing so efficiently poses several challenges to researchers, and requires substantial investment in coding skills. Fortunately, the academic community offers a plethora of resources that can facilitate the downloading of public filing data from EDGAR. For example, Anand, Bochkay, Chychyla, and Leone (2020) provide a comprehensive manual that explains how to collect and organize data from EDGAR. Moreover, the Notre Dame Software Repository for Accounting and Finance (SRAF) provides a central coding repository that includes coding resources that simplify the data retrieval process from EDGAR for researchers. Recent work also provides insights on how accounting researchers can benefit from generative artificial intelligence (GenAI), which can help them to develop code that accelerates textual data acquisition processes (de Kok 2023).

Despite recent technological advances, downloading data from EDGAR can still be time-consuming task that requires significant computational resources, and a stable high-bandwidth internet connection. Moreover, EDGAR filings contain artefacts, such as HTML tags, embedded PDFs, and JPGs, which substantially add to the size of each filing. Although researchers can clean these filings before storing them in their local machine, doing so can add to the download time. Furthermore, as EDGAR filings consist of unstructured data, effective cleaning involves numerous steps and often requires a manual review of the output. These challenges constitute an additional barrier to entry to narrative disclosure research, particularly for researchers who are only beginning to explore textual analysis methods.

Software Repository for Accounting and Finance (SRAF)

In Chapter 2 of this thesis, I download Form 10-K report data from SRAF, which is a central repository for programs and data that can facilitate narrative disclosure research. This repository builds on the work of Loughran and Mc Donald (2011), and serves as a hub for researchers interested in textual analysis. To this end, it offers user-friendly coding tools, and textual analysis resources that allow researchers to work with narrative disclosure data. Moreover, SRAF provides access to Form 10-K and 10-Q filings data, therefore eliminating the need for researchers to invest resources in downloading the data from the SEC's EDGAR website themselves. Furthermore, SRAF also provides clean Form 10-K and Form 10-Q reports that contain only textual information and exclude mark-up tags, ASCII-encoded graphics, and tables. Thus, researchers can save time and resources as they can access the information they need without having to clean the data.[22]

Xbrlresearch.com

In Chapter 3, I obtain fair value footnote narrative data from the Ahn et al. (2020) database, which is downloadable from Xbrlresearch.com. Historically, collecting footnote narrative data has been challenging due to the absence of standardized formats and the extensive variation in labeling used by different firms. Ahn et al. (2020) employ XBRL to efficiently gather disclosure data from Form 10-K reports. Moreover, their dataset focuses exclusively on narrative content within commonly encountered financial statement footnotes. To this end, Xbrlresearch.com contains fair value narrative data from footnotes tagged with the "us-gaap:FairValueDisclosuresTextBlock" tag, the most frequently used tag among firms

[22] To validate the quality of the data, I also downloaded a sample of Form 10-K Reports directly from EGDAR. Data comparisons confirm that SRAF provides high-quality narrative disclosure data.

reporting fair value information, appearing in 73 percent of cases between 2011 and 2016 (Ahn et al. 2020).

Division of Economic and Risk Analysis (DERA)

In Chapter 3, I use Form 10-K report footnote disclosure data, which researchers can source from the DERA. Among other offerings, such as insider transaction data or data from mutual fund prospectus, DERA provides users with a structured data library that contains financial statement data in a format that facilitates research involving narrative disclosures. Specifically, the “Financial Statement and Notes” dataset does not contain whole Form 10-K reports, but instead comprises of textual and numerical disclosure extracts from their financial statements and notes. Similar to Ahn et al. (2020), DERA uses XBRL to gather data from Form 10-K reports. Moreover, this dataset contains narrative as well as tabulated content within financial statement footnotes, whereas the Ahn et al. (2020) data offering contains only narrative footnote information. In addition, this comprehensive dataset is easy to download and store, and comes in a flattened format that facilitates empirical analysis.

However, similar to Xbrlresearch.com data, a limitation when using DERA library data is that they are available only after 2009. Specifically, to harvest data from financial statements the DERA library relies on XBRL, which is a standardized, machine-readable language that allows financial information to be tagged and organized in a structured format. Thus, data are available after XBRL reporting became mandatory. Nevertheless, while the XBRL initiative began in 2009, it came with a phased three-year implementation, with larger firms having to adopt XBRL reporting earlier than smaller ones. An additional limitation of this database is that data accuracy depends on correct and appropriate use of XBRL by registrant firms (e.g., Bartley, Chen, and Taylor 2010, Debreceny, Farewell, Piechocki, Felden, and Gräning 2010).

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