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Debt Dictionaries[1]

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Abstract

Stock and bond investors treat different aspects of firm information as value-relevant, generating distinct mappings of text to returns ("dictionaries"). Comparing stock and bond responses to earnings calls, bondholders emphasize operations and downside risk (relative to growth and innovation). While consistent with asset payoff differences, dictionary differences follow the investor cohort and not the payoff structure. Among bonds that are de facto equities but priced by bondholders—junior debt for which firm value is less than senior debt face value—bond investors continue to interpret information through a creditor's lens. Information ignored by one dictionary but not the other generates price underreaction.

Keywords: Cross-asset returns, Natural Language Processing, Machine Learning, Market Segmentation

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1. Introduction

Following the early observation that asset price movements are difficult to explain solely based on the release of new observable information (Shiller, 1981, Roll, 1984, Roll, 1988), a significant literature has evolved to identify important drivers of asset volatility (Cutler et al., 1989, Mitchell and Mulherin, 1994, Boudoukh et al., 2019). The emergence of quantitative textual analysis tools with the ability to map firm narrative disclosures to stock price movements has contributed enormously to this effort. Among others, Tetlock et al. (2008), Loughran and McDonald (2011), Meursault et al. (2023), and García et al. (2023) have proposed implementable models of business sentiment by projecting stock returns on textual features of corporate news and announcements. The success of these models has demonstrated the importance of qualitative, unstructured features of text toward understanding firm and market-level price behavior.

While the breadth and depth of equity markets make for a natural setting to estimate the text-to-return models described above, in the U.S., traded debt has become an increasingly important source of corporate funding. For instance, since 1997, more than two-thirds of CRSP-Compustat merged firms can be linked to at least one traded bond CUSIP.[2] Meanwhile, a growing consensus suggests a striking degree of segmentation between traded debt and equity markets. Debt and equity of the same firms exhibit lead-lag pricing relationships (Kwan, 1996, Addoum and Murfin, 2019) and require distinct pricing kernels (Choi and Kim, 2018, Binsbergen et al., 2024), leaving movements in bond yields difficult to explain based on corresponding equity returns (Collin-Dufresne et al., 2001). In short, if understanding equity volatility presents a puzzle, the same is doubly true for debt.

In this paper, we use natural language processing tools on firm disclosures to ask what words move debt returns, and more importantly, whether debt and equity investors treat the same earnings call language as value-relevant in systematically different ways. To the extent

[2]See Chuck Fang's Bond-COMPUSTAT link at https://www.chuckfang.finance/.

debt and equity securities respond to different semantic content, we document the distinct dimensions of text data that debt and equity respond to. We then ask whether the observed patterns are best explained by inherent features of the payoff structures of the two claims or by differences in the investor cohorts that price them.

To answer these questions, we analyze debt and equity price responses to words spoken in earnings calls for firms with debt and equity trading at the same point in time. By looking at contemporaneous price responses of the same firms to the same information, we can estimate separate functional mappings between textual content and unsigned stock and bond returns. These functions ($f_{\text{stock}}(\text{text})$ and $f_{\text{bond}}(\text{text})$, respectively), built using three different NLP methodologies, allow us to infer words, phrases, and word embeddings that elicit return volatility in the respective securities. We refer to these functions as "dictionaries," drawing an analogy to classical sentiment dictionaries used in financial text analysis (Loughran and McDonald, 2011). Distinct from some of the prior literature, we estimate our mappings on unsigned return magnitudes, focusing our dictionaries on earnings call themes that garner the selective attention of stock and bond investors. Compared to an alternative approach using signed returns designed to differentiate between "good" and "bad" news, our dictionaries are suited to answer the question at hand: what news moves debt and equity prices?[3]

After estimating separate dictionaries $f_{\text{stock}}(\text{text})$ and $f_{\text{bond}}(\text{text})$, we begin by establishing a new fact: debt and equity claims are priced using their own distinct dictionaries. We show this by rejecting a simple null hypothesis: if the dictionaries used by stock and bond investors are not distinct, then they should be interchangeable in predicting returns for both asset classes. Yet, when we attempt to use the stock dictionary to predict bond returns and vice versa, our results strongly refute the notion of interchangeability. Stock and bond dictionaries are economically and statistically distinct, both in- and out-of-sample. While

[3]Guided by contingent claims models of capital structure (Merton, 1974), we also remap absolute stock and bond returns to the same news about firm enterprise value before estimating our dictionaries. For example, rather than directly comparing raw stock and bond returns, we transform stock returns into corresponding model-implied bond returns derived from a simple Merton model, providing apples-to-apples comparisons across dictionaries.

both react to some degree of overlapping information, the stock dictionary by itself performs poorly in predicting bond returns, and the bond dictionary similarly underperforms in predicting stock returns. Both contain large amounts of incremental information relative to the cross-asset dictionary, implying non-overlapping themes of interest to the two investor cohorts.

Having established the existence of a distinct "debt dictionary" relative to prior stock-based mappings, we follow with a descriptive analysis emphasizing the key thematic differences across the two claims. Immediately, we show that several topic differences appear broadly consistent with what might be predicted by standard corporate finance theory, providing some measure of validation for the methodology. Earnings calls that predict reactions by stock markets emphasize growth-oriented, forward-looking words or phrases. By comparison, earnings calls that predict reactions by bond markets feature more discussions of costs and production. They also tend to highlight downside risk and liquidity at the firm and aggregate levels (although we also show that earnings calls containing more bond words are *not* more likely to be associated with lower stock or bond returns). Finally, using a measure that captures the relative frequency of bond vs. stock dictionary content used in earnings calls, we find the mix of bond vs. stock words in firm disclosure is closely tied to the credit cycle, with management emphasizing bond words when credit spreads are highest. In contrast, firms that are themselves closer to default avoid bond-oriented language, consistent with strategic disclosure.

With these new stylized facts in hand, the second half of the paper asks: what drives the use of separate debt and equity dictionaries? By itself, evidence of differences in dictionaries associated with debt and equity returns could simply reflect differences in the associated payoff structures of these assets: stocks respond to upside potential, while bonds are largely priced based on risk of default. Indeed, the characterization of bond and stock words in the paragraph above appears largely consistent with a payoff-based explanation for dictionary differences. We refer to this explanation of dictionary differences, in which investors use different text-to-return mappings for debt and equity due to the structural differences in their payoff characteristics, as the "payoff hypothesis." A key prediction of the payoff hypothesis explored below is that variation in payoff similarity should predict dictionary similarity and vice versa.

At the same time, dictionary differences may also reflect institutional segmentation in who prices the two claims. Stock and bond investors often sit in different institutions, or in different parts of the same institution, and operate with different mandates, valuation models, information sources, and professional vocabularies. Those institutional differences can generate systematic differences in how the same firm information is interpreted by different markets. The key implication of this "investor-cohort hypothesis," distinct from the payoff hypothesis, is that bond investors will continue to use a debt dictionary even when the claim they price becomes economically equity-like. In that sense, dictionaries correspond to the investor cohort rather than the payoff shape.

Given these alternative interpretations, the second half of the paper attempts to distinguish between explanations in which dictionaries are specific to 1) the asset being priced and 2) the investor doing the pricing. To assess the role of asset payoff differences in explaining dictionary differences, we draw on the contingent claims framework of Merton (1974), which shows that debt and equity of the same firm can be valued as a function of enterprise value. Debt default and recovery are triggered when the value of assets falls below the face value of debt outstanding. This makes debt value equal to the value of a risk-free claim minus the value of a put to equity holders, with strike price determined by firm leverage. Likewise, equity can be valued as a call option on the firm value process. This framework highlights (and quantifies) two key differences in payoffs that could plausibly drive differences in dictionaries. First and foremost, depending on leverage, news about changes in asset value corresponds to different return magnitudes for bonds and equity—that is, debt and equity have different "deltas."[4] Second, text may include news about the second moment of firm enterprise value, which affects debt and equity differently due to concavity/convexity in payoffs. Specifically, positive volatility shocks redistribute firm value from debt to equity. To borrow language from the options markets, equity has positive "vega" while that of debt is negative.[5]

Using the Merton framework, we can characterize, firm-by-firm, stock and bond claims that are economically most similar vs. most dissimilar. Again, our claim is that under the payoff hypothesis, debt and equity dictionaries would diverge the most when their payoff profiles are most dissimilar.

As a first test of this prediction of the payoff hypothesis, we sort firms based on a simple summary statistic for the relative risk profiles of debt and equity claims: the Merton distance-to-default. This measure uses implied asset values and volatility estimates derived from the Merton model to calculate how many standard deviations a firm's asset value sits above the default threshold (the face value of debt). As firms approach the default boundary, debt payoffs become more equity-like, as debt investors increasingly become the primary claimants on any remaining value. Yet, if anything, when sorting across distance-to-default, we find that the debt dictionary's incremental predictive power for debt returns increases as bonds become more equity-like.

As a more comprehensive approach, we also decompose payoff structure differences into separate delta (sensitivity to asset value news) and vega (sensitivity to asset volatility news) components. Again, if payoff differences drive dictionary differences, then stock-bond pairs that are most similar in response to news about the level and risk surrounding enterprise value should have the most similar dictionaries. Yet, as before, the opposite appears to be true in the data. Across both dimensions, as debt becomes more responsive to firm value and as matched equity payoffs become less convex with respect to firm value, the incremental power

[4] Ideally, our scaling of stock and bond returns to give apples-to-apples comparisons before estimating dictionaries should compensate for this, albeit imperfectly.

[5] Debt and equity may also respond differently to changes in the risk-free rate and the slope of the yield curve. By focusing on returns only around earnings announcements, we limit the scope for these factors to drive differential returns.

of debt dictionaries relative to equity dictionaries strengthens considerably. Overall, the cross-sectional variation in dictionary differences does not correspond to patterns predicted by a simple payoff explanation.

Instead, our next set of tests, using a sample of equity-like junior bonds, support an interpretation closer to what we would expect from the investor cohort hypothesis in which, regardless of payoff structure, bond investors strictly apply a bond dictionary to every asset they price. Junior debt provides a close approximation to an idealized setting in which we can ask: which dictionary is used when bond investors value equity-like claims? On one hand, junior debt is traded as debt and is likely to be primarily priced by debt investors. At the same time, its payoff structure can closely resemble equity under certain conditions. We focus on cases where a firm's asset value approaches the face value of senior debt, and junior debt consequently exhibits equity-like convexity—its payoff remains flat if asset value falls but captures the upside if it rises. In this region, junior debt displays both positive vega and an equity-like delta, similar to common stock. When we examine how well each dictionary predicts junior debt returns, we find consistent evidence that the debt dictionary dominates—even among increasingly equity-like junior debt positions, including those with positive model-implied vegas. This strongly suggests that debt investors maintain the same valuation framework even when valuing equity-like claims and it directly rejects a payoff explanation as the sole mechanism driving dictionary use.

In our final set of tests, we examine whether dictionary differences and their (mis)application can generate pricing errors. We find that for equity-like debt, for which stock words should matter (but don't), investors miss important information in earnings calls. This generates economically important mispricing and return predictability. Bonds underreact to news captured by stock dictionaries over a one–to–two–week horizon.

This paper makes contributions to several strands of the finance literature. We provide the first direct evidence on how bond investors respond to textual information relative to stock investors, documenting distinct mappings from language to returns across the two markets. While the existence of a separate debt dictionary—and the manner in which it differs from its equity counterpart—broadly aligns with standard predictions from corporate finance theory, our descriptive evidence also points to new directions for research on strategic disclosure: managers appear to adjust the mix of stock- and bond-coded content in response to both firm-specific and macroeconomic conditions.

More importantly, the paper distinguishes between payoff-based and investor cohort-based explanations for differences in information processing. We show that bond investors continue to apply a debt-oriented interpretive framework even when pricing equity-like claims, providing support for models of categorical thinking (Mullainathan, 2002) and offering a mechanism through which market segmentation can affect prices. Finally, we show that the misapplication of valuation frameworks across the capital structure can generate predictable pricing errors, suggesting a novel explanation for the growing evidence on stock and bond market disagreement.

2. Hypothesis Development and Methodological Overview

Our analysis begins with the question: do stock and bond markets respond differently to the same text-based information? Put differently, when claims issued by the same firm react to the same disclosure, do they exhibit different text-to-return mappings? To answer this question, we construct a sample of paired stock and bond returns around earnings calls for firms with both securities trading at the same time. We then train asset-specific NLP models on these paired observations, allowing us to compare how the same text is translated into valuations across the two asset classes and their respective investor groups. This setup yields two empirical objects: an own-asset mapping, where each dictionary predicts its corresponding asset, and a cross-asset mapping, in which the same dictionary is asked to explain the other claim.

Our empirical strategy for identifying dictionary differences emphasizes coefficient comparisons across two key regressions:

$$|R_i^S| = \beta_1 f^S(\text{text}_i) + \beta_2 f^B(\text{text}_i) + \epsilon_i \tag{1}$$

$$|R_i^B| = \gamma_1 f^S(\text{text}_i) + \gamma_2 f^B(\text{text}_i) + \upsilon_i, \tag{2}$$

where $|R_i^S|$ and $|R_i^B|$ represent the three-day ($t-1$ to $t+1$) absolute returns for stocks and bonds, respectively, subject to scaling adjustments detailed below. The functions $f^S(\text{text})$ and $f^B(\text{text})$ map earnings call text to contemporaneous returns, with $f^S(\text{text}) \equiv |\widehat{R^S}|$ and $f^B(\text{text}) \equiv |\widehat{R^B}|$ representing the fitted values from these mappings. These text-based measures are estimated using NLP models (described subsequently) on a training sample, while equations (1) and (2) are estimated on a separate test sample. To facilitate coefficient comparison, all variables are standardized to have zero mean and unit variance.

