

# Risk Perceptions in Credit Markets <sup>\*</sup>

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## Abstract

This paper studies subjective risk perceptions by constructing and examining a novel dataset linking corporate bond analysts' recommendations to their textual comments. Two stylized facts emerge: (i) bond analysts favor higher-yielding, riskier bonds only in higher-rated categories, even when fundamentals are comparable; moreover, recommendation-sorted portfolios generate positive alphas only in lower-rated bonds; (ii) perceived credit risk extracted from analysts' comments predicts subsequent credit deterioration, but is not reflected in their recommendations for higher-rated bonds. These patterns hold across investor types and client and non-client issuers, suggesting that catering to investors or catering to clients do not fully explain the results. Rather, the evidence supports categorical thinking: analysts infer from credit rating categories instead of rational Bayesian updating, leading them to underweight their perceived bond-specific risks for purportedly safe bonds.

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A key principle of asset pricing is that investors demand compensation for risk. Accordingly, it is of first-order importance to understand how agents perceive risks and form investment decisions. Despite their importance, risk perceptions have received relatively little empirical examination, in part due to the difficulty of obtaining data. Indeed, as [Adam and Nagel \(2023\)](#) highlight, “*Subjective risk perceptions may be as important as the perceived first moments of returns and pay-offs. . . We need more work that explores how investors form beliefs about asset risks.*”

In this paper, I provide some of the first direct evidence on agent perceptions of risk by constructing and examining a novel dataset of bond analyst reports on corporate bonds. This setting is uniquely well-suited to studying risk perceptions for two reasons. First, because the promised cash flows of corporate bonds are known in advance, the core driver of investment decisions is the perception of risk that issuers may fail to make contractual payments. Second, analyst reports provide detailed comments on analysts’ perceptions of bond risks, alongside explicit Overweight-Neutral-Underweight recommendations. As I show in this paper, these comments provide a rich source of information on the relevant perceived credit risks, which can have significant real consequences. For example, systematic underestimation of downside risk can drive excessive credit growth and increase the economy’s vulnerability to financial crises ([Minsky, 1977](#); [Gennaioli, Shleifer and Vishny, 2012, 2015](#)).

By analyzing the analyst reports on investment-grade bonds spanning a decade, I document two sets of novel facts.<sup>1</sup> First, analysts are significantly more likely to recommend higher-yielding, riskier bonds within the A-rated category than within the BBB-rated category, even when controlling for fundamentals. Recommendation-sorted portfolios generate positive alphas only in BBB-rated bonds. Second, analysts’ comments have information content that predicts future credit risk deterioration. However, for higher-rated bonds, analyst actual recommendations are not consistent with their stated beliefs in the comments, suggesting a gap between written comments and final recommendations. To explain these findings, I propose and provide evidence for categorical thinking ([Mullainathan, 2002](#)), in which analysts mentally group bonds by credit rating categories and make inferences based on credit rating labels instead of rational Bayesian updating, causing them to underweight their perceived risks in purportedly safe bonds. Alternative explanations, such as catering to clients or catering to investors, cannot explain the results, as the documented gap in yield spread sensitivity between A- and BBB-rated bonds holds across investor types and client

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<sup>1</sup>Because reports on high-yield bonds are limited, I focus on the investment-grade bonds, which I divide into two groups, following the recommendation definitions. The “higher-rated” group consists primarily of A-rated bonds (A+/A/A-), along with AA- and AAA-rated bonds, which represent approximately 6% of the sample. The “lower-rated” group comprises BBB-rated issues (BBB+/BBB/BBB-). Throughout the paper, I use “A-rated” and “higher-rated” interchangeably, as well as “BBB-rated” and “lower-rated.”

and non-client relationships. My paper suggests that agents exhibit behavioral biases not only in return expectations, as widely documented in prior work, but also in risk perceptions. In particular, I document categorical thinking, a bias related to credit rating labels.

More specifically, I begin by examining how analysts form recommendations. Although reports list several credit indicators, analysts only consistently highlight yield spreads. Accordingly, I test how yield spreads map into recommendations and find a clear, robust asymmetry: analysts issue more favorable recommendations for bonds with higher yields, but only within the higher-rated category. Quantitatively, a one-standard-deviation widening of spreads (about 86 basis points) increases the unconditional probability that an A-rated bond receives the most favorable recommendation by roughly seven percentage points in the cross-section. No such effect exists for the lower-rated category. Moreover, this asymmetry persists even when comparing bonds simultaneously covered by the same analyst within the same industry, after controlling for comprehensive bond- and issuer-level characteristics. This reduces concerns that analyst preferences over these characteristics drive the result. Additionally, analysts' tendency to favor higher-yielding bonds is particularly acute when the yield curve is flat and default spreads are low, i.e., overall market compensation for risk declines.

Since analysts' comments primarily reflect their risk perceptions of issuers and bonds, I examine how Expected Default Frequency (EDF) is incorporated into their recommendations. EDF is a comprehensive, commonly used, and forward-looking metric of credit risk derived from [Merton \(1974\)](#) structural model, with market value of assets, debt obligations, and asset volatility as inputs. I find that analysts issue more favorable recommendations to the bonds with higher credit risk only within A-rated bonds. However, recommendations for BBB-rated bonds are insensitive to default risk. Combining with earlier results, the patterns suggest that analysts believe higher-yielding, riskier A-rated bonds are under-priced, and they perceive less risk than the market for these bonds. If analysts' perceptions are accurate, portfolios that follow their recommendations should earn positive  $\alpha$ .

Evaluating analysts' ability to generate  $\alpha$ , I find that the portfolios that go long on Overweight and short on Underweight produce positive monthly alphas only for BBB-rated bonds (5 bps), after controlling for the bond market risk factor. The alphas become more economically and statistically significant after controlling for additional common factors. In contrast, portfolios for A-rated bonds exhibit negative alphas (-2.1 bps) after controlling for the bond market factor and insignificant positive alphas after controlling for other common factors. These findings imply that analysts are more attentive to risk considerations in their recommendations for lower-rated bonds.

Next, I study the text of analysts' comments to better understand how analysts perceive

risks and how perceptions of risk affect their recommendations. I construct novel quantitative measures of forward-looking risk perceptions inferred from comments.<sup>2</sup> The primary measure involves prompting large language models (LLMs) to parse each comment carefully, evaluate both the frequency and intensity of risk-related language, and assign a risk score. The second measure follows the traditional dictionary-based textual analysis approach (Loughran and McDonald, 2011), counting occurrences of uncertain, weak modal, and negative words.

By relating analysts’ perceived risk scores to EDF, I examine how analysts translate public information into risk perceptions. Intuitively, credit ratings serve as reference points, and a moderate rise in EDF may be viewed as “normal” for BBB-rated issuers but alarming for A-rated issuers. One might therefore expect analysts to exhibit greater sensitivity to EDF changes among A-rated bonds. However, the data reveal a significantly flatter slope for higher-rated bonds, indicating attenuated recognition of credit risk in this segment. Such attenuation may not matter economically, because I find that analysts’ risk assessments still contain forward-looking credit signals that forecast subsequent credit risk realizations. However, analysts’ recommendations fail to forecast them for higher-rated bonds. This discrepancy suggests a gap between analysts’ risk perceptions, as reflected in their comments, and their recommendations to predict future credit events for A-rated bonds.

Motivated by this gap, I examine how recommendations load on perceived-risk scores. Controlling for yield spreads, higher perceived risk leads analysts to issue less favorable recommendations for BBB-rated bonds, but has no significant effect for A-rated bonds. This selective response explains the divergence between analysts’ stated risk concerns and their actual recommendations: analysts explicitly acknowledge downside risk but systematically fail to reflect it in recommendations for purportedly safe bonds. One interpretation is that analysts price risk differently across rating groups and underprice risk in higher-rated bonds. Another is that they assign little weight on their acknowledged risks for higher-rated bonds when forming recommendations. Such behavior aligns with the “local thinking” theory of risk neglect (Gennaioli, Shleifer and Vishny, 2012), wherein agents attend to a limited set of salient states and ignore low-probability adverse outcomes. Given the lower default risk associated with A-rated bonds, analysts may perceive adverse scenarios as unlikely and underweight their own stated concerns. This rating-contingent underweighting of risk aligns closely with psychological explanations based on representativeness, the cognitive bias where people overweight outcomes that appear more likely and underweight tail events (Kahneman and Tversky, 1972; Gennaioli, Shleifer and Vishny, 2015). Additionally, this finding provides

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<sup>2</sup>Analysts’ comments encompass assessments of recent conditions and forward-looking projections of these perceptions, consistent with the forward-looking risk perception framework of Pflueger, Siriwardane and Sunderam (2020).

the empirical support for the mechanism outlined by [Becker and Ivashina \(2015\)](#), who suggest that reaching-for-yield behaviors can reflect underlying risk neglect.<sup>3</sup>

My empirical findings raise two puzzles. First, why do analysts issue more favorable recommendations to higher-yielding, riskier bonds, but without generating positive alphas, only for A-rated ones? Second, why do they underweight risks that they already explicitly recognized in A-rated bonds but not in those rated BBB? I consider three potential mechanisms: (1) catering to clients, (2) catering to investor demand, and (3) categorical thinking.

Catering explanations appear insufficient to explain these asymmetric patterns. Specifically, agency conflicts may incentivize analysts to issue strategically optimistic recommendations for bonds issued by their banks’ clients, potentially generating the A–BBB recommendation asymmetry. To test this catering-to-client mechanism, I link explicitly disclosed client relationships from analyst reports to bond recommendations, and find that the A–BBB asymmetry persists within client and non-client subsamples, across current, past, or prospective client ties. In addition, analysts may strategically tailor their recommendations to institutional investors’ preferences. Specifically, they might cater to insurance companies in the A-rated segment, as insurers face regulatory constraints, primarily hold A-rated bonds, and systematically reach for yield ([Becker and Ivashina, 2015](#)), and cater to mutual funds in the BBB-rated segment, as these funds face fewer constraints and exhibit limited yield-seeking behavior ([Choi and Kronlund, 2018](#)). I test this mechanism by linking analyst recommendations to institutional ownership data and find no supporting evidence.

I propose and provide evidence for a mechanism related to psychology: categorical thinking. According to [Mullainathan \(2002\)](#), individuals simplify inference by relying on coarse categories rather than continuously updating beliefs as rational Bayesians. Credit ratings provide precisely such natural groupings—salient, widely recognized, and reinforced by regulations—with the most prominent distinction within investment grade between A and BBB. Under this categorization, analysts may adopt different stereotypes: they treat A-rated bonds as inherently safe, leading them to discount negative risk signals, while viewing BBB-rated bonds as inherently risky. This cognitive framing can simultaneously generate risk-underweighting and yield-seeking dynamics.

Given two firms with similar fundamentals, the key question is whether rating labels change how analysts map risk into recommendations. In a benchmark where analysts condition only on fundamentals, recommendations respond smoothly and consistently to credit risk and spreads across ratings. Any discontinuity at the A/BBB boundary would indicate

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<sup>3</sup>From [Becker and Ivashina \(2015\)](#), “We expect reaching for yield over ‘post-crisis’ period to become weaker due to an increase in downgrade probabilities, scrutiny, and awareness of previously neglected risks, or a shift in risk preferences.”

that analysts’ inferences depend on rating labels themselves. To test this, I match A-rated and BBB-rated firms on industry and key financial characteristics. Within this matched sample, analyst recommendations still load positively on yield spreads and credit risk for A-rated bonds but not for BBB-rated bonds. This difference in slopes across rating categories is statistically significant, providing evidence of categorical thinking by inferring from coarse credit rating categories.

I provide additional supportive evidence through textual analysis on analyst comments. Analysts employ coarser reasoning by using fewer information categories, frequently omit factual details, and only provide subjective predictions when describing A-rated bonds compared to BBB-rated bonds. Moreover, favorable recommendations predict downgrades for BBB+ bonds but not for A- bonds, while predicting upgrades for A- bonds but not for BBB+ bonds. These patterns are consistent with categorical thinking: analysts discount downside risk in higher-rated bonds and discount upside potential in riskier-rated bonds.

This paper is related to a nascent literature that studies subjective risk perceptions. Existing literature primarily infers market-level risk perceptions using surveys (Amromin and Sharpe, 2014; Giglio, Maggiori, Stroebe and Utkus, 2021; Adam, Matveev and Nagel, 2021; Coutts, Gonçalves and Loudis, 2023; Jo, Lin and You, 2024; Coutts, S Gonçalves, Liu and Loudis, 2024) or observed financial outcomes (Pflueger, Siriwardane and Sunderam, 2020; Lochstoer and Muir, 2022; Bastianello, 2022; Nagel and Xu, 2023; De La O, Han and Myers, 2024).<sup>4</sup> My paper advances this literature by constructing a new dataset where market participants directly discuss their risk perceptions at the firm/bond level.

More broadly, my paper relates to empirical work studying beliefs. A rich literature has explored it in various asset classes such as equities, real estate, and interest rates. Prior studies typically infer expectations in bond markets from related markets (e.g., equity or interest rate markets) and emphasize aggregate-level analysis (Piazzesi, Schneider et al., 2009; Buraschi, Piatti and Whelan, 2022; Gulen, Ion, Jens and Rossi, 2024). My study contributes to this literature by offering the direct empirical evidence on expectations in the corporate bond market, with a particular focus on the cross-section. Moreover, much of the existing literature focuses on return expectations and documents that agents may not have rational expectations. My research shows that behavioral biases arise not only in return expectations but also in beliefs about risk. In particular, I identify a form of categorical thinking, linked to credit rating categories, as one bias.

Additionally, my paper also contributes to recent work on risk neglect in credit markets. Minsky (1977) argues that overly optimistic investor beliefs can drive credit expansion and trigger financial crises. Theoretically, Gennaioli, Shleifer and Vishny (2012) argues that such

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<sup>4</sup>For more related work, see Delao and Myers (2021); Egan, MacKay and Yang (2021); Jensen (2022).

over-optimism often takes the form of risk neglect. Empirical studies have largely assumed or indirectly inferred risk neglect from the finding that investors do not receive higher yield compensation for taking on higher risk (Chernenko, Hanson and Sunderam, 2016; Sørensen, 2022; Zhang, Zhao and Zhao, 2024). My paper provides direct empirical evidence of risk neglect: professional bond analysts neglect their acknowledged risks for higher-rated bonds when issuing recommendations. Such rating-induced neglect aligns closely with psychological explanations based on representativeness, the cognitive bias where people overestimate the probability of outcomes perceived as more likely (Kahneman and Tversky, 1972; Gennaioli, Shleifer and Vishny, 2015).

Lastly, my work relates to research on reaching for yield (RFY)—the preference for higher-yielding bonds within a given rating category. This behavior has been documented among institutional investors, especially within higher-rated segments (Becker and Ivashina, 2015; Choi and Kronlund, 2018; Chen and Choi, 2024). In this paper, I show that investors who follow analysts’ recommendations without reading the accompanying comments carefully can inadvertently reach for yield. This provides the first empirical support for the potential mechanism proposed by Becker and Ivashina (2015), showing that RFY behavior in higher-rated bonds reflects risk neglect induced by categorical thinking.