An important distinction from the approach of García et al. (2023) is that our dictionaries are estimated on unsigned returns. This choice is driven by both statistical and economic considerations. Statistically, our restriction to firms with contemporaneous equity and debt trading makes sample size a binding constraint and associated power considerations first-order. Applying text models to 60-day signed returns, Meursault et al. (2023) find R^2s of less than 1% without controls. In contrast, models of absolute returns achieve substantially higher explanatory power, with out-of-sample R^2 values of 20–30%. This improvement dramatically reduces the number of observations required to maintain reasonable ex ante power expectations for our most basic hypothesis test (i.e., do debt and equity dictionaries differ statistically?).[6]

Economically, models of absolute returns also align more closely with our primary hypotheses. Following Beaver (1979) and the subsequent disclosure literature, we interpret

[6] Consider the effect sizes required for the test $\beta_1 = \beta_2$ in the regression $R_i^S = \beta_1 f^S(\text{text}_i) + \beta_2 f^B(\text{text}_i) + \epsilon_i$. Assuming expected $R^2 \leq 0.01$, x_1 and x_2 are standard normal and coefficients sum to one, 80% power given 5% test size under our test sample (n=3,324) requires that $\beta_1 - \beta_2 \geq 0.5$ In other words, model performance would limit our ability to detect all but the largest dictionary differences.

announcement-period volatility as evidence of market attention to information. Separate absolute return dictionaries for stocks and bonds allow us to test whether the same text commands different amounts of attention across segmented investor cohorts. Relative to signed dictionaries, which emphasize disagreement about whether a given word is good or bad news, unsigned dictionaries emphasize whether a word or topic is salient for one investor cohort but not the other.

Our hypothesis of distinct market-specific dictionaries generates three testable predictions from specifications (1) and (2):

1. **Own-asset relevance:** Each asset-specific dictionary should exhibit a significant relationship with returns of its corresponding asset class. Formally, we expect $\beta_1 > 0$ in equation (1) and $\gamma_2 > 0$ in equation (2).[7]
2. **Cross-asset relevance:** Given that both assets derive value from the same underlying firm, we expect some relationship between each asset's returns and the other asset's dictionary. Specifically, the stock dictionary $f^S(\text{text})$ should help explain bond returns ($\gamma_1 > 0$), and the bond dictionary $f^B(\text{text})$ should help explain stock returns ($\beta_2 > 0$).
3. **Dominance of own-asset dictionary:** While both dictionaries may relate to returns, we expect the own-asset dictionary to dominate. In multivariate specifications including both dictionaries, the coefficient on the other asset's dictionary should be economically and/or statistically insignificant relative to the own-asset dictionary.

Finally, rather than directly estimating and testing dictionaries on raw stock and bond return magnitudes, we work with three pairs of return transformations that rescale returns into more comparable units. As a conceptual benchmark, we might like to know whether bond and stock investors draw the same inferences from earnings calls about enterprise value. To implement this approach, we would need to transform stock and bond returns into matching implied returns on total firm value. However, in practice, the required joint

[7] While this relationship holds by construction in the training sample, our tests focus on out-of-sample validation.

scaling of stocks and bonds becomes unstable for very safe debt, where bond sensitivities approach zero and scaling factors approach infinity. As a feasible alternative, we instead scale stock returns into implied bond returns before estimating dictionaries. Under this transformation, the stock dictionary provides a framework to determine the bond return that stock investors would implicitly infer from a given set of text. This provides a natural benchmark for comparison with the bond dictionary.

We accomplish this via a mix of theory and empirically derived scaling factors, in each case applied to stocks, before estimating dictionaries:

1. **Simple scaled returns:** The function $f^S_{\text{scaled}}(\text{text}) \equiv |\widehat{R^S_{\text{scaled}}}|$ is estimated using stock returns divided by their mean absolute returns in the pre-earnings call period and multiplied by mean absolute returns for the corresponding bonds in the pre-earnings call period. This effectively rescales stocks to match the observed volatility of bonds immediately prior to a given call.
2. **Theory-adjusted returns:** The function $f^S_{dlev_1}(\text{text}) \equiv |\widehat{R^S_{dlev_1}}|$ refers to predicted delevered stock returns based on an implied hedge ratio from an estimated Merton model. This approach to scaling helps us compare the returns that we would expect from stocks if they had the same delta with respect to enterprise value as the firm's bonds. Said otherwise, using $f^S_{dlev_1}(\text{text})$ and $f^B(\text{text})$ allows us to compare what equity investors and bond investors think returns to the same claim (bonds) should be based on the news about asset value. The hedge ratio, defined as the sensitivity of the return on a risky bond to the return on equity, is calculated similarly to Schaefer and Strebulaev (2008) as $h_e = (1/\delta - 1)(1/L - 1)$. L is leverage, calculated as the ratio of total liabilities to the market value of the firm. δ refers to the change in value of equity with respect to the value of the firm, or $N(d_1)$ from the original Black-Scholes formula. Firm value and asset volatility are solved for jointly. Equity volatility, time to maturity, and the risk-free rate (necessary inputs to the calculation) are based on volatility in the prior 12 months of monthly returns and the duration of outstanding bonds provided

in Dickerson et al. (2023), and the risk-free rate is the one-year, constant maturity treasury yield from FRED.[8] For more details on the calculation of the hedge ratio, see the Appendix. Given h_e, delevered stock returns $|R^S_{dlev_1}|$ are $h_e \times |R^S|$.

3. **Regression-adjusted (delevered) returns:** The function $f^S_{dlev_2}(\text{text}) \equiv \widehat{|R^S_{dlev_2}|}$ refers to empirically delevered stock returns using coefficients from leverage-sorted bond-stock return regressions. Specifically, we estimate ten separate regressions of bond returns on stock returns within leverage deciles, using the resulting coefficients to scale stock returns. This method provides an empirical analog to the theoretical delevering above, again mapping stock returns into bond-return units for comparison with the bond dictionary.

Central to our analysis are the estimated functions $f(\text{text})$, which we refer to as dictionaries. These functions map earnings call text to contemporaneous ($t-1$ to $t+1$) daily stock and bond returns. We employ multiple NLP approaches for robustness, as recent research shows that individual approaches can yield substantially different economic measurements (e.g., Ash and Hansen, 2023; Ganguli et al., 2024). Our ensemble combines three approaches from the recent literature:

$$\widehat{|R_i^{(1)}|} = \alpha^{(1)} + \sum_{j=1}^{V} \theta_j^{(1)} t_{ij}^{(1)} \quad \text{(Ridge on BoW)} \tag{3}$$

$$\widehat{|R_i^{(2)}|} = \alpha^{(2)} + \sum_{j=1}^{V} \theta_j^{(2)} t_{ij}^{(2)} \quad \text{(MNIR)} \tag{4}$$

$$\widehat{|R_i^{(3)}|} = \alpha^{(3)} + \sum_{j=1}^{E} \theta_j^{(3)} t_{ij}^{(3)} \quad \text{(Ridge on GTE),} \tag{5}$$

where $\widehat{|R_i^{(m)}|}$ represents the fitted return for model m, $\alpha^{(m)}$ is the model-specific intercept, $\theta_j^{(m)}$ are the coefficients, and $t_{ij}^{(m)}$ are the text representation elements. The first approach

[8]Board of Governors of the Federal Reserve System (US), Market Yield on U.S. Treasury Securities at 1-Year Constant Maturity, Quoted on an Investment Basis [DGS1], retrieved from FRED, Federal Reserve Bank of St. Louis; https://fred.stlouisfed.org/series/DGS1, October 30, 2024.

follows Meursault et al. (2023), using ridge regression on a bag-of-words representation. The second implements the Multinomial Inverse Regression (MNIR) methodology of García et al. (2023) using distributed multinomial regression (DMR) with robust estimation. The third applies ridge regression to GTE-large embeddings (Ganguli et al., 2024; Li et al., 2023) using a concatenated-mean aggregation strategy: for each earnings call, we create 1,000-token overlapping chunks and generate 1,024-dimensional embeddings per chunk using the `Alibaba-NLP/gte-large-en-v1.5` model.[9] We then aggregate these to the document level by concatenating the first four chunk embeddings and adding their mean, yielding $E = 5{,}120$ dimensions: $(4 \times 1{,}024) + 1{,}024$.[10] For the first two models, V denotes vocabulary size. The GTE embeddings $t_{ij}^{(3)}$ are derived using this preprocessing pipeline.

We combine these approaches using a performance-weighted ensemble:

$$\widehat{|R_i|}_{\text{ensemble}} = w_1 \hat{y}_i^{(1)} + w_2 \hat{y}_i^{(2)} + w_3 \hat{y}_i^{(3)}, \tag{6}$$

where $\hat{y}_i^{(m)}$ represents the standardized output from model m, and w_m are weights optimized to minimize root mean squared error (RMSE) on the training sample.[11] This ensemble approach leverages the complementary strengths of each model while mitigating their individual weaknesses. While we present results using the ensemble, our main findings—particularly the importance of asset-specific dictionaries in explaining returns—remain robust to using any individual component model.

[9] Specifically, we tokenize transcripts using quanteda's fastestword tokenizer (Benoit et al., 2018), create overlapping chunks (size=1,000 tokens, overlap=50 tokens), and keep the first five chunks per transcript.

[10] This concatenated-mean approach preserves both positional information (different sections of the call may contain distinct signals) and a holistic document representation. For instance, opening management remarks in early chunks may emphasize different themes than Q&A sections in later chunks.

[11] The weights sum to one and are estimated separately for each dependent variable, allowing the ensemble to adapt to each investor group's characteristics.

3. Data

Our analysis combines several data sources. Earnings call transcripts come from the Capital IQ Transcripts database via Wharton Research Data Services (WRDS) from 2005 to 2021. Corporate bond returns are from the open-source dataset of Dickerson et al. (2023).[12] We obtain stock returns from CRSP and accounting information from Compustat. Analyst forecast data are from IBES, and we calculate earnings surprises as actual earnings per share minus the median analyst forecast, scaled by price at the end of the prior fiscal quarter (Bernard and Thomas, 1989; Brown et al., 1987).[13] Each observation is an earnings call matched to contemporaneous stock and bond returns for the same firm. Call dates are aligned using transcript timestamps: calls beginning by 3:00 p.m. Eastern are matched to same-day returns, later calls are assigned to the next day, and Friday after-market calls are excluded.

Throughout our analysis, bond returns are calculated using clean prices (i.e., quoted bond prices that exclude coupon interest accrued since the last payment date). This choice is motivated by several considerations. In particular, because our focus is on returns around earnings calls, clean prices better isolate changes in valuations associated with new information. In contrast, accrued interest evolves deterministically and is unrelated to news in earnings calls. As a result, returns based on dirty prices may contain predictable variation that could bias estimates of news sensitivity in bond valuations.

Table 1 summarizes the matched sample used in the paper. The sample contains 15,843 earnings call observations with contemporaneous stock and bond returns for the same firm-date. We use a pre-specified five-fold split: folds 1-4, comprising 12,519 observations, are used to estimate the text-to-return mapping functions $f(\text{text})$, while fold 5, containing 3,324

[12] https://openbondassetpricing.com. Last accessed: 10/30/2024.

[13] Transcripts and Compustat data are provided by S&P Global Market Intelligence, Center for Research in Security Prices, LLC (CRSP) data are via Morningstar (formerly provided by the University of Chicago Booth School of Business), and IBES data are via the London Stock Exchange Group (LSEG) (formerly provided by Refinitiv).

observations, is reserved for out-of-sample analysis.[14] This stratified approach ensures robust out-of-sample validation while maintaining sufficient training data.

Table 1: Sample Construction and Training-Test Split

Filtering Step	**Observations**
Total Earnings Calls (as of 07/06/23)	310,827
Calls of Firms With Matched Bond Data	15,843
Training Set	12,519
Test Set	3,324

Table 2 documents the distribution of absolute returns across different scaling approaches. Several patterns emerge. When scaling by pre-announcement return volatility, both the mean and standard deviation of stock returns exceed those of bond returns, consistent with equity markets showing stronger reactions to earnings news relative to their baseline volatility. However, after accounting for leverage—either through our theoretical hedge ratio ($|R^S_{dlev_1}|$) or empirical sensitivities ($|R^S_{dlev_2}|$)—bond returns actually exhibit greater volatility than the corresponding delevered stock returns.[15] This suggests that bonds react to information seemingly ignored by equity markets, exhibit more idiosyncratic price movement, or both. Our analysis of market-specific dictionaries helps distinguish between these possibilities by identifying whether bonds respond to information available to both markets but incorporated only by debt investors.

[14] All junior bond observations are assigned to the test set. This ensures that our tests of dictionary power on equity-like junior debt (discussed in Section 6) use the full available junior debt sample.

[15] Specifically, references to higher volatility refer to the higher means of absolute returns.