## 1 Data

This section describes my main datasets. I start with corporate bond analyst reports and merge them with issuer-level characteristics from CRSP and Compustat, as well as with security-level information using the CRSP Corporate Bond Panel. Additionally, I utilize other datasets, including manually constructed analyst characteristics, client information, and eMAXX holdings. Before turning to results, I also address data-related issues.

### 1.1 Corporate bond analyst reports

The analyst reports are obtained from the Investext database, and information is largely extracted manually due to the unstructured PDF format that precludes automated scraping. The reports are produced by J.P. Morgan. J.P. Morgan’s credit research team consistently ranks as the top Global Fixed Income Research Team by institutional investors, and their analysts set industry standards for impactful research (Institutional Investor, 2013, 2022; Yahoo Finance, 2015; J.P. Morgan, 2023). Bond analyst reports provide information in fixed-income markets (De Franco, Vasvari and Wittenberg-Moerman, 2009; Johnston, Markov and Ramnath, 2009; Gurun, Johnston and Markov, 2016; Gillette, 2023).sk

Analysts provide issuer- or bond-level recommendations relative to the rating index (A



and BBB) or sectors in three categories: Overweight, Neutral, or Underweight.<sup>5</sup> To form recommendations, analysts mainly consider credit ratings from credit rating agencies, current yield spreads (emphasized in bold in the report), and some other firm and bond information to assess their ability to meet debt obligations. Additionally, research quality, accuracy, and client feedback can affect analysts’ compensation.

I use Investment Grade (IG) industry summary reports from September 2013 to March 2023. The reports were issued monthly until 2017, then quarterly from 2017 to 2020, and semiannually. My analysis focuses on U.S. public non-financial firms and the final sample includes over 20 industries. Table 1 shows the number of times covered for each industry. Most industries are covered repeatedly. I apply issuer-level recommendations to individual bonds following disclosures in the IG reports, which also allows me to better control for bond characteristics, such as duration and coupon rate.<sup>6</sup> Figure 1 shows an asymmetric distribution of analyst recommendations across rating groups: analysts issue less favorable recommendations (underweight) for higher-rated bonds and more favorable recommendations (overweight) for lower-rated bonds.<sup>7</sup>

The final sample comprises 327 unique non-financial firms with 104,534 bond-month recommendations over a decade. Panels A, B, and C of Table 2 provide a detailed breakdown of issuers, bonds, and recommendations. Issuers in my sample tend to be larger firms and issue more bonds compared to all public issuers in the WRDS Corporate Bond Dataset, as shown in Panel A of Table A2. In the IG market, the median size of issuers in my sample is \$20,286.37 million in 2018 dollars, compared to \$14,357.75 million in the full sample. Additionally, my bond-month panel closely represents the broader bond universe along key dimensions. During the 2013–2023 period, it covers approximately 80% of all investment-grade bond-month observations in the CRSP/TRACE universe (Panel B of Table 2 and Table A2), with similar distributions of credit ratings, durations, yield spreads, and monthly returns.

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<sup>5</sup>From the disclosures of IG reports: Overweight, Neutral, and Underweight indicate that, over the next three months, the recommended risk position is expected to outperform, perform in line with, or underperform a benchmark of comparable bonds in the same rating bucket (A or BBB) or sector.

<sup>6</sup>According to the reports, “an issuer recommendation applies to all bonds at the same level of the issuer’s capital structure unless I specify a different recommendation for the individual security.” Analysts generally issue uniform recommendations across a firm’s bonds. However, in fewer than 5% of the firm-month observations, they assign different recommendations to individual bonds based on specific factors, such as the bond’s maturity date or its association with the firm’s primary business. In such cases, I review their comments to identify the rationale and apply it consistently across the firm’s bonds.

<sup>7</sup>This pattern is consistent with the finding in De Franco, Vasvari and Wittenberg-Moerman (2009), which shows that the positive skewness in bond analysts’ recommendations is greater for low than high credit quality bonds, largely due to the lack of upside return potential and bond investors’ more asymmetric demand for negative information in high-quality bonds.



### 1.1.1 Constructing variables from comments by LLM

Alongside their recommendations, analysts also provide detailed comments to give a rationale for their recommendations and focus on their perceptions of bond risks. I generate a number of empirical measures of interest by analyzing comments using the 20240418 release of Llama-3.3-70b large language model (“the LLM”).<sup>8</sup> This approach leverages natural language processing and addresses limitations inherent in traditional textual analysis methods. Traditional methods, including keyword counts or unsupervised topic models, rely heavily on predefined dictionaries or statistical groupings. Such reliance restricts their ability to interpret nuanced financial contexts or answer analytical queries. In contrast, LLMs employ transformer-based neural networks trained extensively on large text datasets. These models can capture subtle economic meanings and respond to targeted questions. For instance, analyst comments usually combine factual information (e.g., reported earnings) with subjective interpretations (e.g., earnings forecasts). Traditional methods cannot reliably separate objective financial metrics from forward-looking judgments.

In [section 4](#), I discuss empirical measures constructed by LLMs with related prompts and present the full text of the prompts in [section IA.A](#). To ensure the reliability and reproducibility of the LLM’s outputs, I implement several steps. First, I adopt a “chain-of-thought” prompting approach, requiring the LLM to articulate intermediate reasoning steps before providing a final answer. Prior research has found that chain-of-thought prompting significantly enhances model accuracy, especially in complex tasks ([Wei et al., 2022](#)). Second, I explicitly instruct the LLM to support its reasoning by directly quoting relevant passages from analyst comments, firmly anchoring its conclusions in the source text. Finally, wherever possible, I validate the LLM-generated variables against observable numerical data, ensuring empirical consistency and accuracy throughout my analysis.

## 1.2 CRSP and Compustat

Bond-month level information, such as yields, returns, maturity, and ratings, is from the WRDS Corporate Bond Panel. This panel compiles information from TRACE Standard and TRACE Enhanced datasets and provides an end-of-month quote for publicly traded U.S. corporate bonds starting in 2002. I clean the raw data following [Dick-Nielsen, Feldhütter, Pedersen and Stolborg \(2023\)](#). The yield spread is measured as the bond’s yield minus the

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<sup>8</sup>Llama-3.3-70B was released April 18, 2024. The model includes 70 billion parameters and supports an 8,000-token context length. It was trained on approximately 15 trillion tokens sourced from news articles, code repositories, and specialized domain texts. Llama-3.3-70B provides full access to its weights, and such openness enables deterministic replication, in-domain fine-tuning, and local deployment. These features ensure methodological transparency, making the model particularly suitable for interpreting financial information ([Meta AI, 2024b,a](#)).

interpolated Treasury yield of the same maturity following [Dickerson, Mueller and Robotti \(2023b\)](#). U.S. Treasury yield curve is obtained from The Federal Reserve Board.<sup>9</sup> I include bonds that have available information on credit rating, yield spread, and time to maturity, with maturities exceeding one year. Also, I exclude all convertible and putable bonds in order to better identify the relationship between credit risk and yield spreads.

Firm-level fundamentals come from the CRSP and Compustat database, from which I construct financial variables used in the matching procedure described in [Table 2](#). Bond and firm characteristics are winsorized at the 1% level to mitigate concerns that outliers might be driving the results.

### 1.2.1 No break in firm characteristics at A-BBB cutoff

My identification strategy and falsification tests require firm characteristics at the A-BBB cutoff to be similar to those across other rating cutoffs. Panel D of [Table 2](#) reports the means of firm characteristics by credit rating from AAA to BBB-. There are few AAA and AA firms, so I do not use more granular rating notches within these two rating groups. As expected, as ratings fall, firms become smaller, more leveraged, and less solvent, i.e., Altman’s Z-score falls in near-linear steps from 1.57 (AAA) to 0.65 (BBB-). Profitability measures, such as ROA, operating margin, and cash flow to assets, also decrease gradually, whereas asset tangibility (PPE/Assets) increases, consistent with collateral-backed borrowing among riskier issuers.

What matters for identification is to see whether the A/BBB cutoff shows a structural break in fundamentals. Moving from A- to BBB+ reduces log assets by roughly 0.5 points, raises market leverage by five percentage points, and lowers the Z-score by 0.17. These shifts are indistinguishable from the changes observed between other rating notches, and a few variables even look slightly stronger for BBB+ than for A issuers. Such patterns support the core assumption of the matching design introduced in [section 6](#).

## 1.3 Others

### 1.3.1 Analyst characteristics

I manually collect demographic and career details for each analyst in my sample from LinkedIn and MarketScreener profiles. The data include gender, birth year, undergradu-

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<sup>9</sup>For a given target maturity  $\tau^*$ , I construct the synthetic Treasury yield  $y_{\tau^*}$  by linear interpolation:

$$y_{\tau^*} = y_{\tau_L} + \frac{y_{\tau_U} - y_{\tau_L}}{\tau_U - \tau_L} (\tau^* - \tau_L),$$

where  $\tau_L$  is the largest observed maturity less than or equal to  $\tau^*$  and  $\tau_U$  is the smallest observed maturity greater than or equal to  $\tau^*$ .

ate major, highest degree, prior work experience, year joined J.P. Morgan, and LinkedIn followers. Approximately 40 percent of analysts are women, two-thirds hold undergraduate degrees in economics (with the remainder in STEM fields), and 40 percent hold master’s degrees.

### 1.3.2 Client information

I manually collect and analyze disclosures from analyst reports. Each disclosure explicitly identifies the bank’s specific relationship with issuers. I consolidate the client relationships into three categories: (i) investment banking, which primarily includes lead manager or co-manager underwriting roles and broader advisory services such as mergers, restructuring, etc; (ii) broker and market maker, which are related to liquidity providing and secondary-market trading; and (iii) other significant financial interests, primarily reflecting proprietary positions of analysts’ employer in issuing debt securities exceeding one million USD. Among the matched relationship-linked observations, underwriting mandates represent the largest category.

### 1.3.3 eMAXX holding

The bond holdings data is from Thomson Reuters eMAXX database, covering the sample period from 2013Q4 to 2022Q4. The database contains detailed fixed-income holdings, primarily for insurance companies, mutual funds, and pension funds, at a quarterly frequency. eMAXX compiles holding disclosures from mandatory regulatory filings with the National Association of Insurance Commissioners (NAIC) for insurers, and with the Securities and Exchange Commission (SEC) for mutual funds, asset managers, and public pension funds, along with voluntary disclosures from major private pension plans. However, coverage of banks and hedge funds is limited. Using eMAXX investor type classification codes, I group investors into three categories: insurers (i.e., life insurers and P&C insurers), mutual funds (i.e., active funds and passive funds), and others (e.g., pension funds).<sup>10</sup>

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<sup>10</sup>We classify an investor as an insurer if its FUNDCLASS is in (INS, LIN, PIN, RIN), and as a mutual fund if the FUNDCLASS is in (AMM, ANN, BAL, MMM, MUT, END, QUI, FOF, UIT). Thus, our broad category of mutual funds also includes money market funds, balanced funds, unit investment trusts, funds of funds, and variable annuity funds.

## 2 Recommendations and key credit signals

### 2.1 Conceptual framework for recommendation formation

Recommendations of OW, N, or UW are based on analysts' credit assessments of issuers and their evaluations of bonds' relative value, suggesting that analysts determine whether a bond is underpriced (OW), fairly priced (N), or overpriced (UW) relative to other bonds with similar risk profiles or relative to its risk that analysts perceive. Ultimately, recommendations reflect the disagreement on risk perceptions between analysts and the market.

Consider a one-period economy. Bond  $j$  pays 1 at maturity if it does not default, and 0 otherwise. Investors are risk-neutral and come in different beliefs, indexed by  $k = 1, \dots, K$ . Type  $k$  investors assign to bond  $j$  a default probability  $d_{k,j}$ . Beliefs are ordered from most optimistic (lowest perceived default probability) to least optimistic (highest perceived default probability),  $d_{1,j} < d_{2,j} < \dots < d_{K,j}$ . Investor  $k$ 's valuation of bond  $j$  is

$$v_{k,j} = \frac{\mathbb{E}[\text{Payoff}_{k,j}]}{R_f} = \frac{1 - d_{k,j}}{R_f}, \quad (1)$$

where  $1 - d_{k,j}$  is the subjective expected payoff and  $R_f$  is the risk-free rate. Given a price  $p_j$ , investor  $k$  buys bond  $j$  if and only if  $p_j \leq v_{k,j}$ . Panel A of [Figure 2](#) shows the demand curve. The aggregate demand  $\mu_k$  is the total fraction of investors whose valuations equal or exceed the given price and is a decreasing step function with kinks at the thresholds  $v_{k,j}$ . When  $p > v_{1,j}$ , demand is zero; when  $v_{2,j} < p \leq v_{1,j}$ , all investors with belief  $k = 1$  enter, and so on. In equilibrium, the market price reflects the evaluation of marginal investors with beliefs  $k = m$ :

$$p_j^* = v_{m,j} = \frac{1 - d_{m,j}}{R_f}. \quad (2)$$

An analyst forms a subjective belief  $d_{A,j}$  about the default probability of bond  $j$ , leading to the following valuation:

$$v_{A,j} = \frac{1 - d_{A,j}}{R_f}. \quad (3)$$

As illustrated in panel B of [Figure 2](#), given the market price  $p_j^*$ , the analyst recommends Overweight when her valuation exceeds the market price (i.e., she perceives lower default risk than the market-implied probability  $d_{m,j}$ ) and recommends Underweight when her valuation

is below the market price. Formally,

$$Rec_{A,j} = \begin{cases} \text{Overweight (OW)} & \text{if } V_{A,j} > p^* \Rightarrow d_{A,j} < d_{m,j}, \\ \text{Neutral (N)} & \text{if } V_{A,j} = p^* \Rightarrow d_{A,j} = d_{m,j}, \\ \text{Underweight (UW)} & \text{if } V_{A,j} < p^* \Rightarrow d_{A,j} > d_{m,j}. \end{cases} \quad (4)$$

## 2.2 Recommendation and yield spreads

Since reports list several credit indicators but only consistently highlight yield spreads, I first examine how yield spreads affect recommendations. The empirical strategy is delineated as follows:

$$Rec_{i,t} = \alpha + \beta_1 \text{YieldSpread}_{i,t}^{g=A} + \beta_2 \text{YieldSpread}_{i,t}^{g=BBB} + \mathbf{1}\{g_{i,t} = A\} + \mathbf{X}_{i,t} + \varepsilon_{i,t}, \quad (5)$$

where  $Rec_{i,t}$  is the analyst recommendation for bond  $i$  at time  $t$ , coded as -1 for UW, 0 for N and +1 for OW.  $\text{YieldSpread}_{i,t}$  is the bond's yield spread over the yield of treasuries in the same maturity.  $g$  indicates the bond's rating group, which can be  $A$  or  $BBB$ . The sensitivity of recommendations to yield spreads can vary across rating groups. [Table 3](#) reports the results. In column (1), the coefficient of yield spreads exhibit an asymmetric pattern across rating groups. The coefficient is positive and highly significant for A-rated bonds, but much smaller and statistically insignificant for BBB-rated bonds. A one-standard-deviation (S.D.) widening in the spread (about 86 basis points) raises the unconditional probability that an A-rated bond receives an Overweight recommendation by roughly seven percentage points in the cross section, while leaving the probability for BBB-rated bonds unchanged.<sup>11</sup>

The industry-specific comparison matters if analysts rank bonds relative to sector peers. Column (2) adds industry-fixed effects, and the slope of A-rated bonds falls from 21.76 to 12.884 and remains highly significant. In contrast, the BBB slope remains statistically insignificant. In the next two columns, I present cases where the same analyst covers both A-rated and BBB-rated bonds within the same time period and industry. Column (3) introduces analyst fixed effects to absorb persistent analyst styles. Column (4) adds industry fixed effects and the results stay consistent, indicating that the asymmetric pattern is unlikely to be explained by analysts' recommendation style.

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<sup>11</sup>Marginal effects are calculated using predictions from the ordered logit estimates in [Table A5](#). Specifically, I first evaluate the predicted probability of an Overweight recommendation at the mean yield spread level observed in the sample, and then recalculate the predicted probability after increasing the spread by one standard deviation. The difference between these two probabilities, computed separately for A-rated and BBB-rated bonds, yields the marginal effect. For A-rated bonds, the probability of an Overweight recommendation increases from approximately 10 percent to 17 percent, while for BBB-rated bonds, the corresponding change is negligible, from 26.52 percent to 27.58 percent.

In the remaining columns, I test whether the yield-spread slope for A bonds differs significantly from the slope for BBB bonds and run the following regression:

$$\text{Rec}_{i,t} = \alpha + \beta_1 \text{YieldSpread}_{i,t}^{g=A} + \beta_2 \text{YieldSpread}_{i,t} + \mathbf{1}\{g_{i,t} = A\} + \mathbf{X}_{i,t} + \varepsilon_{i,t}. \quad (6)$$

where the coefficient of  $\text{YieldSpread}_{i,t}^{g=A}$  captures the incremental loading for A relative to BBB. The baseline difference in column (5) is 19.794 and remains large and significant when the comparison is confined to the same industry, the same analyst, or both. Using ordered-logit regression reported in Table A5, this difference means that a one-standard-deviation widening in the spread increases the likelihood of an Overweight by seven percentage points for A-rated bonds relative to BBB-rated bonds.

Finally, I examine whether analysts' preferences over bond and firm characteristics can explain the pattern. Following Gilchrist and Zakrajšek (2012), I control for standard bond-level characteristics that may affect yields through term or liquidity premia, including duration, issue size, trading volume, and coupon rate. I also control for key firm characteristics that reflect financial health, including cash flow to debt, revenue and earnings growth rate, profit margins, and operating leverage. Analyst reports disclose that they use these characteristics to form recommendations. Columns (9)–(12) add these bond and firm controls, and the A-minus-BBB yield-spread coefficients remain statistically significant. Thus, analysts' potential preferences for these fundamentals cannot account for the differential response to yield spreads across rating categories.

### 2.2.1 Yield-seeking behavior over time

Analysts' recommendations may respond to shifts in market conditions. Institutional investors, driven by agency conflicts and client demands, often seek higher-yielding securities during periods of low interest rates to boost portfolio performance (Becker and Ivashina, 2015; Choi and Kronlund, 2018; Acharya and Naqvi, 2019). As information intermediaries, analysts may cater to their clients by assigning greater weights to yield spreads when safe yields are low or compensation for bearing risk declines.

To examine this possibility, I track how their sensitivity to yield spreads evolves over time. Figure 3 plots the time series of yield spread coefficients alongside key measures of aggregate market compensation for risk. First, the one-year Treasury rate shows no negative relation with the spread coefficient, likely because policy rates were persistently low throughout most of the sample (0-2%). Second, the default-risk premium, measured as the BBB–AAA corporate spread, is strongly negatively related to the yield spread coefficient, with correlations of  $-0.28$  for A-rated bonds and  $-0.26$  for BBB-rated bonds. Hence, as the

market’s compensation for credit risk narrows, analysts become more responsive to yield spreads, especially for A bonds. Finally, I evaluate the term spread, the difference between 30-year and 1-year Treasury yields, which measures compensation for bearing duration risk. Similarly, when the yield curve flattens and duration compensation decreases, analysts exhibit greater sensitivity to yield spreads for A-rated bonds (correlations of -0.52 for A-rated bonds and -0.5 for BBB-rated bonds).

In sum, analysts’ recommendations assign greater weight to yield spreads when market compensation for bearing default risk or maturity risk declines, particularly within A-rated bonds. Because analysts’ recommendations can shape investors’ portfolio allocations, their behavior can amplify reaching-for-yield, especially in environments with low risk compensation (Becker and Ivashina, 2015; Choi and Kronlund, 2018; Lian, Ma and Wang, 2019).

### 2.3 Recommendation and credit risk

As analysts’ comments primarily reflect their perceptions of risk for the covered issuers and bonds, I examine how credit risk is incorporated into their recommendations. To proxy for credit risk, I use the firm’s expected default frequency (EDF), which reflects the probability that a firm’s asset value will fall below its debt obligations. EDF is derived from the structural model of Merton (1974) and calculated following the implementation in Bharath and Shumway (2008). Specifically, EDF is computed as the standard normal cumulative density function evaluated at a standardized distance to default:

$$EDF_{it} = \mathcal{N} \left( \frac{-\log(E_{it}/B_{it}) - (\mu_{E_{i,t-1}} - \frac{1}{2}\sigma_{it}^2)}{\sigma_{it}} \right). \quad (7)$$

$E_{it}$  is the market value of firm  $i$ ’s assets,  $B_{it}$  is the book value of its debt,  $\mu_{E_{i,t-1}}$  is the return on the firm’s stock over the past year, and  $\sigma_{it}$  is the volatility of the firm’s asset.<sup>12</sup> Conceptually, EDF captures the distance between the firm’s asset value and its debt obligation, scaled by the standard deviation of the firm’s asset value.

I use EDF as primary measure of firm-level credit risk for several reasons. First, it is theory-based, and the data used to construct it is available publicly, so it’s reasonable to assume that analysts can observe it when making recommendations. Second, because EDF looks forward, it predicts downgrades from credit rating agencies and defaults accurately.<sup>13</sup>

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<sup>12</sup>The book value of debt is approximated by a firm’s current liabilities plus one-half the firm’s long-term liabilities ( $dlc + 0.5 \times dlqt$ ). The volatility of the firm’s assets is estimated as  $\sigma_{it} = \frac{E_{it}}{(E_{it} + B_{it})} \sigma_{it}^E + \frac{B_{it}}{(E_{it} + B_{it})} (0.05 + 0.25 \sigma_{it}^E)$ , where  $\sigma_{it}^E$  is the annualized volatility of the firm’s monthly stock returns over the past year.

<sup>13</sup>I confirm EDF is able to predict future downgrades and defaults using my sample, as shown in Table A3.



This matters because downgrades are salient events and carry reputational consequences for professional analyst. Finally, EDF is widely used in both academia (e.g., [Gilchrist and Zakrajšek 2012](#), [Greenwood and Hanson 2013](#), [Gomes et al. 2019](#)) and industry, making it a natural proxy for capturing comprehensive and objective credit risk in my analysis.<sup>14</sup>

Panel A of [Table 4](#) reports the results. Column (1) shows EDF coefficients are significantly positive for A-rated bonds, but small and statistically insignificant for BBB-rated bonds. Thus, analysts systematically issue more favorable recommendations to higher-rated bonds as EDF risk increases, but remain unresponsive to similar changes in EDF among lower-rated bonds. Adding industry fixed effects in column (2) modestly reduces the A-rated coefficient, without affecting its significance. Columns (3) and (4) present comparisons within the same analysts. The coefficient for A-rated bonds remains positive and significant, while the BBB coefficient remains insignificant. These findings suggest that analysts’ asymmetric responses are not driven by differences in analyst risk preferences.

Columns (5) through (8) directly measure the difference in EDF slopes between A and BBB bonds by interacting EDF with a A indicator. The resulting treatment gap is consistently large and negative, even when restricting comparisons to bonds within the same industry, covered by the same analyst, or both. The ordered logit estimates in [Table A5](#) further illustrate this asymmetry. Raising EDF from its mean (0.565) to one S.D. above (0.685) increases the likelihood of an Overweight recommendation for A bonds by roughly 4.6 percentage points (from 8.6% to 13.2%), yet leaves recommendations for BBB bonds unchanged. Columns (9)–(12) add bond- and firm-level controls, and the treatment gap remains virtually identical, confirming the asymmetry is not driven by observable bond or firm characteristics. Overall, analysts interpret the same default-risk signals differently across the A and BBB rating groups.

## 2.4 Discussion

Cross-sectional variation in recommendations arises from disagreements between analysts and marginal investors regarding perceived risk. For BBB-rated bonds, analysts do not adjust their recommendations in response to fluctuations in risk or yield spreads. In contrast, for higher-yielding or higher-risk A-rated bonds, analysts’ perceptions diverge significantly from those of marginal investors. They are more optimistic about the underlying risk. Analysts may interpret the wider yield spreads in these bonds as reflecting market sentiment or investor irrationality (excessive pessimism). If analysts’ assessments are correct, the portfolios generated following their recommendations should generate positive alpha; otherwise,

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<sup>14</sup>See [Eisenbach, Kovner and Lee \(2017\)](#); [Moody’s Analytics \(2024\)](#)

no alphas would be observed. In the next section, I test this prediction by constructing recommendation-based portfolios.

### 3 Future Performance of Recommendation

I form two-way sorted trading portfolios. At the end of each month, I separately sort A-rated and BBB-rated bonds into three analyst recommendation categories: Underweight (UW), Neutral (N), and Overweight (OW), and then form both value-weighted (VW) and equal-weighted (EW) portfolios for each recommendation group. I hold these portfolios for three months and measure return performance following the rolling-portfolio methodology of Jegadeesh and Titman (1993).

Panel A of Table 5 reports summary statistics for the bonds in these two-by-three portfolios, which hold on average 550 bonds each month. Within the A-rated group, Overweight (OW) portfolios consistently exhibit wider yield spreads compared to Underweight (UW) portfolios, confirming that analysts reward higher yields. Additionally, OW portfolios have longer maturities, indicating that higher-yielding bonds in this segment generally involve greater duration. By contrast, yield and maturity differences within the BBB-rated group are modest, aligning with prior evidence that analysts emphasize safety rather than yield in this category. Further, higher yields or yield spreads are not necessarily associated with poor recent performance, a finding consistent with Chen and Choi (2024). UW portfolios exhibit both lower yields and lower past returns compared to OW portfolios. Age and liquidity (proxied by trading volume and offering amount) are similar across recommendation categories, suggesting these dimensions are unlikely to drive subsequent return differences.

In Panel B of Table 5, I report average excess returns and alphas for the portfolios sorted on ratings and recommendations. To gauge risk-adjusted performance, I report alphas under two benchmark models. I start with the Fama and French (1993) term-structure and investment-grade default factors, the most widely used two-factor system for capturing macro risks that move bond prices. I then include the single corporate-bond market factor advocated by Dickerson, Mueller and Robotti (2023b), who show that, previously proposed bond risk factors do not have any incremental explanatory power over the corporate bond market factor.

Focusing on the excess returns, the average excess returns are higher for higher recommendations in both the A and BBB buckets. The long OW and short UW portfolio (OW-UW) earns 10.2 basis points per month in the A bucket and 9.9 basis points in the BBB bucket for the VW portfolios. The EW portfolios show the same pattern. However, after risk-adjusting returns, the picture diverges across rating buckets. In the A portfolio, the alpha shrinks

to zero under the Fama–French two-factor model and even turns negative once the single corporate-bond market factor is used. In the BBB portfolio, the alpha remains significantly positive relative to the two-factor benchmarks, and remain positive when measured against the market factor alone, with a t-stat equal to 1.41. Such patterns exist if one only looks at OW portfolios.

Next, I examine the individual factors in terms of alphas and factor loadings using the OWUW value-weighted portfolios. [Figure 4](#) reports the betas and alphas. Besides the ones used earlier, I add stock-momentum, bond-momentum, reversal, and downside-risk.<sup>15</sup> For A-rated bonds, the alpha vanishes whenever the regression includes any of the bond factors. And the factors, including bond-market, duration, momentum, downside, or term-structure, carry significant positive loadings, implying that the apparent excess return is simply compensation for conventional risks. By contrast, BBB portfolios continue to deliver economically meaningful and statistically significant alphas in all specifications except the aggregate bond-market factor, with momentum providing only marginal explanatory power. Loadings on other standard factors are economically small and statistically indistinguishable from zero.

These results suggest that, for A-rated bonds, the risk perceptions underlying analysts’ recommendations are less accurate than those of marginal investors. Specifically, analysts are systematically overoptimistic about the risk of higher-yielding, higher-risk bonds. In contrast, the more persistent alpha observed in BBB-rated bonds indicates that analysts more carefully incorporate risk considerations into their recommendations for this segment.

Empirical evidence from recommendations indicates that analysts weight risk differently across rating categories. As illustrated in [Figure 5](#), analysts might understate risk when interpreting available information, or perceive risk accurately but fail to incorporate it fully into their recommendations. Both mechanisms could also operate simultaneously. To distinguish among these explanations, I directly examine analysts’ belief formation by quantitatively analyzing the textual content of their comments in the next section.

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<sup>15</sup>I use factors from [Dickerson, Julliard and Mueller \(2023a\)](#). Specifically, the TERM factor is defined as the return spread between long-term government bonds and the one-month Treasury bill. The default risk factor (DEF) is the difference in monthly returns between a market portfolio of long-term corporate bonds and long-term government bonds. The liquidity factor (LIQ) follows [Pástor and Stambaugh \(2003\)](#), calculated as the average liquidity measure estimated from daily individual bond returns after removing market-wide effects. The bond momentum factor (MOMB), following [Gebhardt, Hvidkjaer and Swaminathan \(2005\)](#), is constructed by independently sorting bonds into five rating groups and five groups based on their past 12-to-2-month cumulative returns (MOM). Within each rating quintile, the long-short momentum return is computed by subtracting the return of the lowest MOM portfolio from the highest. MOMB is the average of these long-short returns across rating quintiles.