Table 2: Summary Statistics: Absolute Return Measures (%)

	Obs	Mean	Std. Dev.	Min	Max
$\lvert R^S_{scaled}\rvert$	15,843	1.52	1.91	0.01	11.42
$\lvert R^S_{dlev_1}\rvert$	15,843	0.27	0.61	0.00	3.25
$\lvert R^S_{dlev_2}\rvert$	15,843	0.17	0.23	0.00	1.16
$\lvert R^B\rvert$	15,843	0.71	0.90	0.00	4.68

4. Main Results: Evidence on Distinct Stock and Bond Dictionaries

Following the framework developed in Section 2, we establish the paper's core empirical fact: stock and bond markets employ distinct dictionaries in processing earnings call information. We do so by testing whether separate stock and bond dictionaries are necessary to explain the cross-section of out-of-sample earnings call returns, and whether own-asset dictionaries dominate that of the cross-asset. Later sections examine what these dictionaries contain and what explains their differences.

We implement this test by comparing bond and stock dictionary coefficients across the three return scaling approaches outlined in Section 2. All variables are standardized, allowing us to interpret coefficient magnitudes as the effect, in standard deviations of the dependent variable, of a one-standard deviation change in the independent variable. These standardized coefficients can also be interpreted as partial correlations between the text-based measures and returns.

Table 3 presents results using our first scaling approach, where absolute stock and bond returns are scaled by their respective pre-announcement average absolute returns. The results speak directly to the three testable implications of separate market dictionaries developed in Section 2.

First, consistent with our prediction about own-asset relevance, Columns 1-4 report strong support from univariate, out-of-sample tests. The stock dictionary better explains stock returns than the bond dictionary, while the bond dictionary better explains bond returns. For example, in the stock return regression, the coefficient on $f^S_{\text{scaled}}(\text{text})$ (Column 1) is 0.413, substantially larger and statistically different from the 0.355 coefficient on $f^B(\text{text})$ (Column 2). Similarly, in the bond return regression, the coefficient on $f^B(\text{text})$ (Column 4) is 0.504, compared to 0.420 for $f^S_{\text{scaled}}(\text{text})$ (Column 3). Note that in these univariate regressions, comparing coefficient magnitudes for the standardized variables is equivalent to comparing R^2s, which are likewise stronger for own-asset dictionary regressions.

Supporting our second prediction regarding cross-asset relevance, the results also reveal connections between the two markets' interpretations of text. Each dictionary shows some ability to explain the other market's returns, suggesting both capture common information about firm value. While the stock dictionary appears to explain bond returns better than the bond dictionary explains stock returns (comparing Columns 2 and 4), this asymmetry proves sensitive to our scaling choice.

Columns 5 and 6 address the third implication of the separate dictionaries hypothesis regarding the dominance of own-asset dictionaries. The results strongly support this prediction: even controlling for the other market's dictionary, each market's own dictionary maintains its explanatory power while cross-market dictionary coefficients become economically and statistically less significant. Unreported tests of significance across coefficients consistently show that the coefficient of the own-asset dictionary is larger than that of the cross-asset dictionary. The limited incremental explanatory power of the second dictionary is also evident in the R^2 statistics, which barely increase when adding the other market's dictionary (0.166 in Column 1 versus 0.170 in Column 5, and 0.233 in Column 4 versus 0.234 in Column 6).

Columns 7 and 8 add firm fixed effects to address potential concerns that our results reflect fixed firm or industry characteristics.[16] For example, certain industries (e.g., oil) might exhibit both higher bond volatility and use specific technical language ("drilling," "reserves") in their calls. Without fixed effects, a bond dictionary might simply associate

[16]Findings are robust to the inclusion of time fixed effects as well. We avoid their inclusion because we are equally interested in evaluating the response to macro-level news—information that would be differenced out with time-fixed effects.

higher bond volatility with these industry-specific terms. While the difference in dictionary power shrinks in the fixed effects model of scaled stock returns (Column 7), this is unique to this scaling. Across six fixed-effects specifications—regressing bond and stock returns on three versions of stock scaling—the own-asset dictionary earns a statistically larger coefficient than the cross-asset dictionary in all but this one specification.

While our initial scaling approach addresses differences in return volatility by rescaling stock returns to match bonds' pre-announcement volatility, we explore two alternative approaches to account for structural differences in how assets respond to firm news: theory-based delevering ($|R^S_{dlev_1}|$) and delevering via regression ($|R^S_{dlev_2}|$).

The first alternative applies a Merton-model-implied hedge ratio to equity returns, matching their theoretical sensitivity to that of bonds. These specifications, comparing $|R^S_{dlev_1}|$ and $|R^B|$, appear in Table 4. The second alternative scales equity returns using empirically estimated hedge ratios based on leverage-sorted portfolios. These specifications, comparing $|R^S_{dlev_2}|$ and $|R^B|$, appear in Table 5. Both approaches preserve our core result: each asset's own dictionary continues to dominate the other asset's dictionary in explaining returns.

The consistency of our findings across all three scaling approaches demonstrates that the importance of market-specific dictionaries is not an artifact of any particular normalization choice. This conclusion is robust not only to different scaling methods but also to our choice of text analysis: in unreported results, we find similar patterns when using any individual component of our NLP ensemble rather than the combined approach.

Table 6 addresses a natural concern: could our results simply reflect different market reactions to earnings surprises rather than different interpretations of call content? We augment our main specifications with controls for the absolute value of the earnings surprise (measured relative to median analyst forecasts). The results remain stable both with and without firm fixed effects (Panels A and B, respectively), confirming that market-specific dictionaries capture genuine differences in how investor cohorts interpret qualitative information rather than differential reactions to quantitative earnings news.

5. Understanding Stock and Bond Dictionaries

Before directly examining why dictionaries differ, we provide descriptive evidence on how equity and credit markets differentially interpret earnings calls. We identify settings where the *text-implied reaction* is strong for one asset class but muted for the other, holding industry constant. These high-contrast calls provide the clearest setting for isolating the vocabulary and themes that most distinctly characterize stock- and bond-oriented language.

Let $f_i^S(\text{text}) \equiv |\hat{R}_i^S|$ and $f_i^B(\text{text}) \equiv |\hat{R}_i^B|$ denote fitted absolute returns for stocks and bonds, respectively. To account for cross-sectional heterogeneity, we convert these fitted values into *FF12-industry-specific* percentile ranks, $P^j(\cdot)$, and define the within-industry divergence:

$$\Delta_i^j = P^j\left(f_i^S(\text{text})\right) - P^j\left(f_i^B(\text{text})\right).$$

We then construct an indicator to isolate observations in the tails of this divergence distribution:

$$\text{ExtremeReaction}_i = \begin{cases} 1 & \text{if } \Delta_i^j > q_{0.90}^j \\ -1 & \text{if } \Delta_i^j < q_{0.10}^j \\ 0 & \text{otherwise} \end{cases}, \tag{7}$$

where q_p^j denotes the p-th percentile cutoff of Δ_i^j within FF12 industry j.

For the empirical implementation, we derive $f_i^S(\text{text})$ from the first principal component of fitted values across three absolute stock return specifications (details in Appendix B). We restrict the sample to the tails ($\text{ExtremeReaction}_i \neq 0$), partitioning calls into two corpora: those associated with extreme stock-specific responses ($\text{ExtremeReaction}_i = 1$) and those associated with extreme bond-specific responses ($\text{ExtremeReaction}_i = -1$). We characterize linguistic divergence in two steps. First, we use scattertext to reveal granular vocabulary differences. Second, we aggregate to standardized economic themes using the Bybee et al. (2024) 180-topic system as a corroborating summary.

5.1. Scattertext

To visualize differences between our two corpora, we employ a scattertext plot.[17] For consistency with our topic analysis, we restrict textual inputs to the Bybee et al. (2024) economic news vocabulary (over 18,000 unigrams and bigrams derived from *Wall Street Journal* articles), excluding proper names and stop words. The scattertext plot positions each term by its frequency rank in the stock-extreme corpus (x-axis) versus the bond-extreme corpus (y-axis). Terms above the diagonal are more characteristic of stock-extreme calls, while terms below the diagonal are more characteristic of bond-extreme calls. Appendix B.1 provides implementation details and tabulations of distinctive terms.

The scattertext analysis reveals systematic differences in the information that equity and credit investors emphasize.

Stock investors appear particularly attentive to growth-oriented, forward-looking discussion. The most stock-distinctive terms are dominated by expansionary language (e.g., "growth," "grow," "strong") and by signals of **geographic expansion** (e.g., "China," "Asia," "Japan"). Stock-extreme calls also tilt toward **technology adoption and innovation** (e.g., "digital," "innovation," "technology") and **strategic capital allocation** (e.g., "acquisition," "buyback," "share repurchase").

Bond investors, in contrast, emphasize operational fundamentals and downside risks. Bond-distinctive language is more grounded in **operations and asset-intensive activity** (e.g., "inventory," "maintenance," "rig," "vessel"), **broader economic challenges** (e.g., "crisis," "downturn," "recession,"), and **financial risk management** (e.g., "liquidity," "debt," "covenants," "default," "bankruptcy").

5.2. Topic Analysis Using Standardized Business News Themes

We next aggregate the same comparison to standardized economic themes to confirm that the word-level patterns reflect broader interpretive differences rather than isolated vo-

[17] https://github.com/JasonKessler/scattertext. Last accessed: 10/30/2024.

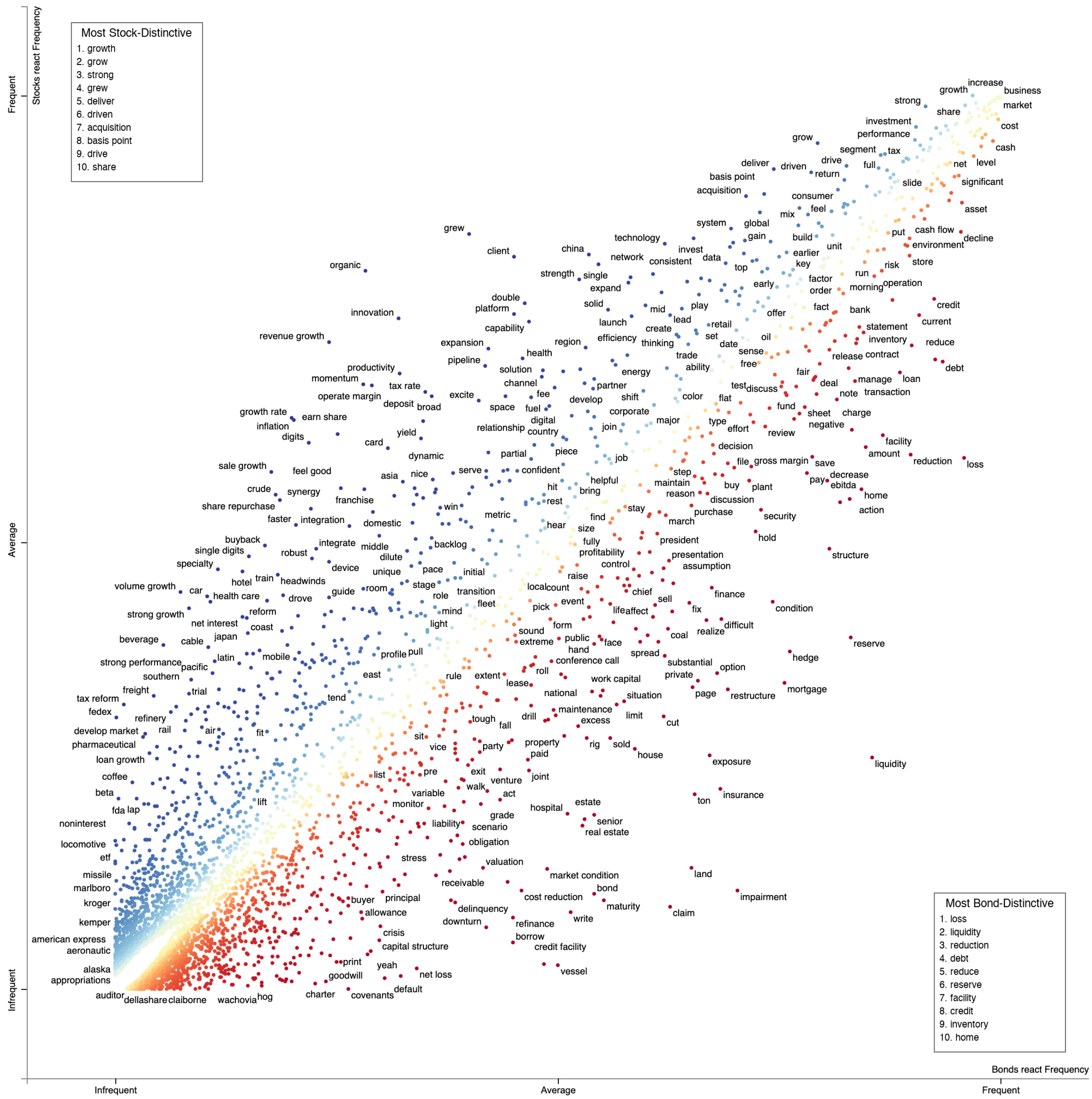

Figure 1: Scattertext Visualization of Stock and Bond Reactions

Notes: This figure presents a scattertext visualization comparing language in contexts where stocks react versus where bonds react. Each point represents a word or phrase, with its position indicating its relative frequency rank in stock-reactive versus bond-reactive contexts. Words closer to the top-right are more common overall, while those closer to the bottom-left are less frequent. Color intensity represents association strength with stock-extreme calls (blue) or bond-extreme calls (red).

cabulary choices. We project each call onto the Bybee et al. (2024) 180-topic classification system and regress the stock-versus-bond extreme indicator on topic prevalences:

$$\text{ExtremeReaction}_i = \alpha + \sum_{k=1}^{180} \beta_k \theta_{i,k} + \epsilon_i. \tag{8}$$

A positive β_k indicates topic k is more prevalent in calls associated with extreme stock responses, while a negative β_k indicates topic k is associated with extreme bond responses. Appendix B.2 provides additional projection details and alternative approaches.

Table 7 reports the topics with statistically significant coefficients, ranked by magnitude. The topic results corroborate the scattertext asymmetry. Stock-extreme calls load more heavily on themes related to growth and forward-looking performance (e.g., "Economic growth," "Revenue growth," "Earnings forecasts") as well as globalization (e.g., "China," "Southeast Asia") and technology (e.g., "Computers," "Internet," "Software"). Bond-extreme calls load more heavily on themes related to distress risk and capital structure (e.g., "Bankruptcy," "Financial crisis," "Default/Credit ratings") and on tangible real-economy themes tied to asset intensity and cyclical exposure (e.g., "Oil market," "Steel," "Real estate," "Machinery").

5.3. Debt Dictionaries and Firm Disclosure

We next examine the generative implications of dictionary differences: what language do firms use and when? Are bond words said more often in good or bad times? And how does disclosure shift during periods of distress, either at the firm or at the macro level?

To construct a measure of the relative frequency of bond- vs. stock-coded words, recall that the dictionary predictions from the prior sections already reflect fitted values from the bond and stock dictionaries. High values of the dictionary predictions imply words that generate volatility for a given asset class (i.e., bond or stock words) were uttered during a given conference call. Thus, we can easily create a "bond news" variable based on bond dictionary predictions, scaled appropriately. In particular, we propose the following variable, defined first at the level of an individual conference call:

$$BONDNEWS_{i,t} = \frac{e^{|\hat{R}_i^B|}}{e^{|\hat{R}_i^B|} + e^{|\hat{R}_i^S|}}, \tag{9}$$

where $f_i^B(\text{text}) \equiv |\hat{R}_i^B|$ and $f_i^S(\text{text}) \equiv |\hat{R}_i^S|$. We exponentiate dictionary fitted values to avoid instances where the denominator is near zero, although results are very similar using a simple difference between $|\hat{R}_i^B|$ and $|\hat{R}_i^S|$. For all results below, the variable is calculated only for the test sample (excluding observations used to train the dictionaries).

Because there are three scaled versions of the stock returns, we calculate $BONDNEWS_{i,t}$ using all three scaled stock predictions, then take the first principal component of the three and use this as our benchmark bond news measure. Finally, for time series results, we calculate a quarterly time series average of the firm-level variable for all conference calls during a given calendar quarter to create $BONDNEWS_t$.

We start with the time series to answer the following question: when do firms cater more to bond topics and how does that vary with measures of aggregate market stress? For our measure of credit market stress, we obtain the BAA–AAA corporate bond yield spread series from the Federal Reserve Bank of St. Louis FRED database (series IDs: BAA and AAA), accessed via the freduse Stata command (Coglianese and Williams, 2006).

The top panel of Figure 2 plots the time series of our measure of bond-coded disclosure. Immediately, we observe a striking correspondence between the frequency of bond words that firms use and credit spreads.[18] Of course, at face value, it might not be too surprising that bond words are more prevalent in "bad times." After all, Table 7 clearly points to

[18]Of course, even though the plot is constructed from a sample of calls excluded from the training sample, we still might worry that there are time series topics that appear jointly in the training and test sets that were associated with volatility and helped generate bond words in the training sample. For example, mentions of the COVID-19 pandemic are associated with bond (and stock) volatility as well as credit market stress. Perhaps words episodically associated with these volatile periods drive the time series correlation. To rule this out, we separately train our models on the first half of the time series and then test the correlation in the second. This ensures no temporal overlap between test and training samples. Even then, we find a correlation of 47% between bond news and spreads and, in a regression of bond news on spreads, a t-statistic of 2.99 using Newey-West standard errors with four lags.

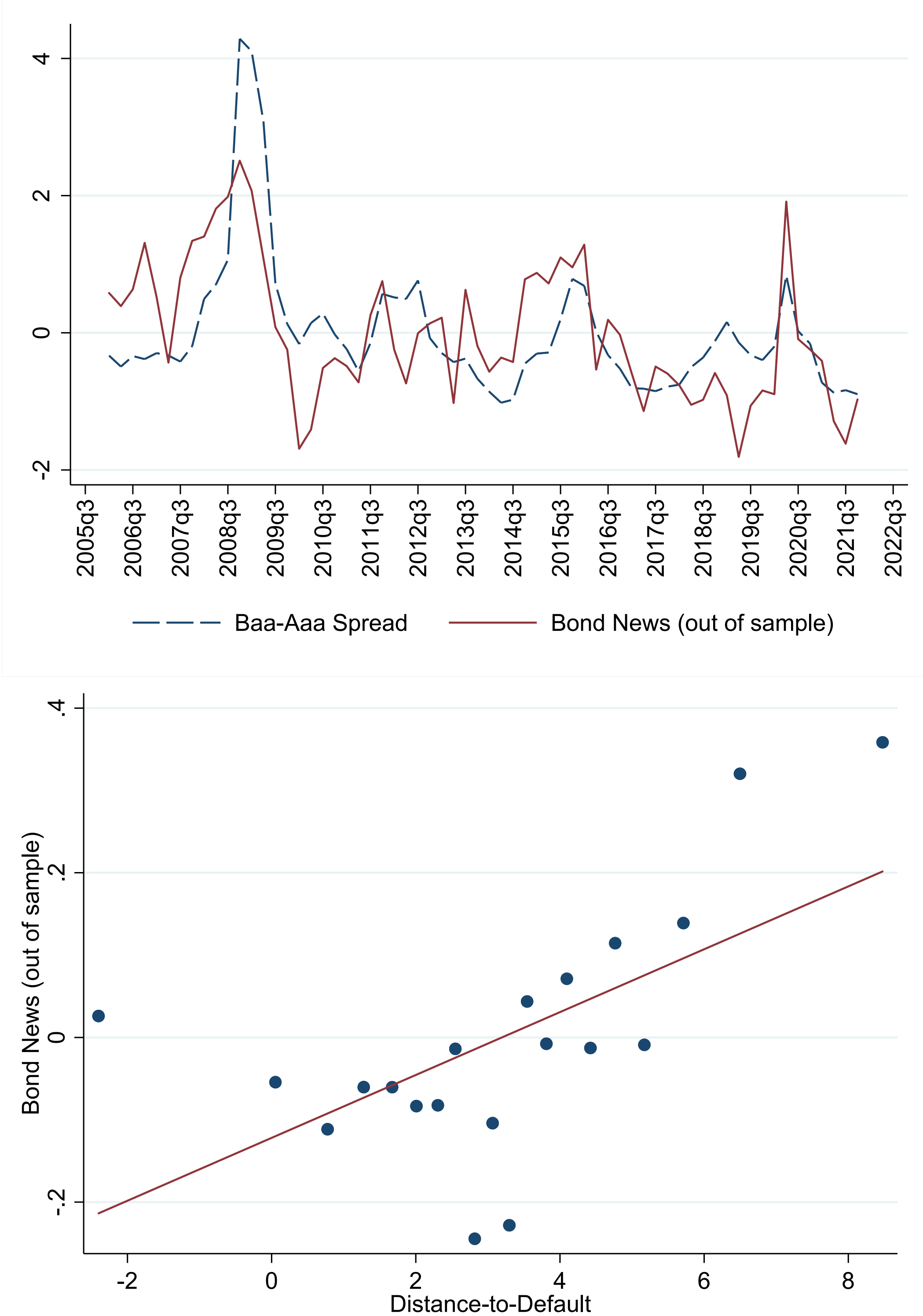

Figure 2: Mix of bond vs. stock news in the time series and cross-section

Notes: The top panel presents a time series of the quarterly average of the variable $BONDNEWS$ against the time series of Baa–Aaa credit spreads, both standardized to share mean zero and unit standard deviation. The bottom panel plots a binned scatterplot of conference call level $BONDNEWS$ against quantiles of firm distance-to-default, controlling for time (year-month) fixed effects. While, in the time series, the mix of disclosure tilts toward bond topics during periods of high credit risk premia, at the firm level, companies close to the default boundary tend to avoid the topics that bond investors react to.

bond words that emphasize downside risk and even distress, while stock words emphasize upside and growth potential. If we were to therefore (incorrectly) make the inference that, on average, $BONDNEWS$ indicates bad news, the time-series plot could be interpreted as firm disclosure simply reflecting higher risks of default or the prevalence of distress. However, when we examine the behavior of $BONDNEWS$ around firm-level distress, we find a more nuanced interpretation.

First, we show that $BONDNEWS$ is not more likely to be associated with bad news on average. In Table 8, we run regressions of $BONDNEWS$ at the firm-conference call level on time-series and cross-sectional characteristics.[19] After confirming in Column 1 the strong association in the time series with credit spreads from Figure 3, Columns 2 to 4 add firm-level characteristics. Column 2 in particular includes the stock and bond announcement returns and shows two precisely estimated null results; the measure $BONDNEWS$ is neither associated with negative (nor positive) stock or bond returns.

In fact, if we interpreted the relationship between credit spreads and $BONDNEWS$ as reflecting firms discussing their own distress more frequently, the evidence suggests the opposite is more likely true. In Columns 3 and 4, we add a firm-level distance-to-default measure calculated at the time of the call by solving the Merton model described in the Appendix. Distance-to-default captures the number of standard deviations firm asset value stands from the face value of debt. We find that, controlling for default risk, the coefficient on credit spreads only gets larger. More importantly, firms closer to default (low distance-to-default) actually express significantly fewer bond words, controlling for the aggregate environment. The bottom panel of Figure 2 presents a binned scatterplot confirming this result visually. While there is evidence of a slight uptick in $BONDNEWS$ for firms in the most extreme distress (low distance-to-default), for most of the plot, the relationship suggests that firms moving away from the risk of actual default are more willing to use

[19] In the table, spreads and distance-to-default are both standardized to have zero mean and unit standard deviation. Announcement returns are also standardized at the firm level.

words associated with a bond market reaction.

To summarize, we find evidence that (1) the average disclosure skews toward more bond words in periods of bond market stress, but (2) that it is relatively safer firms that drive higher bond-word disclosure. Taken together, these findings jointly suggest that, on one hand, managers acknowledge aggregate periods of credit market stress by speaking to bond investors, especially when the firm is healthy. At the same time, they avoid words that trigger bond price volatility when the firm is itself in distress. The second effect, although perhaps less intuitive than the first, could be consistent with strategic behavior around dictionary use and the possibility that managers are aware of the differential effects of their vocabulary on segmented security markets. While intriguing, we leave further exploration for subsequent work and proceed by documenting the mechanism behind the separate asset dictionaries.

6. Asset Dictionaries or Investor Dictionaries?

The evidence above confirms that bond and stock markets employ different dictionaries to extract value inference from companies' textual disclosures. The final sets of tests examine the origins of these differences, and in particular, whether these differences stem from the assets themselves or from the distinct analytical frameworks of different investor groups.

On one hand, the dictionaries might reflect fundamental differences in security design. Stocks are, on average, more sensitive to news about firm value based on equity investors' status as the residual claimants. Meanwhile, as a call option on asset value, stocks have a convex payoff structure. As a result, they tend to react positively to news about increased risk or uncertainty around asset value. In option market parlance, equities are characterized by their positive "vega." In contrast, bonds have a smaller "delta" with respect to news about asset value (at least outside of distressed situations), and senior bonds generate a concave payoff relative to enterprise value.[20] These fundamental differences in payoff structure would

[20] Delta in this context refers to sensitivity to enterprise value, not to be confused with the notation Δ_i^j defined in equation (7).

naturally induce investors to be more vs. less attentive to news about both asset growth and the riskiness of that growth. Many of the dictionary differences we document in earlier sections feel consistent with these payoff differences (e.g., equity emphasis on growth and debt emphasis on downside risk).

Alternatively, dictionary differences may arise from institutional segmentation between investor groups and the resulting differences in analytical approaches to valuation. This would be consistent with recently growing evidence of different pricing kernels or factor risks in stock and bond markets (Choi and Kim, 2018, Binsbergen et al., 2024), as well as the older literature that suggests that bond yields are difficult to reconcile with corresponding equity returns (Collin-Dufresne et al., 2001). If debt and equity investors pay attention to different information when valuing firms, then this would be reflected in the valuation of their corresponding claims.

Finally, these explanations need not be mutually exclusive. For instance, debt investors might rationally place less emphasis on long-term growth initiatives that rarely affect debt repayment, leading credit analysts to develop less expertise in evaluating such information. This specialization, however, could persist even in cases where growth prospects become relevant for debt value, such as in distressed firms where creditors may ultimately become equity holders.

The key empirical distinction between these two hypotheses is as follows: a payoff explanation for dictionary differences suggests dictionaries should align with asset characteristics, whereas the alternative suggests that dictionaries are specific to investor cohorts. Notably, the latter would imply that bond investors will use a bond dictionary to price all assets, suggesting the possibility of mispricing.