### 3.1 Cross-sectional variation of yield-seeking behavior

Prior literature shows that individual characteristics such as gender, experience, and education significantly influence how market participants interpret information and formulate forecasts (Bradley, Gökkaya and Liu, 2017; Cole, Paulson and Shastry, 2014; Peng, Teoh, Wang and Yan, 2022; Bacher, 2024). Motivated by these findings, I explore whether these analyst-specific traits amplify or mitigate the observed asymmetry in responses to yield spreads.

To test for such heterogeneity, I augment the baseline specification by interacting analyst characteristics directly with the difference in yield-spread sensitivity between A-rated and BBB-rated bonds. Specifically, I estimate the following model:

$$\begin{aligned} \text{Rec}_{it} = & \alpha_0 + \beta_1 A_{i,t} + \beta_2 \text{Yield Spread}_{it} + \beta_3 (A_{i,t} \times \text{Yield Spread}_{it}) + \beta_4 M_{i,t} + \beta_5 (A_{i,t} \times M_{i,t}) \\ & + \beta_6 (M_{i,t} \times \text{Yield Spread}_{it}) + \beta_7 (A_{i,t} \times M_{i,t} \times \text{Yield Spread}_{it}) + \gamma_{yrmon} + \gamma_{industry} + u_{it}. \end{aligned} \quad (8)$$

In this specification,  $A_i$  equals one for A-rated bonds and zero for BBB-rated bonds.  $M_j$  denotes one of analyst-specific characteristics, including gender, major, highest degree obtained, LinkedIn follower count, and tenure at JP Morgan. The key coefficient of interest is the triple interaction term  $A \times \text{YieldSpread} \times \text{Trait}$ . This coefficient measures how analyst characteristics influence the difference in yield-spread sensitivity between A-rated and BBB-rated bonds. ?? presents the results of  $\beta_7$ . Columns (1)–(2) link recommendation asymmetry to gender and show that male analysts exhibit a significantly smaller yield-seeking gap between A-rated and BBB-rated bonds compared to female analysts.

It’s possible that an educational background and training shape analysts’ frameworks for forming expectations. To investigate this dimension, I use STEM versus economics undergraduate majors and master’s versus bachelor’s degrees as proxies for analytical rigor and training intensity. Columns (3) to (6) show that analysts with STEM degrees or master’s degrees display a significantly reduced yield-seeking gap relative to those with economics majors or bachelor’s degrees, respectively.

In addition, analysts’ professional incentives, shaped by career tenure and public visibility, can further influence their recommendation patterns. I proxy public visibility with two top-half indicators: high public visibility, defined as having more than 750 LinkedIn followers (the median in my sample), and long firm tenure, defined as more than ten years at J.P. Morgan (again, the sample median). Columns (7)–(10) reveal that analysts with higher public visibility or longer professional tenure exhibit a significantly larger yield-seeking gap between A-rated and BBB-rated bonds. These findings imply that career incentives and reputational concerns amplify analysts’ selective responsiveness to yield spreads.

Taken together, these results demonstrate that analyst characteristics—particularly gender, education, public visibility, and professional tenure—shape the extent to which analysts differentially respond to yield spreads across bond-rating categories.

## 4 Thinking process in comments

I structure the analysis around two dimensions: (1) the evaluation of credit risk, and (2) the interpretation of yield spreads. Risk perception plays a foundational role in analysts’ decision-making process, which involves subjective interpretation of firm-level fundamentals, industry dynamics, and broader macroeconomic conditions. Yield spread can be observed directly as publicly available data. Additionally, while analysts frequently omit explicit references to yield, they consistently highlight factors related to risk improvement or deterioration. For each dimension, I first describe how I transform analysts’ unstructured comments into structured data using LLMs, and then present empirical comparisons across rating groups from their belief formation perspective.

### 4.1 Credit risk evaluation

Risk evaluation can be viewed as a two-step process as shown in [Figure 5](#). First, analysts translate publicly available information into an internal perceived credit risk. Second, they convert this perceived risk, together with other considerations, into specific investment recommendations. The EDF-related recommendation asymmetry may originate at either stage. Analysts may understate risk when interpreting available information, or they may perceive sufficient risk but fail to incorporate it into their recommendations fully. Both channels may also operate jointly. Investigating these channels requires a quantitative measure of analysts’ perceived risk. Ideally, analysts would directly provide such numerical scores of their perceived risk; however, such scores don’t exist. Consequently, I construct two complementary text-based measures.

#### 4.1.1 Perceived risk measure

My first measure is to use a large language model (LLM) to transform analysts’ comments into a single perceived risk score. Recent studies demonstrate that large language models (LLMs) can reliably capture nuanced textual contexts, interpret specialized financial terminology, and assign scores guided by prompts ([Laarits, Matthies, Vasudevan and Yang, 2025](#)). Specifically, I prompt the LLM to emulate an experienced credit analyst. For each analyst comment, the LLM identifies the signals that either heighten (downside) or reduce (upside)

credit risk and carefully assesses both the frequency and intensity of such expressions. It then aggregates the information into a perceived-risk score, ranging from  $-4$  (extreme safety) to  $+4$  (extreme risk). The sign of the score captures the overall stance embedded in the analyst’s language: positive for a net perceived risk, negative for a net perceived safety, and zero for neutrality. The magnitude captures the strength of the perceived risk or safety. The LLM prompt used for this step is provided in [Figure A1](#).

[Table A1](#) presents examples of comments, corresponding recommendations, and the perceived-risk score assigned by the LLM. The first two examples, DuPont (January 2015) and GE (August 2018), highlight explicitly negative language, such as “revenue headwinds,” “lukewarm profitability,” and “elevated leverage,” earning higher risk scores ( $+3$  and  $+2$ ). By contrast, the DTE comment (November 2014) emphasizes improvements in the balance sheet and management’s commitment to strong BBB ratings, receiving a negative risk score ( $-2$ ) and an Overweight recommendation. The final excerpt, Coca-Cola (May 2015), features highly favorable language and yields an even lower risk score ( $-3$ ). These examples confirm that the LLM-derived scale effectively captures both the direction and intensity of risk perceptions. Also, they demonstrate the measure’s flexibility in accurately capturing a diverse range of issuer characteristics, market conditions, and credit events. For instance, the perceived risk for GE notably declines from August 2018 to December 2020, as management’s deleveraging strategy gains credibility.

To further ensure reliability, I construct a second perceived-risk measure using the dictionary-based method of [Loughran and McDonald \(2011\)](#); [Zhang, Zhao and Zhao \(2024\)](#). Specifically, I parse each analyst comment and count occurrences of uncertain, weak-modal, and negative words from predefined word lists. Frequently appearing uncertain words in analyst commentary include terms such as “risk(s),” “could,” “exposure,” “negative,” and “weaker.” Because analysts naturally employ more uncertain and negative language when discussing serious risk factors, higher frequencies of these words indicate a greater extent of risk factors and higher perceived credit risk.

The dictionary-based measure is well-established, transparent, and perfectly reproducible. However, the cost of transparency is rigidity, so this measure has several limitations in a few cases. For instance, it can overlook contextual nuances and misinterpret negations (e.g., “not a liquidity concern”). Additionally, the dictionary approach fails to adapt to new, specialized financial terminology, such as “covenant-lite structure,” that emerges after the word lists were created in 2011. Lastly, it only captures downside sentiment, neglecting potential upside or risk improvements. In contrast, the LLM-based measure effectively addresses these limitations by interpreting entire sentences rather than isolated words, accurately capturing negations, contextual subtleties, and new financial concepts. Additionally, it provides a

symmetric and directional assessment of risk, distinguishing clearly between increasing and decreasing perceived risk. However, the LLM approach lacks the complete transparency of a dictionary-based measure and may potentially introduce model-based subjectivity over time (Ye et al., 2024; Lin et al., 2024).

Each measure brings distinct strengths and weaknesses, so I use both measures together in my main analysis. In my sample, the two perceived-risk measures are positively and significantly correlated (correlation = 0.27), suggesting they capture related but distinct dimensions of analysts’ credit-risk perceptions.

#### 4.1.2 From public information to risk assessment

With measures of perceived risk established, I now examine how analysts translate objective default risk (EDF) into their textual assessments of credit risk. Table 6 presents regression results of the textual risk measures on EDF interacted with bond-rating categories and plus a separate dummy variable for A-rated bonds.

In column (1), I regress the LLM-based perceived risk score on EDF, controlling for time fixed effects. The EDF slope is positive and insignificant for A-rated bonds, and positive and significant for BBB-rated bonds. In column (2), I add industry fixed effects, and the EDF slope for A-rated bonds becomes significant, with other results remaining largely unchanged. These results indicate that analysts perceive higher risk as default risk increases. The intercept for A-rated bonds is positive. Given EDF values range from zero to one, analysts have a lower perceived risk for A-rated bonds relative to BBB-rated bonds in general.

Next, I test whether the two objective risk sensitivities differ significantly. I re-estimate the model with BBB as the reference group, so the coefficient on the interaction term now captures the incremental loading for A relative to BBB. The estimate is negative and highly significant. In other words, an extra SD increase in EDF translates into a lower boost in the perceived risk when the bond is A-rated than when it is BBB-rated.

In columns (5) to (8), I re-estimate the model using the number of uncertain texts as the dependent variable, and findings remain largely unchanged. A higher intercept and a flatter slope for A bonds together imply that analysts start more cautiously but accelerate their concern more slowly as EDF rises. This finding is interesting. Intuitively, credit ratings serve as reference points for analyst expectations, and a moderate increase in default risk (EDF) might be acceptable for a BBB issuer, but would be alarming for a safer A-rated issuer. If analysts react more strongly when default risk deviates from rating-based expectations, their comments should reflect greater EDF slope for A-rated bonds than BBB bonds.

#### Predicting Future Realization of Risk

Based on analyst comments and prior literature, CRA downgrades are salient and can



carry reputational consequences for analysts. Especially when the downgrade risk is predictable using public information, such as EDF, a rational analyst is expected to predict future downsides and defaults in the correct direction.<sup>16</sup> I test this prediction by relating analyst recommendations and perceived risks to subsequent downgrades and defaults. Specifically, I estimate a series of logit models, where the dependent variable equals one if the issuer experiences a downgrade (DG) within three, six, or twelve months, or a default (DF) within three years, and zero otherwise. Table 7 reports these regression results.

Columns (1)–(4) examine the predictive power of analyst recommendations for downgrades and defaults. Column (1) shows that for BBB-rated bonds, moving from Underweight to Overweight in the cross section reduces the predicted three-month downgrade probability from 7.6% to 2.7%. However, recommendations have no significant predictive content for A-rated bonds. Extending the prediction horizon to six and twelve months (columns 2–3), the results remain robust. Column (4) focuses on defaults over a three-year horizon and the sign of predictability reverses for A-rated bonds. A more favorable recommendation (from Underweight to Overweight) increases the default probability from 0.7% to 3.3%. For BBB-rated bonds, the corresponding effect remains statistically insignificant. These findings suggest that recommendations can predict short-term downgrades only within the BBB rating category. For safer A-rated bonds, favorable recommendations fail to predict short-term deterioration and instead appear associated with increased longer-term default risk. Defaults rarely occur without warning and typically follow a sequence of credit deterioration and rating downgrades.

Columns(5)–(12) exploit the LLM-derived perceived risk score and uncertain word count as key explanatory variables. For BBB bonds, the rise in the risk score (from 0 to +3) lifts the predicted downgrade risk from 3.7% to 9.5%. The corresponding increase for A bonds is similar. Word-count uncertainty yields a similar pattern. For default, the predictive strength of the LLM score is more pronounced in A-rated bonds; however, the effect becomes statistically less precise for BBB-rated bonds at the three-year horizon. Overall, the comments-based perceived risk measure flags credit deterioration well ahead of rating agency actions.

These results are puzzling, as analysts’ recommendations fail to predict subsequent risk realizations in the higher-rated segment. To address this puzzle, I next explore how analysts incorporate their perceived risks into final recommendations.

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<sup>16</sup>Appendix shows that EDF is able to predict future downgrades and defaults in the granular rating group in my sample.

### 4.1.3 From risk assessment to recommendations

[Table 8](#) reports regressions of analysts’ recommendations on textual risk measures. The key explanatory variables are the perceived risk proxies, the LLM-generated risk scores (columns 1 to 4) or uncertainty word counts (columns 5 to 8), each interacted with bond rating indicators (A and BBB). All regressions control for a rating group dummy and time fixed effects. Alternate columns further include yield spreads interacted with rating groups and industry fixed effects.

In columns (1)–(4), the interaction term between perceived risk and the BBB rating is negative and statistically significant, indicating that the bonds with higher perceived risk will receive less favorable recommendations in this rating category. Conversely, the same perceived risk score shows a positive but insignificant relationship with recommendations for A-rated bonds, suggesting analysts do not adjust recommendations downward in response to higher perceived textual risk in higher-rated bonds. Columns (5)–(8) repeat the analysis using the uncertain word-count measure. Consistent with the LLM-based results, the loadings of uncertain text in the A group are positive and in the BBB group are negative. The weaker statistical significance likely reflects the reduced nuance and inability to fully capture sentence-level context of the uncertain word-count measure relative to the LLM-generated measure.

Taken together, these results help resolve the gap between what analysts say and what they recommend. Although analysts explicitly acknowledge downside risks in their comments, they systematically fail to incorporate these risks into recommendations for bonds perceived as safer. This selective response aligns closely with the “local thinking” framework of risk neglect proposed by [Gennaioli, Shleifer and Vishny \(2012\)](#), wherein investors underestimate the probability of adverse outcomes deemed unlikely to happen. Because an A rating carries lower default risk and lower regulatory capital charges, analysts may dismiss adverse scenarios as remote or irrelevant. Consequently, they discount or disregard even their own articulated risk concerns when issuing investment recommendations. In short, analysts neglect risk in purportedly safe bonds, and this is a plausible driver of the recommendation asymmetry. In addition, this finding provides the first empirical evidence for the mechanism suggested by [Becker and Ivashina \(2015\)](#), who argue that reaching-for-yield behavior can reflect risk neglect.

## 4.2 Yields evaluation

This section examines analysts’ evaluations of yield. Unlike credit risk, which must be inferred from firm fundamentals, yield spreads are directly observable market data. Thus,

analysts do not estimate the numerical level of yield spreads; instead, they qualitatively assess whether a given spread is sufficiently “wide” or “tight,” conditional on their underlying risk perceptions. This framework implies two potential mechanisms behind the recommendation asymmetry. First, analysts might perceive identical increases in yield spreads as more attractive for A-rated bonds than for BBB-rated bonds. Second, analysts might place differing weights on identical qualitative yield assessments when making final recommendations across rating categories.

To disentangle these possibilities, I proceed in three steps. First, I construct a numerical yield-tone measure by categorizing analysts’ qualitative assessments (e.g., “wide,” “fair,” or “tight”). Second, I test whether a given numeric spread increase is more frequently described as “wide” for A-rated bonds than for BBB-rated bonds. Third, I examine whether analysts translate identical qualitative yield assessments differently into final recommendations across ratings.

#### 4.2.1 Yields tone measure

I quantify analysts’ qualitative evaluations of yield through a structured yield tone score, derived directly from their comments. Specifically, the LLM scans each paragraph to identify explicit references to yields, and comments without valuation references are excluded from subsequent tone analyses. Then, the LLM classifies language by directional tone: positive terms (e.g., “wide,” “attractive,” “rich,” etc.) receive a score of +1, neutral expressions (e.g., “fair,” “range-bound,” etc.) receive 0, and negative phrases (e.g., “tight,” “compressed,” “limited room,” etc.) receive −1.<sup>17</sup> The exact LLM prompt is provided in [Figure A2](#). The procedure results in approximately 38,000 yield-tone scores. Among these, 42% are classified as “tight,” 27% as “neutral,” and 31% as “wide.”

#### 4.2.2 From true yield to yield tone

Panel A of [Table 9](#) examines how numeric yield spreads shape analysts’ qualitative language. Columns (1)–(4) regress the LLM-derived yield tone on yield spreads, rating indicators, and their interactions. Column (1) controls for time fixed effects only. It shows that yield spread increases are characterized as more attractive for A-rated than BBB-rated bonds. Column (2) adds perceived risk scores. The risk score coefficient is negative, consistent with higher perceived risk making analysts less likely to describe yields as attractive or wide, as the spread no longer adequately compensates for elevated risk. After adding industry fixed effects in columns (3) and (4), the key findings remain robust.

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<sup>17</sup>Analysts explicitly discuss yield spreads at roughly equal frequencies (around 40 percent of notes) across both rating groups. This rules out the possibility that analysts rarely mention yields for BBB-rated bonds.

Notably, the sensitivity of qualitative yield tone to yield spreads is approximately twice as large for A-rated bonds as for BBB-rated bonds, highlighting substantial differences in how analysts interpret identical numeric information across rating categories. Columns (5)–(8) further confirm this asymmetry: analysts systematically describe equivalent increases in numeric spreads as more attractive when the issuer carries an A rating.

### 4.2.3 From yield tone to recommendation

Having established the asymmetry in how analysts qualitatively interpret identical yield spreads, I now examine whether differences also appear in how they translate these qualitative assessments into recommendations. Panel B of [Table 9](#) regresses analysts’ numeric recommendations on the yield-tone measure, rating-category indicators, and their interactions. Columns (1) and (2) show a consistent and strong relationship between yield tone and analyst recommendations. Columns (3) and (4) show that the interaction term between yield tone and bond rating is negligible and not statistically significant, with and without industry fixed effects. Thus, the influence of yield-tone language on recommendations remains essentially uniform across ratings.

This symmetry implies that the observed recommendation asymmetry does not stem from how analysts incorporate qualitative yield assessments into recommendations, but from when analysts convert numeric spreads into qualitative judgments. Specifically, identical yield spreads are more frequently described as “wide” for A-rated bonds.

The empirical results raise two puzzles. First, why do analysts issue more favorable recommendations to higher-yielding, riskier bonds, but without generating positive alphas, only for A-rated ones? Second, why do they underweight risks that they already explicitly recognized in A-rated bonds but not in those rated BBB? I consider three potential mechanisms: (1) catering to clients, (2) catering to investor demand, and (3) categorical thinking.

## 5 Traditional mechanisms

### 5.1 Catering to clients

Agency conflicts may explain the observed recommendation asymmetry between A- and BBB-rated bonds, as analysts face incentives to issue strategically biased recommendations to their clients ([Lin and McNichols, 1998](#); [Michaely and Womack, 1999](#); [Mehran and Stulz, 2007](#)). For instance, employers of analysts provide investment banking services to issuers, and therefore analysts can issue more optimistic research to attract or retain such client relationships. Analysts also can face brokerage incentives, as optimistic recommendations

boost trading volumes and commission revenues (Ajinkya, Atiase and Gift, 1991; Agrawal and Chen, 2012).

To evaluate client-driven incentives, I collect and analyze disclosures from analyst reports that identify the bank’s relationships with issuers. I then consolidate the client relationships into three categories: (1) investment banking, which primarily provides underwriting and broader advisory services such as mergers and restructuring; (2) broker and market maker, which involve liquidity provisions and secondary-market trading; and (3) other significant financial interests, such as proprietary positions in holding debt securities exceeding one million USD. I match client relationships by company names to my sample dataset. The resulting sample contains 14,315 observations across 170 unique firms with at least one disclosed relationship. The investment banking represents the largest category (95%) , followed by brokerage roles (5%) and proprietary interests (3%).<sup>18</sup>

If analysts cater to client issuers, these issuers should receive more OW recommendations. However, the data does not support this prediction. The distribution of recommendations for client-affiliated issuers is consistent with the non-client sample and shows no systematic optimism toward clients.<sup>19</sup> I also employ regression analysis to explicitly test whether client relationships drive the rating-related asymmetry:

$$\begin{aligned} \text{Rec}_{it} = & \alpha_0 + \beta_1 \mathbf{1}\{g_{i,t} = A\} + \beta_2 \text{YieldSpread}_{it} + \beta_3 \text{YieldSpread}_{i,t}^{g=A} + \beta_4 M_{i,t} + \beta_5 M_{i,t}^{g=A} \\ & + \beta_6 (M_{i,t} \times \text{YieldSpread}_{it}) + \beta_7 (M_{i,t} \times \text{YieldSpread}_{i,t}^{g=A}) + FE + u_{it}. \end{aligned} \quad (9)$$

In this specification,  $\mathbf{1}\{g_{i,t} = A\}$  is one for A-rated bonds and zero for BBB-rated bonds.  $M$  denotes client relationships. The key coefficient of interest is  $\beta_7$ , which measures how client relationships influence the difference in yield-spread sensitivity between A-rated and BBB-rated bonds.

Table 10 reports results. All regressions control for firm and bond characteristics, as well as time and industry fixed effects. Columns (1)–(4) report OLS estimates of the coefficient  $\beta_1$  from Equation 6, separately for issuers with and without disclosed client relationships. The significant positive coefficients on the interaction between the A-rating indicator and yield spreads confirm that the core recommendation asymmetry holds in both subsamples.

Columns (5)–(10) test whether client relationships amplify the recommendation asymmetry by estimating Equation 9 and focusing on  $\beta_7$ . Columns (5)–(6) separately examine three relationship types, and only the “Financial interest” category shows a weakly significant positive effect. Such relationships constitute only a small fraction of disclosed client ties

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<sup>18</sup>Percentages sum to over 100%, as the broker house can provide multiple services simultaneously to the same issuer.

<sup>19</sup>In the client sample, recommendations are distributed as follows: OW (22%), N (52%), and UW (26%).

and all client categories should have similar directional effects if analysts cater to clients. I then combine the three categories into a single client dummy. Columns (7) and (8) report the results and show that  $\beta_7$  remains statistically indistinguishable from zero.

Lastly, even if an analyst’s employer has no active relationship with a *currently* covered firm, it may anticipate *future* business opportunities or retain the *previous* business. Therefore, columns (9) and (10) broaden the client relationship definition to include ties established within 12 months before the official start date or maintained within 12 months after the official end date of a disclosed relationship. Results provide no evidence that analysts cater to issuers with current or potential client ties.

Overall, catering to clients does not explain the observed recommendation asymmetry. This is unsurprising given the heightened regulatory scrutiny following the landmark 2003 analyst settlement, which, combined with analysts’ reputational concerns, can constrain strategic distortions and encourage analysts to provide honest recommendations.<sup>20</sup>

## 5.2 Catering to investors

Catering to investor demands may explain the observed asymmetry in analyst recommendations. As the main holders of corporate bonds, institutional investors differ in their constraints and preferences. Insurance companies are constrained by strict regulatory capital requirements and systematically reach for yield within investment-grade bonds (Becker and Ivashina, 2015). By contrast, mutual funds face fewer regulatory constraints and, on average, do not exhibit yield-seeking behavior (Choi and Kronlund, 2018). If analysts seek reputational recognition among these investors, they might strategically tilt recommendations toward the corresponding investor preferences: emphasizing yield opportunities for the bonds predominantly held by insurance companies and adopting a more cautious stance for the bonds dominated by mutual funds.

To test the mechanism of catering to investor demands, I link recommendations to eMAXX holdings and compute, for each bond-month, the percentage of ownership by investor type as shares held by that type divided by outstanding shares. This measure captures the bond’s exposure to each type of investor. In the merged sample, insurers dominate the investor base for most bonds: roughly 70% of bond-months show insurers’ holdings more than twice mutual-fund holdings, half of observations show insurers’ holdings exceed five times over mutual-fund holdings, and a quarter of observations show insurers’ holdings exceed ten

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<sup>20</sup>In April 2003, ten major Wall Street firms paid \$1.4 billion in penalties to resolve charges that their analysts routinely issued overly optimistic research to attract investment banking business. The settlement also imposed structural reforms, prohibiting analysts from participating directly in sales activities and mandating separation between research and investment banking operations (U.S. Securities and Exchange Commission, 2003).

times over mutual-fund holdings.

If analysts cater to investor demand, recommendations should display a larger A–BBB asymmetry in yield sensitivity where insurers dominate the investor base. I employ the Equation 9 and define  $M_{i,t} = 1$  if insurers’ holdings of bond  $i$  at time  $t$  are at least  $k$  times mutual-fund holdings, for thresholds  $k \in \{2, 5, 10\}$ . The coefficient of interest,  $\beta_7$  measures how the A–BBB spread slope changes when the insurer-to-mutual-fund holdings ratio exceeds  $\kappa$ , relative to when it does not. A positive  $\beta_7$  indicates a larger A–BBB slope gap under insurer dominance.

Table 11 reports the results. Columns (1)–(2) report OLS estimates of the coefficient  $\beta_1$  from Equation 6 for the merged sample. The coefficient on the A–rating interaction with yield spreads,  $\beta_1$ , is positive and statistically significant, confirming that the core recommendation asymmetry holds in the merged sample. Columns (3) to (8) report OLS estimates of  $\beta_7$  from Equation 9.  $\beta_7$  is statistically indistinguishable from zero across the insurer-dominance thresholds ( $k = 2, 5, 10$ ). Hence, the A–BBB spread-slope gap does not vary with insurer dominance, providing no support for investor-catering as the driver of the asymmetry.

## 6 Behavioral mechanism: rating-induced categorical thinking

Based on the findings, I hypothesize and provide evidence that bond analysts exhibit categorical thinking shaped by rating group labels. Intuitively, A-rated bonds are viewed as “safe and low return”, while BBB-rated bonds are perceived as “risky and high return”. If bond analysts adopt this mental framing, they may apply asymmetric inference to A and BBB group bonds. Specifically, analysts underweight credit risk signals and emphasize yield spread in A-rated bonds, while discounting the upside potential and focusing on downside risk in the BBB-rated bonds. This would give rise to both risk neglect and reach-for-yield dynamics, consistent with explanations that link yield-seeking behavior to risk neglect, proposed by Becker and Ivashina (2015).<sup>21</sup>

### 6.1 Institutional background: the A through BBB rating boundary

This section outlines two institutional features of credit ratings that motivate the empirical approach. After reviewing the institutional background, I describe the empirical design that exploits these features.

#### Institutional regulations on A-BBB

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<sup>21</sup>From Becker and Ivashina (2015), “We expect reaching for yield over ‘post-crisis’ period to become weaker due to an increase in downgrade probabilities, scrutiny, and awareness of previously neglected risks, or a shift in risk preferences.”



Regulations and market conventions have long drawn distinctions between A- and BBB-rated bonds. These differences date back over a century to the origins of formal credit ratings and continue to shape market practices today. When Moody’s initially introduced its credit rating system in 1909, it grouped AAA, AA, and A bonds into a “first-grade,” while BBB and BB bonds into a “second-grade” (Harold, 1938; Fons, 2004). Early regulatory interpretations reinforced this distinction. For instance, *American Banker* concluded that early regulations practically limited investments to A-rated bonds. It was not until 1938 that Moody’s persuaded regulators that BBB-rated bonds were neither “distinctly nor predominantly speculative,” thereby classifying BBB bonds as investment-grade (Harold, 1938). Today, although both A-rated and BBB-rated bonds are classified as investment-grade under most regulatory frameworks, many institutions—including banks, insurance companies, and market indices—still distinguish significantly between these ratings.<sup>22</sup> Over time, the regulatory and institutional reinforcement has led market participants to naturally believe that A-rated bonds are inherently safer than BBB-rated bonds.

### Limitations of credit ratings

Credit ratings are designed to give investors an informed assessment of a firm’s credit-worthiness (S&P Global Ratings, 2023). However, extensive research highlights structural limitations of credit ratings that reduce their accuracy and timeliness. A notable limitation is rating inertia, the deliberate emphasis on stability that discourages frequent rating adjustments (S&P Global Ratings, 2010; Cantor and Mann, 2006). Credit rating agencies (CRAs) prioritize stability over accuracy and often require sustained changes in firm fundamentals before updating ratings. This conservatism can delay both downgrades and upgrades.

Conflicts of interest within CRAs can also compromise rating accuracy and credibility (Opp, Opp and Harris, 2013; Mathis, McAndrews and Rochet, 2009; Bolton, Freixas and Shapiro, 2012; Kronlund, 2020). Theoretical and empirical evidence suggest reputational concerns fail to prevent CRAs from catering to issuer interests. Conflicts of interest can arise from agencies deliberately understating risk to secure issuer business and issuers selectively purchasing the most favorable ratings available. Recent literature further documents credit rating inflation that can also compromise the accuracy of credit ratings (Griffin, Nickerson

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<sup>22</sup>Under Basel III regulations, commercial banks apply credit rating-based risk weights to corporate bond holdings, directly influencing their regulatory capital requirements. Specifically, bonds rated A receive a 20% risk weight, while bonds rated BBB receive a 50% risk weight (Basel Committee, 2019). Similarly, insurance companies must hold more capital when investing in lower-rated bonds. Specifically, under the NAIC framework, the risk-based capital charges increase from 0.4% for A-rated bonds to 1.3% for BBB-rated (National Association of Insurance Commissioners, 2021). Additionally, prominent market indices, such as Bloomberg and ICE corporate bond indices, provide separate performance metrics for A-rated and BBB-rated bonds (Bloomberg, 2024; ICE, 2024). Although the SEC’s net capital rule does not explicitly assign rating-specific risk weights, it implicitly relies on credit ratings when broker-dealers calculate net capital requirements based on asset risk categories (U.S. Securities and Exchange Commission, 2022).

and Tang, 2013; He, Qian and Strahan, 2012; Eling and Hau, 2015).<sup>23</sup>

Given these frictions within CRAs, there is reason to believe that ratings tend to lag behind market-based indicators of credit risk (Cantor and Mann, 2006). As Bongaerts, Cremers and Goetzmann (2012) highlight, credit ratings are assigned primarily for regulatory purposes and do not provide significant incremental information about a firm’s credit quality. The disconnect between ratings and underlying fundamentals creates a natural setting where firms with similar fundamental characteristics can receive different ratings within the investment-grade category.