We distinguish between these "asset-based" and "investor-based" explanations through two approaches. First, we examine how the importance of market-specific dictionaries varies with the similarity of debt and equity payoffs. If dictionaries primarily reflect payoff structures and align with asset characteristics, the stock dictionary should become increasingly important in explaining bond returns as bonds become more equity-like. Conversely, if dictionaries reflect institutional segmentation, each market's own dictionary should retain its dominant explanatory power regardless of payoff similarity, i.e., bonds will still be valued like bonds, even when they feature stock-like characteristics. We test between these hypotheses by repeating our regressions of bond returns on own- and cross-asset dictionary predictions across firm-level sorts that vary in the degree to which bonds exhibit equity-like payoff structures. We show that as bonds become more stock-like according to several payoff-based metrics, their reliance on bond dictionaries increases rather than diminishes.

Our second approach exploits a natural experiment using junior bonds with a payoff structure closely resembling that of equity. Figure 3 illustrates how junior debt can be viewed as a bull-call spread on firm assets in a Merton framework. These bonds pay face value when firm value exceeds total debt, but become subordinate to senior claims in default. Around the senior debt boundary, junior bonds are equity-like: the payoffs are locally convex and exhibit both positive sensitivity to firm value (delta) and positive sensitivity to the volatility of firm value (vega). Because these securities have equity-like payoffs but are likely to be traded and priced by bond investors, they provide a unique setting to separate the effects of payoff structure from those of investor identity in determining which dictionary better explains returns.

We identify junior bonds by focusing on firm-dates where multiple bonds with different ratings exist within the same firm. We classify bonds with ratings below the firm's highest-rated issue as junior debt. For each observation, we calculate D_{junior} as the face value of these junior bonds and D_{senior} as total Compustat debt less D_{junior}. We then implement a modified Merton model that treats junior debt as a bull-call spread—equivalent to a long call option with strike price D_{senior} and a short call with strike price $D_{senior} + D_{junior}$. This allows us to estimate both the firm value (V_a) and the sensitivity (vega) of junior debt value to asset volatility (σ_a). We focus our analysis on junior bonds that are most equity-like: those where either $V_a \leq D_{senior}$ or the calculated vega is positive.

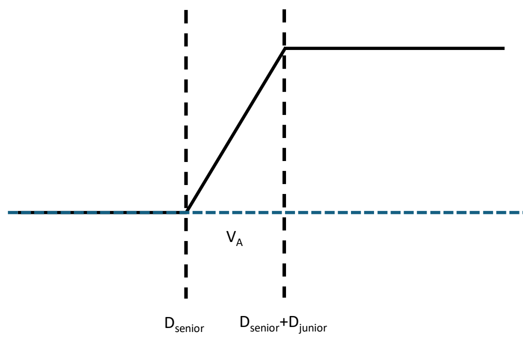

Figure 3: Junior Debt Payoff as a Bull-Call Spread on Firm Assets

Notes: The payoff from junior debt resembles a bull-call spread on the value of total firm assets (a purchased call and a sold call at strike prices equal to senior debt and total debt, respectively). For value of assets (V_a) near D_{senior}, the payoff is convex and therefore exhibits locally positive vega (sensitivity to volatility of V_a) and delta (sensitivity to the value of V_a). We find that, among junior bonds for which $V_a \leq D_{senior}$ or for which calculated vega is positive, a bond dictionary better explains returns than a stock dictionary.

Before examining the junior debt sample, we conduct a broader analysis of how payoff structure affects dictionary importance. Table 9 presents our baseline test, sorting firms by their distance-to-default—the number of standard deviations between current firm value and the default boundary ($\frac{V_a - D}{V_a \times \sigma_a}$). This measure captures where firms sit relative to the "kink" in their payoff diagrams. As firms approach default, debt becomes more equity-like through an increasing probability of creditors becoming residual claimants. Of course, this characterization is incomplete: even distressed debt typically maintains negative exposure to volatility, unlike equity. We address this distinction in subsequent tests. Inputs in the distance-to-default estimate for each firm-month come from our earlier solutions of the two Merton equations that link assets to equity and asset volatility to equity volatility.

Our analysis of distance-to-default sorts examines all three return specifications described earlier: scaled returns ($|R^S_{scaled}|$ and $|R^B|$), theory-adjusted returns ($|R^S_{dlev_1}|$ and $|R^B|$), and regression-adjusted returns ($|R^S_{dlev_2}|$ and $|R^B|$). For each specification, we estimate a bond return regression that includes both dictionaries, where we focus on the coefficient of the bond dictionary to measure its incremental explanatory power for bond returns.

If payoff structure drives dictionary differences, we should observe systematic patterns as we move across distance-to-default quartiles. Specifically, as firms approach default (moving right to left in our tables), bond payoffs become more similar to stock payoffs and we should see declining importance of the bond's own-asset dictionary. Table 9 reports the coefficients from the own-asset dictionary ($f^B(\text{text})$), as well as the difference between the own-asset and cross-asset dictionary coefficients as a measure of the incremental importance of the bond dictionary in explaining bond returns. Focusing on the firms with the highest and lowest distance-to-default, we find that bonds that are closer to default are consistently associated with more incremental importance of a separate bond dictionary, not less. In other words, if anything, the bond dictionary's explanatory power for bond returns increases (rather than decreases) as bonds become more equity-like. This is driven largely by the growth in the own dictionary coefficients; bond dictionaries become more useful in explaining bond returns as firms draw closer to default.

Table 9 sorts only on distance-to-default, but payoff differences between debt and equity stem from two distinct channels: different sensitivities to firm value (deltas) and opposite sensitivities to volatility (vegas). Of course, our initial scaling of stock returns in the three specifications should partially correct for the different deltas. However, these corrections are imperfect and cannot eliminate unobserved or mismeasured differences in payoffs generating the need for separate dictionaries. To better isolate the effects of payoff differences, we follow Table 9, this time adding a double sort. First, we sort firms into quartiles based on their hedge ratio—the relative sensitivity of bond returns to equity returns for a given change in firm value. High hedge ratio firms have more equity-like bonds in terms of delta. Within each hedge ratio quartile, we then sort firms based on vega, capturing the divergence in how debt and equity respond to volatility news. Since the vega of stocks and bonds are the mirror image of one another (i.e., holding value constant, a shock to asset volatility benefits equity by devaluing bonds), we sort only on the vega of stocks. High vega firms are those where debt and equity have the most divergent payoffs. In contrast, low vega firms have the most similar payoffs.[21]

For parsimony, Table 10 reports results only for the extreme quartiles of both sorts across our three return specifications. As in Table 9, we report 1) the coefficient on the own-asset bond dictionary (f^B(text)) from regressions including both dictionaries and 2) the difference in coefficients across the two dictionaries. If payoff structure drives dictionary differences, we should expect bonds' own-asset dictionary to be most important when payoffs are most different, i.e., among firms with low hedge ratios (different deltas) and high vegas (different responses to volatility).

The results again contradict a payoff-based explanation. Among bonds, high hedge ratio firms, where bonds are most equity-like, consistently show stronger own-dictionary effects. This pattern appears in all three specifications examining bond returns. The vega sorts also undermine evidence for payoff-driven dictionary differences. Moving from low to high vega should make debt and equity payoffs more distinct, implying stronger own-asset dictionary effects. However, we find no such pattern. For bonds, the effect actually reverses in half our specifications. In all three specifications, the coefficient on bond dictionaries grows for firms with less concave debt payoffs (less convex equity). Moreover, in all three specifications, the coefficient on bond dictionaries relative to that on stock dictionaries grows for firms with less convex equity.

The results to this point present a mixed message. On one hand, topic modeling and LLM summaries of bond vs. stock topics appear consistent with payoff differences being an important driver of how investors make value inference using text. At the same time, across different types of firms, the results suggest a more complicated picture. Differences in dictionaries appear to be driven by assets that have the most similar payoff structure.

Whereas our prior set of tests exploit a large cross-section of firms to examine how dictionary differences track payoff differences, our next set of tests zoom in on a smaller

[21]Formulas for the hedge ratio and vega are described in the Appendix, although it is important to note that we scale dollar vega by asset value (rather than equity value) so that equity and debt vegas are symmetric for each firm.

sample of assets chosen to understand whether dictionaries are asset or investor driven. We do so by creating a setting where bond investors price an asset that is nominally a bond but functionally equity. To do this, we focus on distressed junior bonds, which we argue are priced by bond investors but exhibit payoff characteristics more consistent with equity.

To this end, we identify junior debt as bonds that have ratings suggesting effective subordination to at least one other bond. Among these bonds, we solve a Merton model and focus analysis on 1,026 issues that either have positive implied vega or trade when implied asset values fall below the face value of senior debt. For robustness, we also report results focusing on a smaller sample containing only those bonds with positive implied vega (see the Appendix for details on calculation of junior debt vega). Both samples represent a highly selected set of firms — those operating under distress while maintaining traded public debt. While this selection limits generalizability, it provides exactly the variation needed to separate the effects of payoff structure from investor identity.

We examine these samples using the same empirical framework as our main analysis. For both samples, we estimate regressions of bond returns on stock and bond dictionaries using all three scaling approaches: scaled returns ($|R^B|$ regressed on $f^S_{\text{scaled}}(\text{text})$ and $f^B(\text{text})$), theory-adjusted returns ($|R^B|$ regressed on $f^S_{dlev_1}(\text{text})$ and $f^B(\text{text})$), and regression-adjusted returns ($|R^B|$ regressed on $f^S_{dlev_2}(\text{text})$ and $f^B(\text{text})$). Distinct from prior tests conducted at the firm-by-time level, here we exploit the fact that some firms may have several bonds trading simultaneously, giving us multiple observations per firm-date. To avoid overweighting firm-dates with many bonds trading, we weight the regression sample to give equal weight to each PERMNO×Earnings Call combination.

The results in Table 11 consistently show large, positive coefficients on the bond dictionary and coefficients near zero or negative on the stock dictionary. Columns 1-3 report results on a subset of junior bonds for which asset value is below the most leftward “kink” in Figure 2. In Columns 4-6, we calculate the Merton-implied vega of junior debt and limit the sample to firms for which it is strictly positive. The bond dictionary coefficients are both statistically significant and, with the exception of one specification in our smallest sample, significantly different from the stock dictionary coefficients at the 10% level at least.

Taken together, the descriptive language evidence and payoff-similarity tests support a coherent interpretation with two components. On one hand, the descriptive evidence is consistent with payoff differences helping to shape how debt and equity investors respond to textual narratives about firm value. Especially notable is equity and debt investors' differential emphasis on growth vs. risk language. That pattern is exactly what we would expect if security design helps shape what each market pays attention to.

At the same time, the results in this section suggest that dictionaries remain distinct even as debt and equity payoffs converge. The junior bond evidence provides perhaps the strongest test of competing explanations. These securities offer a unique setting where payoff structure and investor identity push in opposite directions, and the results are unambiguous: bond investors maintain their distinct approach to information processing even when pricing equity-like securities. Combined, the evidence is consistent with distinct bond dictionaries that may emerge from payoff differences but that are then used more broadly by bond investors across the asset class, even when pricing equity-like payoffs. In the next section, we turn to the potential pricing implications of that mismatch, and examine whether bonds underreact when there is disagreement between payoff structure and the dictionary used by investors.

7. Bond Mispricing and Return Predictability

In our final set of tests, we consider the potential for mispricing generated by investor-specific approaches to information processing. If investors in a particular asset class interpret value-relevant information only through a distinct class-specific lens, then they may miss important aspects of information releases that are relevant in determining prices and expected returns. Crucially, this is most likely to be the case when payoff structures across asset classes are similar, when cross-asset dictionaries should be most relevant to valuation (but as we have shown, are also most ignored).

To test this idea, we consider the predictive power of returns implied by the stock dictionary for future bond returns. Specifically, for firms with an earnings call in week t, we utilize the predicted absolute stock return implied by the stock dictionary. We multiply this absolute prediction by the observed sign of the stock return on the day of the call to compute a signed predicted return implied by the stock dictionary. Similarly, we compute a signed predicted bond return by multiplying the absolute bond dictionary-implied bond return by the sign of the bond return on the day of the earnings call. We then assess the incremental ability of the signed stock return predictions to explain future same-firm bond returns (incremental relative to the predicted return implied by the bond dictionary). As in earlier tests, we conduct this exercise across subsamples designed to capture firms with the most similar and dissimilar payoff structures across the two asset classes using a Merton model-implied distance-to-default (DTD) measure.

Our primary specification is a pooled cross-sectional regression of h-period ahead cumulative bond returns on signed return predictions implied by the stock and bond dictionaries. In computing future bond returns, we are careful to avoid look-ahead bias. In particular, for earnings calls falling on Mondays through Wednesdays of week t, we compute the 1-week-ahead return based on returns from Monday through Friday of week $t+1$. In contrast, for firms with earnings calls on Thursdays and Fridays of week t, we compute the 1-week-ahead return based on returns from Monday through Friday of week $t+2$. We then calculate cumulative returns over the following weeks for use in our predictive regressions. To account for potential delayed reaction to earnings announcements among bonds, we control for the actual stock return on the earnings announcement date in all specifications. We also include fixed effects at the weekly level and account for heteroskedasticity and clustering in standard errors on both the firm and time dimensions.

Table 12 presents the results from these tests. Across panels, we implement three specifications for $f(\text{text})$ and corresponding return measures. Within each panel, we compare the predictive power of the return implied by the stock dictionary in week t for h-week-ahead bond returns across subsamples of low- and high-DTD firms. Importantly, we also include bond dictionary-implied returns in all regressions, though we do not report the coefficient for this regressor in the interest of brevity. Consequently, the coefficient on the stock dictionary predictor reflects the incremental predictive effect on bond returns—–as predicted by the stock dictionary—beyond what is already predicted by the bond dictionary.