## 6.2 Empirical design: matching

The previous section suggests two stylized facts that motivate my empirical approach. First, institutional regulations and investment mandates treat A- and BBB-rated bonds differently, reinforcing the natural market perception that these categories reflect meaningful economic differences. As a result, investors and analysts may aggregate information at the coarse rating group level and form assessments based on rating group stereotypes. A-rated bonds are commonly viewed as safe assets, while BBB-rated bonds are viewed as risky.

Second, structural limitations in credit ratings, such as rating inertia and conflicts of interest, imply that some A-rated firms are very similar to BBB in terms of financial health characteristics. That is, there are firms rated in the BBB group that should be in the A group and vice versa. By leveraging rating frictions, I use matching methodology to isolate the effect of the rating category itself. Specifically, I match A and BBB firms based on industry and firm characteristics and compare analysts’ interpretations of the credit signals.

My benchmark matching procedure uses industry, size, leverage, Altman’s z-score, EDF, and cash holdings. These variables have the most explanatory power in regressions of the A versus the BBB group on firm characteristics. Each month, I take an A firm and find a BBB firm that is the closest in terms of my matching variables in the same industry. I use a caliper-based nearest-neighbor matching that is adapted to a panel setting, following Asker, Farre-Mensa and Ljungqvist (2015). To ensure high-quality matches in which the A firm and its BBB match are very similar, I impose a tight 0.35 caliper value.

The matching sample provides a setting to directly test rating-driven categorical thinking: whether analysts interpret the same credit signals differently purely depending on the firm’s rating label. Next, I introduce the matching procedure to construct pairs of similar A-rated and BBB-rated firms.

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<sup>23</sup>Specifically, CRAs inflated ratings beyond their models when facing competition, and they tend to assign overly optimistic ratings to asset-backed securities structured by large issuers who generate significant fee revenue. Becker and Milbourn (2011) demonstrate that increased competition among rating agencies has reduced the quality and informativeness of credit ratings from established agencies like S&P and Moody’s.

### 6.2.1 Characteristics of matched A and BBB firms

Each month, an A (A−, A, A+) non-utility firm is matched to the BBB (BBB−, BBB, BBB+) firm that is closest in terms of log assets, book leverage, market leverage, EDF, cash to assets, Z-score, and PPE to assets. AAA and AA issuers are excluded because they are more likely to differ markedly in credit quality from BBB firms. I measure distance as the absolute difference between the log odds of the propensity scores obtained from the logit model, and a BBB candidate is accepted as the nearest neighbor only when the distance lies within a caliper of 0.35.<sup>24</sup> Utility firms are matched similarly, except that the Z-score is omitted.

Table 12 reports the mean characteristics for each set of firms and the difference in means. The full sample contains 3,265 A and 5,287 BBB firm-month observations. The matched sample consists of 1,556 A-rated firm-month observations matched to 846 unique BBB-rated firm-month observations. The share of outlying notches (A+ and BBB−) falls from 25% in the full sample to 10% in the matched sample. Most matched pairs link issuers right on the A/BBB boundary. This concentration suggests that the matching algorithm lines up bonds with comparable credits.

Our matching procedure successfully picks A and BBB firms that have similar size, leverage, solvency, tangibility, and profitability. In the raw data, BBB issuers carry 14.5 percent more leverage than their A-rated counterparts. After matching, the gap shrinks to 2.7 percent and is no longer statistically significant. Furthermore, none of the other differences in characteristics between A firms and matched BBB firms are statistically or economically significant. Overall, my matching procedure selects a sample of A and BBB firms that are very similar along observable dimensions. Next, I explore what credit signals analysts should respond to when forming recommendations.

### 6.3 Rational benchmark: The same credit signal shouldn't be treated differently in the matched A and BBB firms

My identifying assumption is that, for A-rated and BBB-rated firms with identical observable fundamentals at a given time, the expected response of future bond performance to underlying credit signals is the same. Under this assumption, the rating label itself carries no additional predictive content once fundamentals are controlled. In other words, within fundamentally matched firms, the predictive power of yield spreads or EDF for future excess

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<sup>24</sup>Prior simulation and empirical work (Cochran Rubin 1973; Austin 2011) shows that keeping matches within roughly 0.20–0.50 standard deviations of the logit of the propensity score removes most observable covariate bias while preserving sample size. In my data, the pooled standard deviation of the log-odds score is  $\approx 1.4$ , so I choose caliper  $\approx 0.25 \times 1.4 \approx 0.35$ .

returns should not differ significantly across rating groups.

Specifically, I test the specification using Equation 5 and Equation 6, and replace the dependent variable with the next 3-month excess returns. Columns (1) to (6) report estimates for the full sample of U.S. public non-financial firms from 2013 to 2023.<sup>25</sup> The yield spread predicts future returns much more strongly for BBB bonds than for A bonds. A 10 basis points widening in the spread raises next three-month excess returns on BBB bonds by about 11 basis points, whereas the corresponding increase in A bonds is only 0.8 basis points and is statistically indifferent from zero. Column (2) confirms that the 10.2-basis-point slope gap is highly significant. Column (3) shows that a higher EDF helps forecast positive excess returns for BBB bonds but slightly negative ones for A bonds, and column (4) shows that the differential response on EDF is statistically significant. Columns (5) and (6) enter both signals jointly, and the EDF coefficients become statistically insignificant, indicating that the risk information is already embedded in the yield spread. The difference of yield spread effect remains positive and highly significant.

Columns (7)–(12) repeat the above analysis in the matched sample. After matching, the spread’s and EDF’s forecasting slope converges across rating buckets. Column (7) shows that a ten-basis-point widening in yield spreads predicts only a 2.3-basis-point higher excess return for BBB bonds relative to their A-rated matches, and this difference is statistically indistinguishable from zero ( $t = 0.74$ ), as shown in column (8). Column (10) similarly shows that the corresponding difference based on EDF is insignificant. Columns (11) and (12) combine yield spreads and EDF, the results keep consistent. Overall, the evidence supports the assumption that matched A- and BBB-rated issuers exhibit similar return dynamics, with yield spreads and EDF forecasting future returns indistinguishably across these A and BBB rating groups.

Overall, if analysts are rational, then I should expect  $\beta_{1,A}$  is statistically indifferent from  $\beta_{1,BBB}$  and  $\beta_{2,A}$  is statistically indifferent from  $\beta_{2,BBB}$ . Any systematic divergence in these coefficients would indicate rating-driven inference behavior consistent with categorical thinking.

#### 6.4 Categorical thinking evidence: The same credit signal is treated differently in the matched A and BBB firms

Table 13 presents estimates from Equation 5 and Equation 6. I construct the sample in two steps: Each month and industry, an A-rated issuer is matched to a BBB-rated issuer with nearly identical fundamentals, and every bond those matched firms have outstanding that

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<sup>25</sup>I also exclude utility firms from this test because the Z-score, used in matching, is not applicable to utilities.

month is then added to the panel. All specifications include pair-by-month-by-industry fixed effects, so any remaining difference is attributable to the rating label itself.

In column (1) the spread interaction is positive and highly significant for A-rated bonds but negative and insignificant for BBB-rated bonds, so the same price signal is interpreted as good news on the A side and as noise or worse on the BBB side. Column (2) shows that  $\beta_{1,A}$  is statistically indifferent from  $\beta_{1,BBB}$ . Column (3) controls for bond characteristics, including Macaulay duration, the log of issue size, coupon, and a callability flag, and the A-minus-BBB spread coefficients become slightly larger and their t-statistic strengthens, confirming that differences in bond characteristics do not drive the pattern. Column (4) adds analysts FE, and the results show that even when two bonds come from the same industry, share comparable issuer and bond fundamentals, and are covered by the same analyst, the analyst still reacts to an identical spread change in markedly different ways. Analysts upgrade A-rated bonds with higher yield spreads but leave their BBB-rated counterparts largely unchanged or mark them down.

Columns (5)-(8) replace the yield spread with the issuer’s expected default frequency (EDF). I can find that  $\beta_{2,A}$  is statistically different from  $\beta_{2,BBB}$  and the treatment gap remains large and negative even when the comparison is restricted to the same industry, the same analyst, or both. Across every specification the standalone BBB indicator carries a positive and significant coefficient. One interpretation is that, once fundamentals are matched, a BBB label signals misclassification: the bond looks A-like on the fundamentals and analysts anticipate an eventual upgrade, so they lean more favorably toward it. A second possibility is that analysts may infer that BBB bonds, all else equal, offer a better payoff than their A-rated twins and therefore deserve a stronger recommendation.

## 6.5 Other supportive evidence 1: Coarser information sets

Because analysts mention topics they consider relevant, systematic differences in the types and frequencies of cited concepts across rating categories reveal whether their information sets vary with ratings. To capture both what analysts discuss and how frequently they discuss it, I convert each comment into structured variables using LLMs. Specifically, I use LLMs to separate analysts’ factual observations from subjective judgments and to systematically catalog the financial concepts they mention. This approach generates detailed and interpretable measures of analysts’ information sets. To ensure high-quality information extraction, I implement a multi-step prompting process. The steps are described below.

### 6.5.1 Information Extraction

#### Step one: Decompose comments to factual and subjective content

Analysts’ comments generally mix observable facts about current corporate conditions with subjective forecasts of future outcomes. Facts reflect analysts’ information sets, while subjective statements provide insight into their forward-looking beliefs. Since the determinants of analysts’ subjective expectations may differ substantially from those of their factual observations, clearly separating these two types of content is essential to systematically understand the expectation-formation process.

I thus begin by decomposing each analyst comment into two distinct parts using LLM: (i) a factual description, which explicitly references realized events or publicly observable firm conditions, and (ii) a subjective prediction, which expresses the analyst’s personal judgments, forecasts, or expectations about future developments. The LLM prompt used for decomposition is provided in the [Figure A3](#).

[Figure A4](#) illustrates the decomposition approach using an analyst’s commentary on General Electric from August 14, 2018. The factual description summarizes objectively observable conditions such as GE’s wider bond spreads relative to other single-A industrial peers, its strategic plan announced in June (including the spin-off of the Healthcare business and exit from Baker Hughes JV), elevated leverage, and its stated financial targets. In contrast, the subjective prediction captures the analyst’s judgment-driven views: specifically, that uncertainty, execution risk, and the weak outlook for key end markets justify the Neutral recommendation. By explicitly separating the factual from subjective content, this method yields structured variables that distinctly represent analysts’ stated information sets apart from their forward-looking beliefs and opinions.

#### Step two: Extract financial concepts

Next, the LLM scans both factual descriptions and subjective predictions to identify key financial concepts explicitly mentioned by analysts. This step serves two key purposes. First, it transforms unstructured, high-dimensional analyst commentary into discrete, economically interpretable terms (e.g., “bond spreads,” “leverage,” “execution risk”), enabling manageable analysis of information sets. Second, by strictly limiting extraction to explicitly stated phrases, it ensures transparency and reproducibility, avoiding inference. The LLM prompt used for this step is provided in the [Figure A3](#).

[Figure A4](#) illustrates the financial concept extraction. The LLM identifies explicitly mentioned financial concepts separately from the factual and subjective components. From the factual content, the model extracts concepts such as “underlying business trends,” “credit metrics,” “execution risk,” etc. From the subjective component, it identifies concepts reflecting the analyst’s forward-looking judgments, including “execution risk,” “weak outlook,” and

“changes in business,” etc. This example demonstrates the LLM’s capability to reliably capture financial concepts from both factual observations and subjective predictions, thereby laying the groundwork for structured analysis.

### **Step three: Label concepts**

To further distill extracted financial concepts into economically interpretable variables, I classify each concept into predefined categories at three levels: firm-specific, sector-specific, and macroeconomic. At the firm level, I follow the standard factor structure commonly used by credit rating agencies (CRAs), including Business Profile, Leverage, Liquidity, Profitability, and Firm-specific Events (S&P Global Ratings, 2023). To ensure greater granularity, I supplement these categories with basic balance-sheet components, such as Assets, Cash, Debt, and Equity. The sector-specific categories include Regulation/Policy and Supply–Demand dynamics, while macro-level concepts comprise Monetary & Fiscal Policy and Country/Global Growth & Shocks. The complete taxonomy is detailed in Appendix. To guarantee consistency, the LLM assigns each concept to exactly one category using a structured and rule-based prompt.

For example, in the GE commentary, the concept “bond spreads” is categorized under Bond (firm-level), “elevated leverage” under Leverage (firm-level), “end-market weakness” under Supply–Demand dynamics (sector-level), and “execution risk” under Firm-specific Events (firm-level). This labeling procedure converts high-dimensional textual information into structured data suitable for further analysis.

### **6.5.2 What information - Types of financial concepts**

The pie chart of Figure 6 shows the proportion of different types of financial concepts that analysts consider. My taxonomy captures more than 70 percent of all extracted terms, leaving only 27 percent in the residual “Other” bucket (grey). Firm-level concepts (purple) represent approximately 60% of the total. Sector-level considerations (green) account for about 10%, and macroeconomic factors (blue) represent only around 4%.

This distribution is stable across bond ratings, which is unsurprising given that both ratings fall within the investment-grade category. Analysts consistently rely on the core set of credit fundamentals required by clients, investors, and regulators. Additionally, my analysis focuses exclusively on public nonfinancial firms, which are subject to similar disclosure requirements, so analysts can have access to similar types of information across these ratings.



### 6.5.3 How much information - Quantities of financial concepts

Having identified what types of financial concepts analysts mention, I now explore how extensively they discuss each category. Specifically, I examine whether analysts consistently provide the same level of detail across bond ratings, or trim the discussion when a bond already wears a safer label.

The bar chart of [Figure 6](#) plots the number of financial concepts mentioned per comment. The blue bars are A-rated bonds, and the purple bars are BBB-rated bonds. Analysts systematically mention fewer concepts for A-rated bonds relative to BBB-rated bonds across nearly every category, as indicated by the lower blue bars compared to purple. The numbers above each bar indicate that most differences are statistically significant. This pattern implies that when a bond carries a safer A rating, analysts streamline their comments, possibly assuming certain risks or financial details require less explicit elaboration. Conversely, the more extensive discussion observed for BBB-rated bonds likely reflects analysts' greater attention to marginal credits, necessitating more detailed justifications of their assessments.

Next, I shift from what topics are covered to where the detail is less inside each note. This slide presents a similar idea in a regression analysis to ensure the result is not driven by time, sector, or issuer mix. [Table 14](#) reports concept counts for the whole note, then splits them into the factual section, the forward-looking section, and finally the probability that no factual block is given at all.

In columns (1)-(3), I use the number of concepts in the whole note, and show that analyst comments on A-rated bonds contain roughly two fewer financial concepts per note on average. This difference remains significant even after controlling for credit risk and industry-time fixed effects. In columns 4-9, I break down the comments into factual descriptions and subjective predictions. And I find that the gap is particularly strong in subjective, forward-looking comments.

Another interesting observation is that analysts sometimes omit factual descriptions altogether and directly provide their predictions, especially for bonds that appear safe. To better understand this behavior, in columns (10)-(12), I specifically examine the likelihood that analysts skip factual information entirely. I find that analysts are indeed more likely to omit factual details when discussing A-rated bonds. However, this effect becomes smaller and statistically insignificant after controlling for issuer-specific risk factors.

Together, these findings strongly suggest that analysts use coarser analysis and may expend less cognitive effort when discussing bonds perceived as safer. Such lower mental effort—fewer financial concepts, omitted factual sections, and reduced detail—may lead analysts to underestimate underlying risks in higher-rated bonds.

## 6.6 Other supportive evidence 2: A- and BBB+ upgrades and downgrades

I next focus on the boundary between A- and BBB+, where even a single-notch move carries significant implications. A downgrade from A- to BBB+ can raise funding costs, prompt index exclusion, and draw closer investor scrutiny, and is followed by negative return performance, whereas an upgrade from BBB+ to A- can have the opposite effects. If analysts paid enough attention to risk on both sides of this line, their calls should flag downgrades in A- and upgrades in BBB+. Panel C shows the opposite. A more favorable recommendation has no predictive content for downgrades in A-, but it anticipates downgrades in BBB+. Conversely, the recommendation predicts upgrades only in A- and not in BBB+. The pattern is consistent with analysts discounting downside risk once a bond is rated A while overlooking upside potential when it sits in the lower investment grade bucket.

The fact that strong analyst recommendations precede defaults in A-rated bonds, despite the observable signals, suggests that they may underweight downside risk in bonds perceived as categorically safe. In contrast, recommendations in the BBB segment are more aligned with future credit outcomes, showing more accurate and timely responsiveness to deteriorating fundamentals. This asymmetry in predictive power supports the original hypothesis that analysts apply different inference rules across rating groups: they emphasize upside and discount risk in A-rated bonds while treating BBB-rated bonds with greater caution. These patterns are consistent with categorical thinking.

## 7 Conclusion

I study how bond analysts perceive credit risk in the corporate bond market. I find that analysts' risk perceptions are rating-contingent: they favor riskier bonds and under-weight their perceived risks only when forming recommendations for higher-rated bonds. To explain this asymmetry, I propose and present evidence of categorical thinking: analysts mentally classify bonds based on coarse rating categories, leading them to underweight bond specific risks for purportedly safe bonds. Investors who follow these recommendations inadvertently reach for yield. This paper provide direct micro-evidence evidence on risk perceptions, moving beyond purely Bayesian information processing. In addition, the results suggest that rating categories shape risk perceptions and show that people not only exhibit behavioral biases in subjective return expectations, but also in subjective risk perceptions.

Figure 1. Distribution of recommendations across credit ratings

This figure shows the distribution of analyst recommendations (Underweight, Neutral, and Overweight) across rating groups from A+ to BBB-. The sample is at the bond-month level and from 2013 to 2023. Blue bars represent bonds rated A+ to A-, and purple bars represent bonds rated BBB+ to BBB-. AA and AAA firms are combined into A+ categories due to few observations.

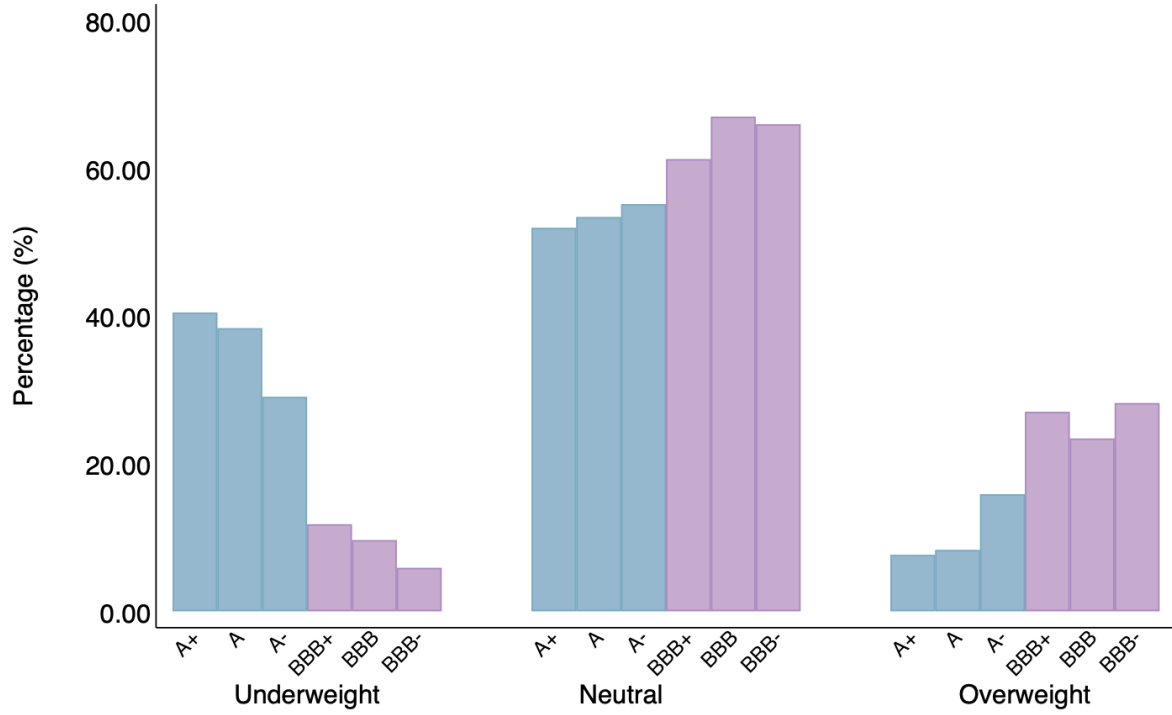


Figure 2. Recommendation formation based on analyst vs. market beliefs

This figure illustrates a step demand curve for a bond. In Panel (a), prices fall in steps  $p_1 > p_2 > p_3 > p_4$  as quantity demanded increases  $\mu_1 < \mu_2 < \mu_3 < \mu_4$ . The dotted lines show the equilibrium, where the market price  $p^*$  reflects the evaluation of marginal investors  $V_m$ , and the corresponding price is  $p^* = v_m$ . Panel (b) shows that the recommendation depends on whether analysts regard the bond as rationally priced. That is, whether their assessment of its risk aligns with the marginal investor's. If  $d_A < d_m$ , then  $v_A > p^*$  (Overweight); if  $d_A = d_m$ , then  $v_A = p^*$  (Neutral); if  $d_A > d_m$ , then  $v_A < p^*$  (Underweight).

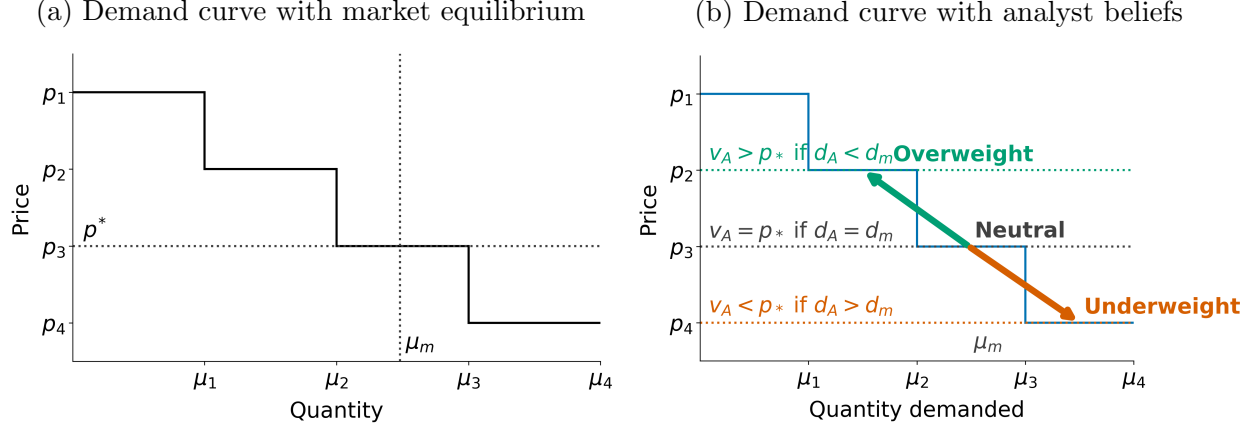
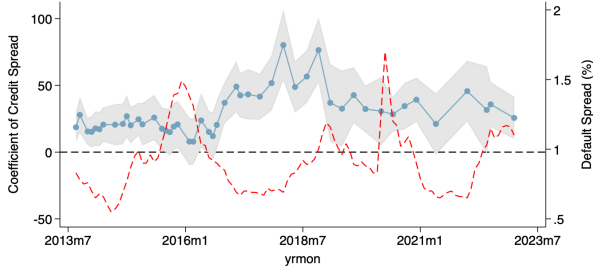


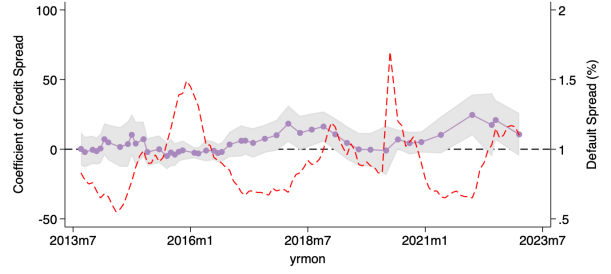
Figure 3. Time series of yield-seeking behavior

This figure plots the time series of yield spread coefficients in Equation 5 alongside key measures of aggregate market compensation for risk. The default-risk premium is measured as the BBB–AAA corporate spread. The term spread is measured as the difference between 30-year and 1-year Treasury yields. The coefficients of yield spread is negatively correlated with default spreads and slopes of treasury yields.

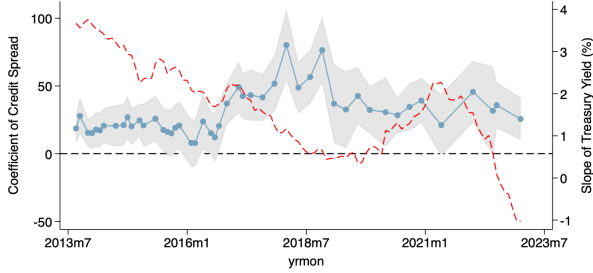
(a) A Bonds



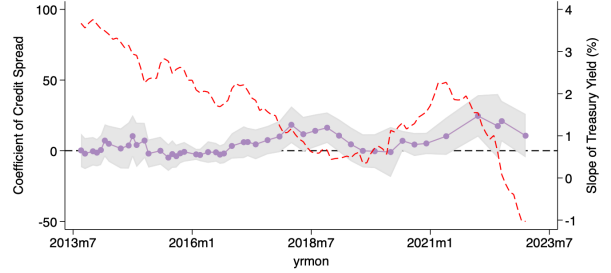
(b) BBB Bonds



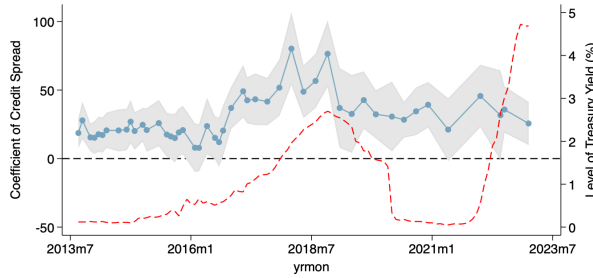
(c) A Bonds



(d) BBB Bonds



(e) A Bonds



(f) BBB Bonds

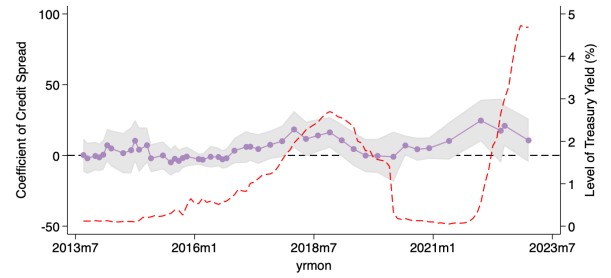


Figure 4. Alphas and Betas

This figure examine the individual factors in terms of alphas and factor loadings using the OWUW value-weighted portfolios, and reports the betas and alphas. Factors include bond market factor, duration, stock market momentum, term structure risk, liquidity risk, bond-momentum, reversal, and default risk. Factors are downloaded from [Dickerson, Julliard and Mueller \(2023a\)](#). Specifically, the TERM factor is defined as the return spread between long-term government bonds and the one-month Treasury bill. The default risk factor (DEF) is the difference in monthly returns between a market portfolio of long-term corporate bonds and long-term government bonds. The liquidity factor (LIQ) follows [Pástor and Stambaugh \(2003\)](#), calculated as the average liquidity measure estimated from daily individual bond returns after removing market-wide effects. The bond momentum factor (MOMB), following [Gebhardt, Hvidkjaer and Swaminathan \(2005\)](#), is constructed by independently sorting bonds into five rating groups and five groups based on their past 12-to-2-month cumulative returns (MOM). Within each rating quintile, the long-short momentum return is computed by subtracting the return of the lowest MOM portfolio from the highest. MOMB is the average of these long-short returns across rating quintiles.