We first focus on the estimates in Panel A, where predictions are generated from the model where the stock dictionary is estimated using scaled stock returns. The estimates for low DTD firms, where stocks and bonds have the most similar payoffs, show a strong predictive relation between signed stock predictions and future bond returns. For example, a one standard deviation shift in the prediction based on the stock dictionary corresponds to a one-week-ahead bond return of about 9 basis points, with statistical significance at the 1% level. Looking further ahead, the predictive power of the signed stock predictor translates to a statistically significant cumulative bond return through a horizon of two weeks, with statistical significance falling below standard thresholds for horizons of three weeks and beyond. In contrast, the estimates for the sample of high DTD firms exhibit a distinct non-relation between signed predictions from the stock dictionary and future bond returns. The effect is especially weak over the relatively short horizons where the predictive power among low DTD firms is the strongest.

We find similar results in panels B and C of Table 12, where we respectively focus on results where the stock dictionary is estimated using theory-adjusted and regression-adjusted stock returns. As before, we find a strong predictive effect of signed returns implied by the stock dictionary on future bond returns among low DTD firms, where stocks and bonds should move most closely. Furthermore, we find the absence of a predictive relationship among high DTD firms.

From an economic perspective, the significance of the predictive effects in panels B and C are similar to those in panel A. In particular, a one standard deviation shift in the signed stock predictions correspond to one-week-ahead bond returns of about 8-9 basis points. An alternative interpretation based on the inter-quartile range of the predictor's distribution implies predictive effect sizes of about 15-16 basis points. In annual terms, this corresponds to bond return predictability of approximately 7.8-8.3%. This magnitude is comparable to that of established drivers of cross-sectional bond returns (e.g., Bao et al., 2011; Jostova et al., 2013).

Taken together, these results further support the notion that bond investors ignore important aspects of the information content in earnings calls when bond payoffs are similar to those of stocks. Our evidence suggests that this information is incorporated into bond prices over the following 1-2 weeks, consistent with a mispricing and correction interpretation.

8. Discussion

Our analysis establishes several new facts about market segmentation and textual information processing. First, debt and equity prices respond differently to identical textual information in earnings calls. These differences stem from distinct weighting functions (dictionaries) that investor groups apply to words, phrases, and word embeddings. While payoff differences might seem a natural explanation for these patterns, our evidence suggests otherwise. Instead, we find that segmentation between investor groups, each with its own investment culture and expertise, drives these distinct approaches to information processing. Perhaps our strongest evidence comes from junior bonds: even when pricing securities with equity-like payoffs, bond investors maintain their characteristic approach to information processing. We show that these dictionary differences matter in the sense that they can generate the opportunity for mispricing and impact firm disclosure.

The nature of these differences appears systematic and economically sensible. Equity investors focus on information about technology, innovation, growth, and international expansion—factors tied to upside potential. Bond investors emphasize crises and liquidity concerns, consistent with their traditional focus on downside risk. However, our evidence suggests that these differences extend beyond what pure payoff differences would predict. We propose that while differences may originate from divergence in security payoffs, they likely persist through other channels. For instance, if bond payoffs are typically insensitive to long-term margins or innovation, credit analysts may rationally develop less expertise in evaluating these factors. These initial specialization choices could then be reinforced by institutional structures, where knowledge spillovers remain confined within departmental or organizational boundaries, further cementing distinct approaches to evaluating textual disclosures.

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Table 3: Out-of-Sample Explanatory Power of Stock and Bond Dictionaries (Scaled $|R|$ Specification). This table presents results from regressions explaining scaled stock and bond returns using text-based dictionaries derived from daily returns around earnings announcements ($t-1$ to $t+1$ period). The absolute stock and bond returns are divided by the average absolute stock returns in the period preceding the earnings call, and then multiplied by average absolute bond returns in the period preceding the earnings call. The dictionaries $f^S_{scaled}(\text{text}) \equiv |\widehat{R^S_{scaled}}|$ and $f^B(\text{text}) \equiv |\widehat{R^B}|$ are constructed using an ensemble of text regressions. All variables are normalized to zero mean and unit variance. Standard errors are double-clustered at the firm and year-month levels.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	$\lvert R^S_{scaled}\rvert$	$\lvert R^S_{scaled}\rvert$	$\lvert R^B\rvert$	$\lvert R^B\rvert$	$\lvert R^S_{scaled}\rvert$	$\lvert R^B\rvert$	$\lvert R^S_{scaled}\rvert$	$\lvert R^B\rvert$
$f^S_{\text{scaled}}(\text{text})$	0.413***		0.420***		0.332***	0.034	0.198***	0.025
	[0.026]		[0.037]		[0.033]	[0.029]	[0.047]	[0.050]
$f^B(\text{text})$		0.355***		0.504***	0.100***	0.478***	0.152***	0.471***
		[0.029]		[0.036]	[0.037]	[0.040]	[0.051]	[0.063]
Observations	3,324	3,324	3,324	3,324	3,324	3,324	3,127	3,127
R^2	0.166	0.130	0.154	0.233	0.170	0.234	0.069	0.130
Firm FE	N	N	N	N	N	N	Y	Y

Table 4: Out-of-Sample Explanatory Power of Stock and Bond Dictionaries (Theory-Adjusted $|R^S|$ Specification). This table presents results from regressions explaining theory-adjusted stock and raw bond returns using text-based dictionaries derived from daily returns around earnings announcements ($t-1$ to $t+1$ period). The stock returns are adjusted using the Merton model to match the bond returns. The dictionaries $f^S_{dlev1}(\text{text}) \equiv \widehat{|R^S_{dlev1}|}$ and $f^B(\text{text}) \equiv \widehat{|R^B|}$ are constructed using an ensemble of text regressions. All variables are normalized to zero mean and unit variance. All specifications include firm fixed effects α_f. The standard errors are clustered at the firm level and at the year-month level.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	$\lvert R^S_{dlev1}\rvert$	$\lvert R^S_{dlev1}\rvert$	$\lvert R^B\rvert$	$\lvert R^B\rvert$	$\lvert R^S_{dlev1}\rvert$	$\lvert R^B\rvert$	$\lvert R^S_{dlev1}\rvert$	$\lvert R^B\rvert$
$f^S_{\text{dlev1}}(\text{text})$	0.615***		0.418***		0.585***	-0.017	0.502***	-0.045
	[0.033]		[0.037]		[0.047]	[0.037]	[0.059]	[0.052]
$f^B(\text{text})$		0.504***		0.504***	0.036	0.518***	0.046	0.521***
		[0.033]		[0.036]	[0.040]	[0.049]	[0.045]	[0.066]
Observations	3,324	3,324	3,324	3,324	3,324	3,324	3,127	3,127
R^2	0.309	0.218	0.153	0.233	0.309	0.233	0.146	0.131
Firm FE	N	N	N	N	N	N	Y	Y

Table 5: Out-of-Sample Explanatory Power of Stock and Bond Dictionaries (Regression-Adjusted $|R^S|$ Specification). This table presents results from regressions explaining regression-adjusted stock and raw bond returns using text-based dictionaries derived from daily returns around earnings announcements ($t-1$ to $t+1$ period). The stock returns are adjusted based on the β of the regression of stock returns on bond returns within a decile of leverage in the period preceding the earnings call. The dictionaries $f^S_{dlev2}(\text{text}) \equiv \widehat{|R^S_{dlev2}|}$ and $f^B(\text{text}) \equiv \widehat{|R^B|}$ are constructed using an ensemble of text regressions. All variables are normalized to zero mean and unit variance. Standard errors are clustered at the firm and year-month levels.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	$\|R^S_{dlev2}\|$	$\|R^S_{dlev2}\|$	$\|R^B\|$	$\|R^B\|$	$\|R^S_{dlev2}\|$	$\|R^B\|$	$\|R^S_{dlev2}\|$	$\|R^B\|$
$f^S_{\text{dlev2}}(\text{text})$	0.634***		0.393***		0.591***	0.026	0.385***	0.033
	[0.030]		[0.040]		[0.037]	[0.032]	[0.057]	[0.049]
$f^B(\text{text})$		0.505***		0.504***	0.057**	0.484***	0.110**	0.469***
		[0.030]		[0.036]	[0.029]	[0.034]	[0.044]	[0.061]
Observations	3,324	3,324	3,324	3,324	3,324	3,324	3,127	3,127
R^2	0.367	0.233	0.142	0.233	0.369	0.233	0.125	0.130
Firm FE	N	N	N	N	N	N	Y	Y

Table 6: SUE and Stock and Bond Dictionaries. This table presents results from regressions explaining absolute stock $|R^S|$ and bond $|R^B|$ returns using text-based dictionaries derived from daily returns around earnings announcements ($t-1$ to $t+1$ period). In each panel, we implement three specifications for $f(\text{text})$ and the corresponding return measures. Columns 1-2 correspond to scaled returns for stocks and raw bond returns $|R^S_{\text{scaled}}|$ & $|R^B|$ and associated dictionaries. Columns 3-4 correspond to theory-adjusted stock returns and raw bond returns $|R^S_{dlev_1}|$ & $|R^B|$ and associated dictionaries. Finally, Columns 5-6 correspond to regression-adjusted stock returns and raw bond returns $|R^S_{dlev_2}|$ & $|R^B|$ and associated dictionaries. All dictionaries are constructed using an ensemble of text regressions. All variables are normalized to zero mean and unit variance. Absolute standardized unexpected earnings (|SUE|, relative to median analyst consensus) are included as a control. In Panel B, all specifications also include firm fixed effects α_f. Standard errors are double-clustered at the firm and year-month levels.

Panel A: |SUE| Controls

	$\lvert R^S_{scaled}\rvert$	$\lvert R^B\rvert$	$\lvert R^S_{dlev1}\rvert$	$\lvert R^B\rvert$	$\lvert R^S_{dlev2}\rvert$	$\lvert R^B\rvert$
$f^S(\text{text})$	0.325***	0.038	0.581***	-0.009	0.557***	-0.013
	[0.033]	[0.028]	[0.045]	[0.035]	[0.035]	[0.030]
$f^B(\text{text})$	0.057	0.414***	-0.003	0.449***	0.036	0.452***
	[0.037]	[0.040]	[0.036]	[0.046]	[0.029]	[0.034]
|SUE|	3.505***	4.728***	2.985***	4.734***	3.744***	4.769***
	[0.869]	[0.683]	[0.605]	[0.684]	[1.016]	[0.684]
Observations	3,260	3,260	3,260	3,260	3,260	3,260
R^2	0.187	0.262	0.319	0.262	0.389	0.262
Firm FE	N	N	N	N	N	N

Panel B: |SUE| Controls and Fixed Effects

	$\lvert R^S_{scaled}\rvert$	$\lvert R^B\rvert$	$\lvert R^S_{dlev1}\rvert$	$\lvert R^B\rvert$	$\lvert R^S_{dlev2}\rvert$	$\lvert R^B\rvert$
$f^S(\text{text})$	0.204***	0.043	0.495***	-0.045	0.368***	0.011
	[0.046]	[0.049]	[0.057]	[0.050]	[0.056]	[0.048]
$f^B(\text{text})$	0.103**	0.419***	0.018	0.482***	0.087**	0.445***
	[0.052]	[0.063]	[0.041]	[0.064]	[0.043]	[0.060]
|SUE|	4.753***	3.961***	2.613***	3.974***	4.130***	3.941***
	[1.372]	[1.194]	[0.744]	[1.187]	[1.270]	[1.188]
Observations	3,063	3,063	3,063	3,063	3,063	3,063
R^2	0.093	0.144	0.150	0.144	0.148	0.143
Firm FE	Y	Y	Y	Y	Y	Y

Table 7: Stock- and Bond-Distinctive Economic Topics. This table lists all economic topics from Bybee et al. (2024) where the coefficient β_k is statistically significant at the 5% level, based on t-statistics derived from the regression specification in Equation (8). Topics are ranked by the magnitude of their regression coefficient β_k.

Rank	Stock-Distinctive Topics	Bond-Distinctive Topics
1–10	Economic growth, Revenue growth, Earnings forecasts, Record high, Earnings, Small business, Optimism, Convertible/preferred, Profits, Exchanges/composites	Product prices, Earnings losses, Credit ratings, Bank loans, Fees, Financial crisis, Short sales, Bankruptcy, Company spokesperson, Mortgages
11–20	China, Taxes, Couriers, Small changes, Federal Reserve, Major concerns, Buffett, Changes, Computers, Takeovers	Nonperforming loans, Savings & loans, Executive pay, Insurance, Retail, C-suite, Bond yields, Oil market, Commodities, Machinery
21–30	Soft drinks, Macroeconomic data, Size, Trade agreements, Southeast Asia, Share payouts, Phone companies, Small caps, Software, Broadcasting	Steel, Recession, Treasury bonds, Mining, Job cuts, Mid-level executives, SEC, Control stakes, Options/VIX, Health insurance
31–40	Germany, Latin America, France/Italy, Long/short term, Negotiations, Rail/trucking/shipping, Mexico, International exchanges, Key role, Space program	Real estate, Cable, Drexel, News conference, Publishing, People familiar, Environment, Agreement reached, Watchdogs, Lawsuits
41–50	Internet, Fast food, Japan, Spring/summer, Electronics, Nuclear/North Korea, UK, Acquired investment banks, Music industry, Canada/South Africa	M&A, Corporate governance, Pensions, Wide range, Tobacco, Justice Department, Activists, Problems, Indictments, Sales call
51–60	Iraq, Casinos, Airlines, Russia, Economic ideology, Middle East	European sovereign debt, Unions, Challenges, Agriculture, National security, Regulation, Scenario analysis, Accounting, Clintons, Committees
61–70		Courts, Political contributions, Bush/Obama/Trump, Gender issues, Reagan, Police/crime, US Senate, Management changes

Table 8: Bond News Disclosure. This table presents regressions of the variable $BONDNEWS$ calculated at the level of the individual conference call (firm-month). In Column 1, $BONDNEWS$ is regressed on quarterly Baa-Aaa bonds spreads. In Column 2, it is regressed on announcement stock and bond returns and time fixed effects. In Column 3, $BONDNEWS$ is regressed on Baa-Aaa spreads and firm distance-to-default. In Column 4, time fixed effects are added to absorb Baa-Aaa spreads.

BONDNEWS	(1)	(2)	(3)	(4)
Baa-Aaa spreads	0.603***		0.646***	
	[0.072]		[0.076]	
Announcement Stock Returns (signed)		0.015		
		[0.011]		
Announcement Bond Returns (signed)		0.002		
		[0.023]		
Firm Distance-to-Default			0.096**	0.109**
			[0.043]	[0.045]
Observations	3,324	3,324	3,324	3,324
R^2	0.042	0.161	0.047	0.166
Year-Month FE	N	Y	N	Y

Table 9: Payoff Differentials and Dictionary Power: Distance-to-Default. This table presents results from regressions explaining bond returns using text-based dictionaries derived from daily stock and bond returns around earnings announcements ($t-1$ to $t+1$ period). The sample of firms is split into quartiles based on model-implied distance-to-default. We report statistics for firms in the highest (Q4) and lowest (Q1) quartiles. γ_1 and γ_2 coefficients come from: $|R_i^B| = \gamma_1 f^S(\text{text}) + \gamma_2 f^B(\text{text}) + \epsilon_i$. We implement three specifications for $f(text)$ and the corresponding return measures. In Panel A, the stock dictionary f^S_{scaled} is estimated using scaled stock returns, $|R^S_{\text{scaled}}|$. In Panel B, the stock dictionary f^S_{dlev1} is estimated using theory-adjusted stock returns, $|R^S_{\text{dlev1}}|$. In Panel C, the stock dictionary f^S_{dlev2} is estimated using regression-adjusted stock returns, $|R^S_{\text{dlev2}}|$. The dictionaries are constructed using an ensemble of text regressions. All variables are normalized to zero mean and unit variance within each subsample. The standard errors are clustered at the firm level and at the year-month level. ***, **, and * indicate significance at the 1, 5, and 10% level.

Panel A: $|R_i^B| = \gamma_1 f^S_{scaled}(\text{text}) + \gamma_2 f^B(\text{text})$

	DTD Q1	DTD Q4
γ_2	0.464***	0.171***
	[0.050]	[0.051]

	DTD Q1	DTD Q4
$\gamma_2 - \gamma_1$	0.468***	0.117
	[0.094]	[0.092]

Panel B: $|R_i^B| = \gamma_1 f^S_{dlev1}(\text{text}) + \gamma_2 f^B(\text{text})$

	DTD Q1	DTD Q4
γ_2	0.491***	0.257***
	[0.071]	[0.052]

	DTD Q1	DTD Q4
$\gamma_2 - \gamma_1$	0.352***	0.074
	[0.125]	[0.088]

Panel C: $|R_i^B| = \gamma_1 f^S_{dlev2}(\text{text}) + \gamma_2 f^B(\text{text})$

	DTD Q1	DTD Q4
γ_2	0.443***	0.261***
	[0.040]	[0.053]

	DTD Q1	DTD Q4
$\gamma_2 - \gamma_1$	0.417***	0.360***
	[0.072]	[0.095]

Table 10: Payoff Differentials and Dictionary Power: Hedge Ratio and Vega Doublesorts. This table presents results from regressions explaining bond returns using text-based dictionaries derived from daily returns around earnings announcements ($t-1$ to $t+1$ period). The sample of firms is split into quartiles based on hedge ratio, and then quartiles of vega. We report statistics for firms in the highest (Q4) and lowest (Q1) quartiles. γ_1 and γ_2 coefficients come from: $|R_i^B| = \gamma_1 f^S(\text{text}) + \gamma_2 f^B(\text{text}) + \epsilon_i$. We implement three specifications for $f(text)$ and the corresponding return measures. In Panel A, the stock dictionary f^S_{scaled} is estimated using scaled stock returns, $|R^S_{\text{scaled}}|$. In Panel B, the stock dictionary f^S_{dlev1} is estimated using theory-adjusted stock returns, $|R^S_{\text{dlev1}}|$. In Panel C, the stock dictionary f^S_{dlev2} is estimated using regression-adjusted stock returns, $|R^S_{\text{dlev2}}|$. The dictionaries are constructed using an ensemble of text regressions. All variables are normalized to zero mean and unit variance within each subsample. The standard errors (unreported) are clustered at the firm level and at the year-month level. ***, **, and * indicate significance at the 1, 5, and 10% level.

Panel A: $|R_i^B| = \gamma_1 f^S_{scaled}(\text{text}) + \gamma_2 f^B(\text{text})$

γ_2	Vega Q1	Vega Q4	$\gamma_2 - \gamma_1$	Vega Q1	Vega Q4
h_e Q1	0.083	0.019	h_e Q1	-0.004	-0.171
h_e Q4	0.509***	0.250**	h_e Q4	0.593***	0.043

Panel B: $|R_i^B| = \gamma_1 f^S_{dlev1}(\text{text}) + \gamma_2 f^B(\text{text})$

γ_2	Vega Q1	Vega Q4	$\gamma_2 - \gamma_1$	Vega Q1	Vega Q4
h_e Q1	0.267***	0.129	h_e Q1	0.467***	0.074
h_e Q4	0.556***	0.467***	h_e Q4	0.704***	0.527**

Panel C: $|R_i^B| = \gamma_1 f^S_{dlev2}(\text{text}) + \gamma_2 f^B(\text{text})$

γ_2	Vega Q1	Vega Q4	$\gamma_2 - \gamma_1$	Vega Q1	Vega Q4
h_e Q1	0.237***	0.199**	h_e Q1	0.390***	0.258*
h_e Q4	0.442***	0.305***	h_e Q4	0.436**	0.135

Table 11: Stock vs. Bond Dictionaries for Equity-like Junior Debt. This table presents results from regressions explaining junior bond returns using text-based dictionaries derived from daily returns around earnings announcements ($t-1$ to $t+1$ period). The dictionaries are constructed using an ensemble of text regressions. Two categories of junior debt are considered: those for which the implied value of assets is below the face value of senior debt and those for which implied vega is calculated as positive from the Merton model including the junior tranche of debt. All variables are normalized to zero mean and unit variance. The standard errors are clustered at the firm level and at the year-month level.

	Positive vega $\mid V_a \leq D_{senior}$			Positive vega		
$\lvert R^B \rvert$	(1)	(2)	(3)	(4)	(5)	(6)
f^B(text)	0.771***	0.896***	0.659***	0.999**	2.275***	1.239***
	[0.202]	[0.318]	[0.167]	[0.492]	[0.726]	[0.449]
f^S_{scaled}(text)	-0.133			0.137		
	[0.202]			[0.580]		
$f^S_{dlev_1}$(text)		-0.264			-1.898**	
		[0.237]			[0.862]	
$f^S_{dlev_2}$(text)			-0.010			-0.144
			[0.172]			[0.379]
Observations	1,026	1,026	1,026	262	262	262
R^2	0.178	0.186	0.177	0.158	0.266	0.159

Table 12: Predictive Regressions of Bond Returns. This table presents results from pooled cross-sectional regressions of h-period-ahead cumulative bond returns on signed return predictions implied by the stock and bond dictionaries. Predictions are generated using fitted values for γ_1 and γ_2 coefficients from: $|R_i^B| = \gamma_1 f^S(\text{text}) + \gamma_2 f^B(\text{text}) + \epsilon_i$. Specifically, for firms with an earnings call in week t, we utilize the predicted absolute stock return implied by the stock dictionary. We multiply this absolute prediction by the observed sign of the stock return on the day of the call to compute a signed predicted return implied by the stock dictionary. Similarly, we compute a signed predicted bond return by multiplying the absolute bond dictionary-implied bond return by the sign of the bond return on the day of the earnings call. We implement three specifications for $f(text)$ and the corresponding return measures. In Panel A, the stock dictionary f^S_{scaled} is estimated using scaled stock returns $|R^S_{\text{scaled}}|$. In Panel B, the stock dictionary f^S_{dlev1} is estimated using theory-adjusted stock returns, $|R^S_{\text{dlev1}}|$. In Panel C, the stock dictionary f^S_{dlev2} is estimated using regression-adjusted stock returns, $|R^S_{\text{dlev2}}|$. The dictionaries are constructed using an ensemble of text regressions. For brevity, the table reports only the coefficient on the stock dictionary-implied return. We avoid look-ahead bias as follows: For earnings calls falling on Mondays through Wednesdays of week t, we compute the 1-week-ahead return based on returns from Monday through Friday of week $t + 1$. For firms with earnings calls on Thursdays and Fridays of week t, we compute the 1-week-ahead return based on returns from Monday through Friday of week $t+2$. We then calculate cumulative returns over the following weeks. All regressions control for the stock return on the earnings announcement date and include week fixed effects, and standard errors are adjusted for heteroskedasticity and clustering at the firm and week levels.

	Cumulative bond return (%), $t+h$ weeks					
	$h=1$	$h=2$	$h=3$	$h=4$	$h=5$	$h=6$
	Panel A: $\lvert R_i^B\rvert = \gamma_1 f^S_{scaled}(\text{text}) + \gamma_2 f^B(\text{text})$					
Signed stock pred (t), Low DTD	0.030***	0.024**	0.018	0.025	0.021	0.015
	(0.008)	(0.011)	(0.013)	(0.017)	(0.021)	(0.023)
Signed stock pred (t), High DTD	0.008	0.009	0.012	0.013	0.012	0.010
	(0.006)	(0.008)	(0.009)	(0.011)	(0.011)	(0.012)
	Panel B: $\lvert R_i^B\rvert = \gamma_1 f^S_{delev1}(\text{text}) + \gamma_2 f^B(\text{text})$					
Signed stock pred (t), Low DTD	0.029***	0.021*	0.016	0.024	0.022	0.013
	(0.010)	(0.013)	(0.016)	(0.020)	(0.024)	(0.025)
Signed stock pred (t), High DTD	0.008	0.010	0.015	0.015	0.016	0.011
	(0.007)	(0.009)	(0.010)	(0.012)	(0.012)	(0.014)
	Panel C: $\lvert R_i^B\rvert = \gamma_1 f^S_{delev2}(\text{text}) + \gamma_2 f^B(\text{text})$					
Signed stock pred (t), Low DTD	0.030***	0.022*	0.014	0.018	0.015	0.005
	(0.010)	(0.013)	(0.016)	(0.019)	(0.024)	(0.026)
Signed stock pred (t), High DTD	0.007	0.007	0.014	0.014	0.017	0.011
	(0.007)	(0.009)	(0.011)	(0.013)	(0.013)	(0.014)

Appendix A. Derivation of Debt Sensitivities

In this appendix, we describe a simple structural model of credit risk, extend this model to include both junior and senior debt, and derive sensitivities to the level and volatility of underlying firm asset value.

Appendix A.1. Baseline Structural Credit Risk Model

We start with a simple structural model of credit risk based on the work of Merton (1974). In particular, we assume that V_a, the total value of firm assets, follows a geometric Brownian motion and can be written as follows:

$$\partial V_a = \mu V_a \partial t + \sigma_a V_a \partial z, \tag{A.1}$$

where μ is the mean rate of return on firm assets and σ_a is the constant standard deviation of return on firm assets.

Firm assets are financed by a combination of debt and equity. Equity is a residual claim denoted by E. Debt has a face value given by D_{total} and has maturity T. If total firm assets V_a are greater than the total face value of debt D_{total} at maturity, then debt holders receive D_{total} and equity holders receive $E = V_a - D_{total}$. Otherwise, equity holders receive nothing and, under the absence of bankruptcy costs, debt holders receive the asset value of the firm V_a.

Given the discussion above, equity can be viewed as a European call option on firm assets with exercise price equal to D_{total}. Accordingly, we can write the value of equity as follows, using the standard Black-Scholes call option formula:

$$E = V_a N(d_1) - e^{-rT} D_{total} N(d_2), \tag{A.2}$$

where

$$d_1 = \frac{ln(V_a/D_{total}) + (r + 0.5\sigma_a^2)T}{\sigma_a\sqrt{T}}, \quad d_2 = d_1 - \sigma_a\sqrt{T}. \tag{A.3}$$

Similarly, the total debt claim can be viewed as the short end of a European put option on firm assets with exercise price equal to D_{total}. Hence, using the standard Black-Scholes call option formula and letting $N(\cdot)$ represent the standard normal cumulative distribution function, we can write the value of debt as:

$$D = V_a N(-d_1) - e^{-rT} D_{total} N(-d_2). \tag{A.4}$$

Appendix A.2. Sensitivity of Return on Total Debt to Return on Equity

We calculate the sensitivity of the return on total debt to the return on equity (denoted h_e) by noting that:

$$h_e \equiv \frac{\partial D/D}{\partial E/E} = \frac{\partial D}{\partial E}\frac{E}{D} = \frac{\partial D/\partial V_a}{\partial E/\partial V_a}\frac{E}{D} \tag{A.5}$$

We first solve for $\frac{\partial E}{\partial V_a}$ and then for $\frac{\partial D}{\partial V_a}$.

Taking the derivative of the expression in equation A.2 with respect to V_a, we have that:

$$\frac{\partial E}{\partial V_a} = N(d_1) + V_a n(d_1)\frac{\partial d_1}{\partial V_a} - e^{-rT} D_{total} n(d_2)\frac{\partial d_2}{\partial V_a}. \tag{A.6}$$

Note that $n(d_1) = \frac{1}{\sqrt{2\pi}} e^{-0.5d_1^2}$ and that $n(d_2) = n(d_1 - \sigma_a\sqrt{T})$ simplifies to $n(d_2) = n(d_1)\frac{V_a}{D_{total}}e^{rT}$. Also note that $\frac{\partial d_2}{\partial V_a} = \frac{\partial d_1}{\partial V_a}$.

Substituting these expressions into equation A.6, we have the following:

$$\begin{aligned}\frac{\partial E}{\partial V_a} &= N(d_1) + V_a n(d_1)\frac{\partial d_1}{\partial V_a} - e^{-rT}D_{total}n(d_1)\frac{V_a}{D_{total}}e^{rT}\frac{\partial d_1}{\partial V_a} \\ &= N(d_1).\end{aligned} \tag{A.7}$$

Similarly, we take the derivative of equation A.4 with respect to V_a:

$$\frac{\partial D}{\partial V_a} = N(-d_1) - V_a n(-d_1)\frac{\partial d_1}{\partial V_a} + e^{-rT}D_{total}n(d_2)\frac{\partial d_2}{\partial V_a}. \tag{A.8}$$

Again, we note that $n(d_1) = \frac{1}{\sqrt{2\pi}} e^{-0.5d_1^2}$, $n(d_2) = n(d_1)\frac{V_a}{D_{total}}e^{rT}$, and $\frac{\partial d_2}{\partial V_a} = \frac{\partial d_1}{\partial V_a}$. Furthermore, symmetry of the normal distribution implies that $N(-d_1)$ is equivalent to $1 - N(d_1)$ and that $n(-d_1) = n(d_1)$.

The expression in equation A.8 then simplifies to:

$$\begin{aligned}\frac{\partial D}{\partial V_a} &= 1 - N(d_1) - V_a n(d_1)\frac{\partial d_1}{\partial V_a} + e^{-rT}D_{total}n(d_1)\frac{V_a}{D_{total}}e^{rT}\frac{\partial d_1}{\partial V_a} \\ &= 1 - N(d_1).\end{aligned} \tag{A.9}$$

Hence, given the expressions in equations A.7 and A.9, the sensitivity of the return on total debt to the return on equity, denoted $h_e \equiv \frac{\partial D/D}{\partial E/E}$, is given by:

$$h_e = \frac{N(d_1)}{1 - N(d_1)}\frac{E}{D}. \tag{A.10}$$

Alternatively, letting L denote D/V and δ denote $N(d_1)$, we obtain the same expression as Schaefer and Strebulaev (2008):

$$h_e = \left(\frac{1}{\delta} - 1\right)\left(\frac{1}{L} - 1\right). \tag{A.11}$$

Appendix A.3. Incorporating Senior and Junior Debt

Next, we allow debt to have multiple tranches, senior and junior, with respective face values given by D_{senior} and D_{junior}, and total debt given by $D_{total} = D_{senior} + D_{junior}$. Both debt claims are assumed to have maturity T.

The senior debt claim can be viewed as the short end of a European put option on firm assets with exercise price equal to D_{senior}. Hence, we can write the value of senior debt as:

$$DS = V_a N(-k_1) - e^{-rT}D_{senior}N(-k_2), \tag{A.12}$$

where

$$k_1 = \frac{ln(V_a/D_{senior}) + (r + 0.5\sigma_a^2)T}{\sigma_a\sqrt{T}}, \quad k_2 = k_1 - \sigma_a\sqrt{T}. \tag{A.13}$$

The junior debt claim can be viewed as a bull call spread, constructed as a portfolio of a long European call option on firm assets with exercise price D_{senior} and a short European call option with exercise price D_{total}. Accordingly, the value of the junior debt claim can be written as:

$$DJ = V_a N(k_1) - e^{-rT} D_{senior} N(k_2) - \left[V_a N(d_1) - e^{-rT} D_{total} N(d_2) \right]. \tag{A.14}$$

Appendix A.4. Debt Sensitivities to Asset Volatility

We calculate the sensitivity of the return on total debt to asset volatility (i.e., vega of total debt) by taking the derivative of the expression in equation A.4 with respect to σ_a:

$$\frac{\partial D}{\partial \sigma_a} = -Vn(-d_1)\frac{\partial d_1}{\partial \sigma_a} + e^{-rT} D_{total} n(d_2) \frac{\partial d_2}{\partial \sigma_a}. \tag{A.15}$$

Noting that $n(d_2) = n(d_1)\frac{V_a}{D_{total}}e^{rT}$, $\frac{\partial d_2}{\partial \sigma_a} = \frac{\partial d_1}{\partial \sigma_a} - \sqrt{T}$, and $n(-d_1)$ is equivalent to $n(d_1)$, we have that the vega of total debt is given by:

$$\frac{\partial D}{\partial \sigma_a} = -Vn(d_1)\sqrt{T}. \tag{A.16}$$

To calculate the vega of junior debt, we take the derivative of equation A.14 with respect to σ_a. Note that by symmetry of payoffs with the put option in equation A.4 and given the total debt vega in equation A.16, the vega of the European call option with exercise price D_{total} is $Vn(d_1)\sqrt{T}$. By extension the vega of the European call option with exercise price D_{senior} is $Vn(k_1)\sqrt{T}$. Hence, we have that the vega of junior debt is:

$$\frac{\partial DJ}{\partial \sigma_a} = Vn(k_1)\sqrt{T} - Vn(d_1)\sqrt{T} = V\sqrt{T}\left[n(k_1) - n(d_1)\right]. \tag{A.17}$$

Appendix B. Dictionary Analysis Details

This appendix provides implementation details for the descriptive diagnostics in Section 5.1 and Section 5.2, including (i) the construction of the stock-extreme and bond-extreme call corpora, (ii) the scattertext ranking and distinctiveness measures under the Bybee et al. (2024) vocabulary restriction, and (iii) the topic projection and document-level regression procedure.

Appendix B.1. Scattertext Implementation Details and Distinctive Terms

Appendix B.1.0.1. Dense ranking. Scattertext plots each term by its frequency rank in each corpus using a dense ranking system. Formally, for a term t in corpus C, its rank $R(t, C)$ is:

$$R(t, C) = 1 + |\{t' \in C : \text{freq}(t', C) > \text{freq}(t, C)\}|, \tag{B.1}$$

where $\text{freq}(t, C)$ denotes the frequency of term t in corpus C.

Appendix B.1.0.2. Scaled F-Score for distinctiveness. To highlight characteristic terms for each corpus, we also report the Scaled F-Score, which favors terms that are both frequent within a category and concentrated in that category. For term w_i and category c_j, define precision $\text{prec}(i, j)$ as the share of w_i occurrences that appear in c_j, and $\text{freq}(i, j)$ as the frequency of w_i within c_j. The score is:

$$F(i, j) = 2 \cdot \frac{\text{prec}(i, j) \cdot \text{freq}(i, j)}{\text{prec}(i, j) + \text{freq}(i, j)}, \tag{B.2}$$

following Kessler (2017).

Appendix B.1.0.3. Term tabulations. This appendix reports (i) the most stock-distinctive and bond-distinctive terms by Scaled F-Score and (ii) the largest rank differences across corpora (unigrams and bigrams), using the Bybee et al. (2024) vocabulary after excluding proper names and stop words. Table B.1 lists terms ordered by Scaled F-Score (the harmonic mean of precision and frequency), which prioritizes words that are both frequent within and exclusive to a specific investor group. Table B.2 lists terms ordered by Rank Difference, which highlights terms with the largest disparity in usage between the two corpora (i.e., terms that are common in one context but rare in the other).

Table B.1: Top Distinctive Terms Ranked by Scaled F-Score. This table lists the top 100 terms for stock and bond reactions, sorted by their Scaled F-Score. The sorting metric is the harmonic mean of a term's precision (exclusivity to the category) and frequency (prevalence within the category), identifying the most representative terms for each group.

Rank	Stock-Distinctive Terms	Bond-Distinctive Terms
1–20	growth, grow, strong, grew, deliver, driven, acquisition, basis point, drive, share, client, investment, segment, return, full, revenue, global, organic, technology, performance	loss, liquidity, reduction, debt, reduce, reserve, facility, credit, inventory, home, current, loan, action, decline, amount, EBITDA, structure, cash, asset, charge
21–40	China, invest, system, consumer, earn, tax, volume, bite, mix, margin, basis, continue, service, customer, single, adjust, feel, guidance, increase, opportunity	cost, decrease, hedge, mortgage, operation, store, approximate, transaction, company, capital, period, financial, environment, manage, note, statement, close, level, save, cash flow
41–60	higher, Europe, brand, great, expectation, record, business, talk, outlook, sort, strength, program, range, strategy, point, kind, product, start, benefit, add	gross, pay, contract, price, bank, condition, production, risk, significant, compare, impairment, number, position, morning, process, additional, relate, flow, estimate, release
61–80	long, operate, good, long term, expand, offset, line, important, network, team, high, project, shareholder, gain, income, expect, side, part, impact, build	balance, challenge, issue, slide, time, sheet, market, work, net, call, negative, portfolio, deal, sale, fair, balance sheet, prior, equity, hold, give
81–100	coming, couple, term, double, America, area, innovation, data, big, move, mention, international, focus, platform, trend, pretty, follow, top, consistent, question	security, interest, insurance, economic, expense, due, improve, account, material, detail, place, guess, average, run, fact, restructure, future, plan, put, complete

Table B.2: Top Distinctive Terms Ranked by Rank Difference. This table lists the top 100 terms for stock and bond reactions, sorted by the magnitude of the difference between their rank in the stock extreme reaction corpus and their rank in the bond extreme reaction corpus. Stock-distinctive terms are those with the largest negative rank difference (ranking much higher in stock calls), while bond-distinctive terms are those with the largest positive rank difference (ranking much higher in bond calls).

Rank	Stock-Distinctive Terms	Bond-Distinctive Terms
1–20	organic, revenue growth, grew, growth rate, inflation, innovation, sale growth, momentum, digits, operate margin, crude, volume growth, earn share, client, productivity, share repurchase, specialty, strong growth, car, single digits	liquidity, impairment, claim, land, vessel, insurance, credit facility, maturity, reserve, ton, bond, write, mortgage, exposure, borrow, hedge, refinance, loss, restructure, market condition
21–40	beverage, buyback, health care, hotel, tax rate, synergy, faster, tax reform, broad, feel good, double, platform, FedEx, card, expansion, deposit, China, freight, headwinds, capability	downturn, cost reduction, senior, real estate, estate, option, cost structure, house, net loss, hospital, cut, page, structure, private, condition, collateral, reduction, default, delinquency, home
41–60	pipeline, franchise, cable, net interest, yield, strength, continue strong, integrate, single, reform, strong performance, robust, decade, integration, pharmaceutical, train, develop market, coast, excite, southern	action, receivable, valuation, sold, EBITDA, difficult, covenants, realize, situation, rig, limit, substantial, facility, secure, yeah[a], print, bad, capital structure, obligation, amount
61–80	chemical, refinery, solution, Pacific, Asia, domestic, infrastructure, device, Japan, loan growth, Latin, upstream, space, industrial, engine, trial, adjust earn, wind, proposition, mobile	decrease, stress, debt, scenario, goodwill, crisis, excess, community, finance, hold company, property, act, joint, reduce, coal, work capital, charter, securitization, carry, flexibility
81–100	expand, technology, constant, operate profit, nice, drove, consecutive, shareholder, renewable, health, middle, refine, revenue grew, truck, advance, medical, revenue increase, solid, channel, curious	fix, label, liability, hold, paid, reduce cost, agreement, charge, joint venture, grade, expenditure, require, statutory, spread, pay, values, allowance, asset sale, requirement, loan

[a] The term “yeah” appears in responses to analyst questions.

Appendix B.2. Topic Projection and Ranked Topic Lists

Appendix B.2.0.1. Topic projection. We project earnings call text onto the pre-estimated Bybee et al. (2024) topic definitions. Let $\phi_{k,v}$ denote the weight of term v in topic k, and let $w_{d,v}$ denote the frequency of term v in call d. We compute topic prevalence as:

$$\theta_{d,k} = \sum_{v \in V} w_{d,v} \times \phi_{k,v}, \tag{B.3}$$

yielding $\theta_d = (\theta_{d,1}, \ldots, \theta_{d,180})$ for each call.

Appendix B.2.0.2. Regression specification. We estimate Equation 8 in the main text, where coefficients β_k capture which standardized themes are associated with stock-extreme versus bond-extreme calls. Table 7 in the main text reports the topics with statistically significant coefficients.