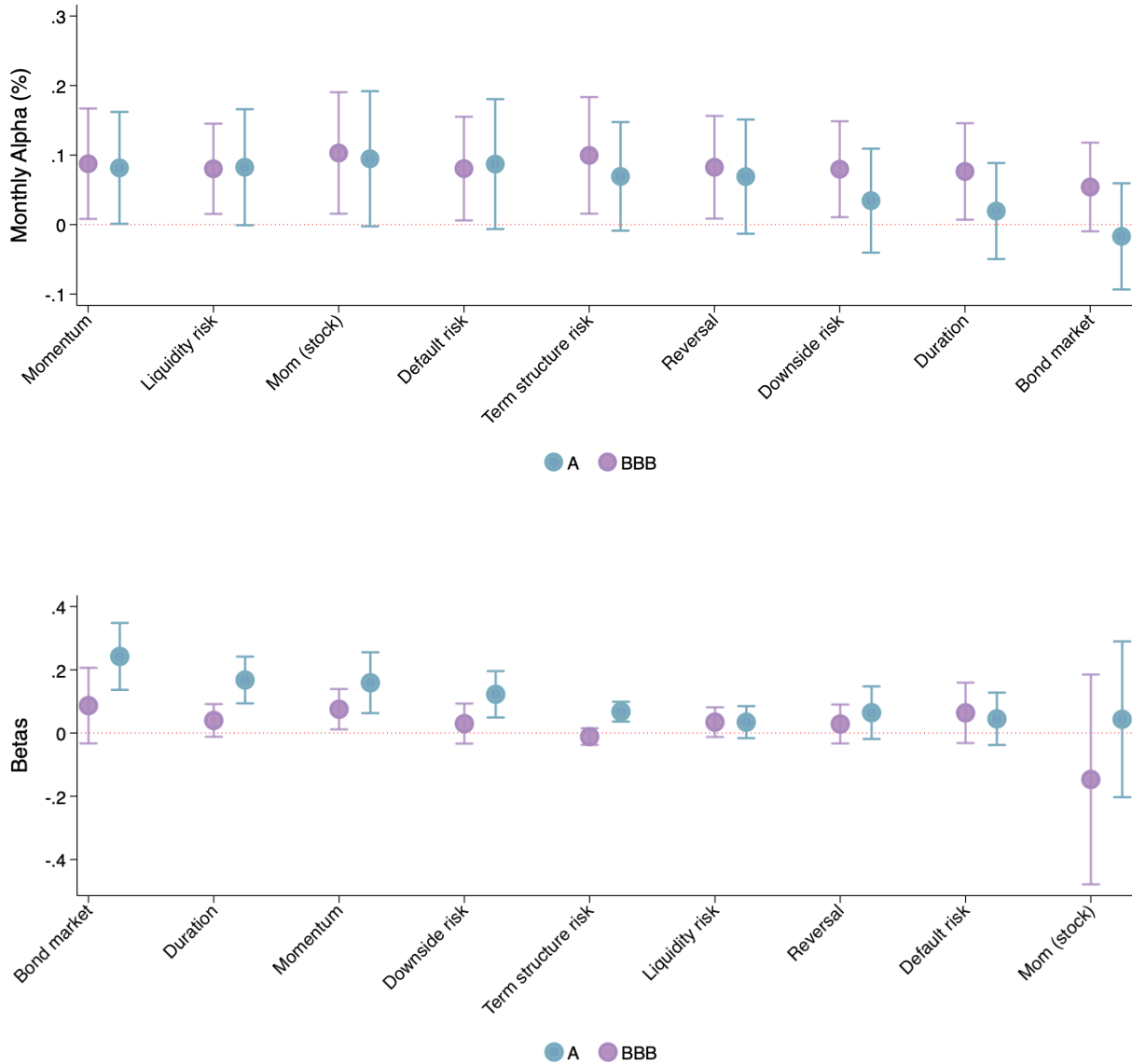


Figure 5. Recommendation formation process

This figure illustrates the analyst recommendation formation process in three stages: data collection, belief formation, and recommendation formation. Analysts first observe basic information such as credit ratings and yield spreads. Depending on this information, analysts either directly form beliefs or gather additional objective information. They then articulate their beliefs through textual comments, and form final investment recommendations.

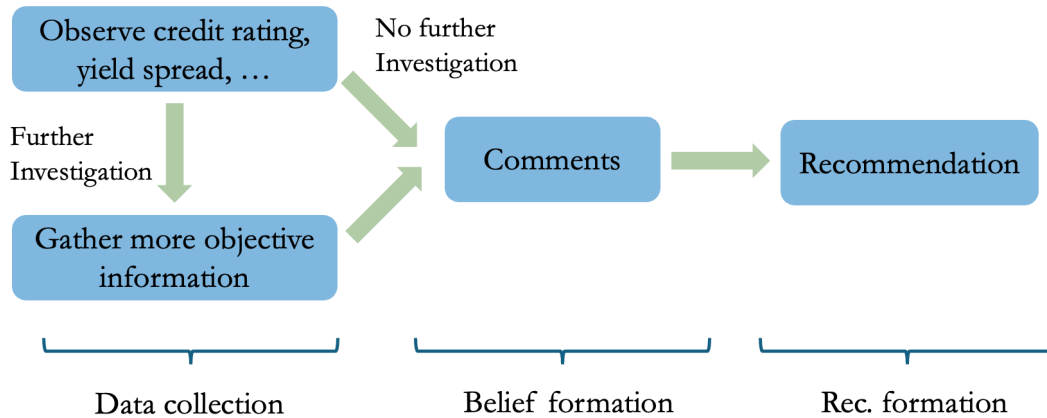
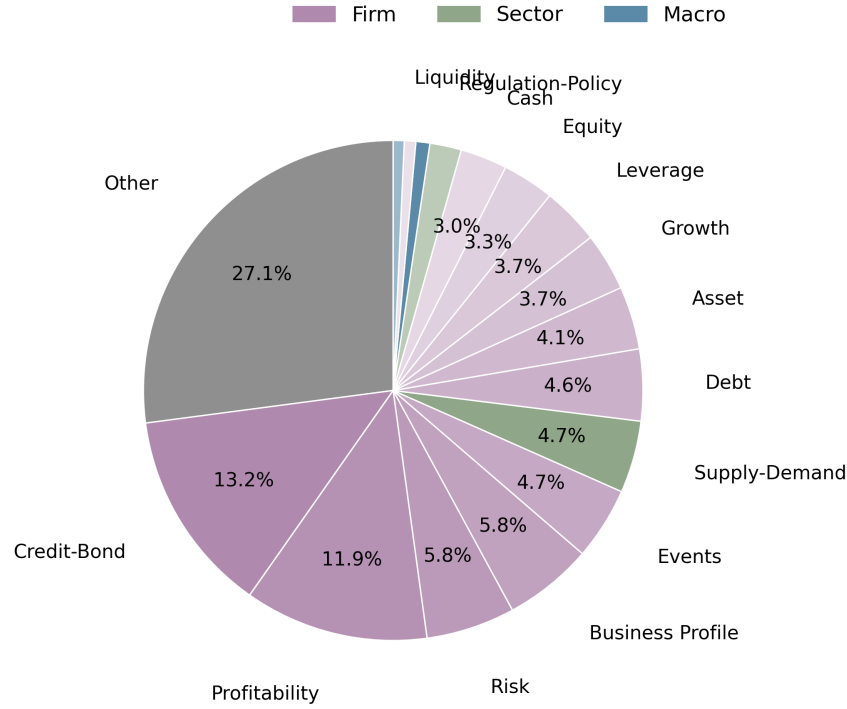


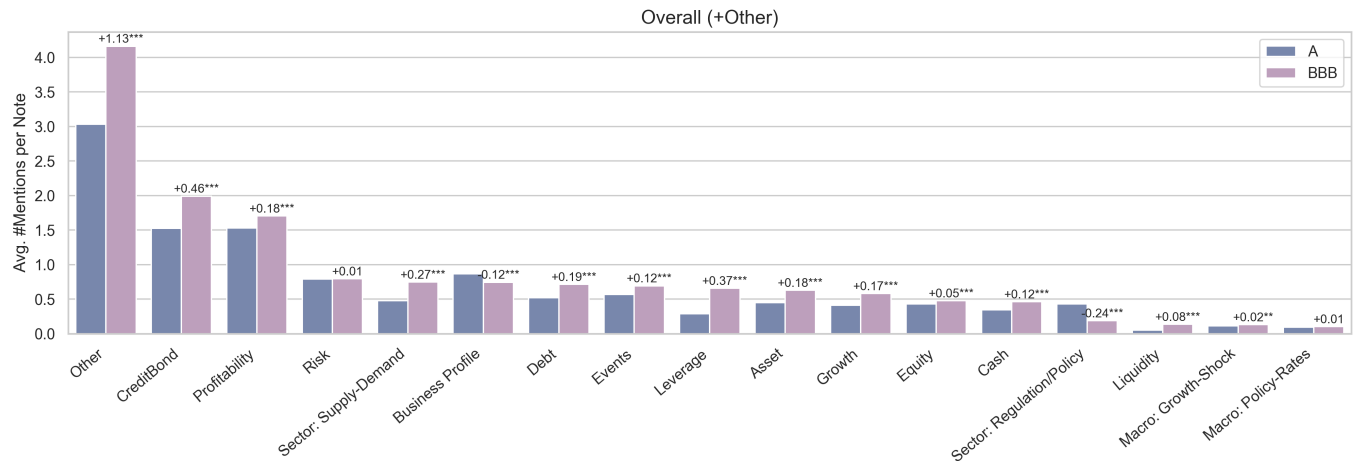


Figure 6. Analysts considerations

The pie chart shows the proportion of different types of financial concepts that analysts consider. The colors represent different concept types: purple for firm, green for sector, blue for macro, and grey for concepts that do not fit into these categories. The bars plot the number of financial concepts mentioned per comment. The blue bars are A-rated bonds, and the purple bars are BBB-rated bonds.



(a) Types of financial concepts



(b) Quantities of financial concepts

Table 1. Summary statistics of industry

This table presents the number of months each industry is covered in my sample, across Investment Grade (IG) reports. IG reports are available from September 2013 to March 2023, issued monthly until 2017, then quarterly from 2017 to 2020, and semi-annually after that. Most industries receive repeated coverage over time. The row of Others includes additional sectors, such as Lodging and Housing (Homebuilders and Building Materials).

Sector	Months	Bond-month obs.	Share(%)
Utilities	48	22 560	22.5
Energy/MLPs/Midstream	43	13 012	13.0
Food/Beverage/Tobacco	48	11 875	11.8
Healthcare	48	9 598	9.6
Technology	48	6 057	6.0
Non-Food Retail	48	5 347	5.3
Manufacturing	47	4 597	4.6
Transportation	45	4 637	4.6
Telecom	47	4 491	4.5
Aerospace/Defense	48	4 018	4.0
Chemicals	47	3 085	3.1
Consumer Products	48	2 796	2.8
Automotive	37	2 571	2.6
Paper & Packaging	48	1 496	1.5
Cable/Satellite	47	1 376	1.4
Diversified Media	47	1 160	1.2
Metals/Mining	48	914	0.9
Others	48	850	0.8
<i>Total</i>		100 408	100.0

Table 2. Summary statistics of issuers, bonds, and recommendations in the sample

The table provides descriptive statistics for issuers, bonds, and recommendations in my sample. Panel A presents firm-month-level financial characteristics, including the number of bonds issued per firm and firm size. Panel B summarizes bond-month-level characteristics, such as credit rating, duration (in years), time to maturity (in years), yield spread, and monthly bond returns. For credit ratings, I use the lower rating if rated by two CRAs and the middle rating if rated by three CRAs (Becker and Ivashina, 2015). Yield spreads are calculated based on the methodology in Dickerson, Mueller and Robotti (2023b). Panel C presents the distribution of recommendations at both the firm and bond levels. I assign firm-level recommendations to bonds based on the disclosure. When analysts issue different recommendations for individual bonds (fewer than 5% cases), I calculate firm-level recommendations as the average of bond-level recommendations. A firm-level recommendation is classified as OW if the average falls within [0.5, 1], N if within (-0.5, 0.5), and UW if within [-1, -0.5]. Panel D reports the means of firm characteristics by credit rating for my sample of nonfinancial firms.

Panel A: Firm-month level variables								
	N	Mean	SD	1st	25th	50th	75th	99th
Number of bonds per firm	8,323	12.06	10.86	1	5	9	16	53
Size (in million)	8,323	41,966.26	77,533.09	1,536.92	8,940.99	20,286.37	46,060.24	287,491.6
Panel B: Bond-month level variables								
Duration (years)	104,061	7.73	4.94	1.16	3.55	6.44	12.26	17.85
Time to maturity (years)	104,061	11.41	9.28	1.17	3.83	7.50	20.00	29.67
Yield spread (%)	104,061	1.30	0.86	0.13	0.71	1.13	1.66	4.25
EDF	104,061	0.56	0.11	0.19	0.51	0.58	0.64	0.73
Monthly bond return (%)	99,309	0.58	2.50	−5.27	−0.39	0.27	1.39	8.50
Offering amount (log)	104,061	13.27	0.68	11.79	12.77	13.12	13.81	14.96
Coupon (%)	99,309	4.46	1.76	1.05	3.20	4.25	5.70	8.88
Trading volume (log)	104,061	16.23	1.91	10.84	15.13	16.49	17.57	19.82
Credit rating	104,061			BBB−	BBB	BBB+	A	AAA
Number of uncertain words	104,061	3.26	2.99	0	1	3	5	14
Panel C: Recommendations in the firm-month or bond-month level								
	Firm		Bond					
	(N)	(%)	(N)	(%)				
UW (Rec = -1)	1,987	23.87	21,955	21.87				
N (Rec = 0)	4,848	58.25	59,803	59.56				
OW (Rec = 1)	1,488	17.88	18,650	18.57				
Total	8,323	100.00	100,408	100.00				
Panel D: Means of firm characteristics by credit ratings								
	AAA	AA	A+	A	A-	BBB+	BBB	BBB-
Assets	11.998	11.618	11.101	10.516	10.628	10.098	10.045	9.746
Book leverage	0.229	0.448	0.487	0.516	0.478	0.489	0.527	0.487
Market leverage	0.069	0.229	0.254	0.251	0.301	0.255	0.302	0.339
Cash/Asset	0.182	0.073	0.181	0.079	0.065	0.080	0.068	0.058
Z-Score	1.574	1.433	1.052	1.172	1.001	1.002	0.757	0.654
PPE/Asset	0.224	0.352	0.322	0.403	0.420	0.404	0.375	0.407
ROA	0.031	0.025	0.019	0.018	0.014	0.016	0.013	0.007
PM	0.186	0.100	0.133	0.107	0.101	0.102	0.073	0.024
Sales growth	0.021	−0.007	0.010	0.011	0.031	0.025	0.033	0.091
Earnings Growth	−0.006	0.042	0.095	0.134	0.124	0.077	0.096	−0.003
CF/PPE	0.422	0.267	0.423	0.228	0.313	0.291	0.281	0.193

Table 3. Recommendation and yield spreads

This table presents two complementary OLS regression specifications. The first quantifies how yield spreads shape analyst recommendations across A-rated and BBB-rated firms. The second tests whether sensitivities of recommendations to yield spreads differ significantly between two rating categories.

$$\text{Rec}_{i,t} = \alpha + \beta_1 \text{YieldSpread}_{i,t}^{g=A} + \beta_2 \text{YieldSpread}_{i,t}^{g=BBB} + \mathbf{1}\{g_{i,t} = A\} + \mathbf{X}_{i,t} + \varepsilon_{i,t},$$

$$\text{Rec}_{i,t} = \alpha + \beta_1 \text{YieldSpread}_{i,t}^{g=A} + \beta_2 \text{YieldSpread}_{i,t} + \mathbf{1}\{g_{i,t} = A\} + \mathbf{X}_{i,t} + \varepsilon_{i,t},$$

where the dependent variable  $\text{Rec}_{i,t}$  is the analyst recommendation for bond  $i$  at time  $t$ , coded -1 = Underweight, 0 = Neutral, +1 = Overweight.  $\text{YieldSpread}_{i,t}$  is the bond's yield spread over the yield of treasuries in the same maturity and expressed in decimals.  $g$  indicates the bond's rating group, which can be  $A$  or  $BBB$ . Controls  $\mathbf{X}_{i,t}$  include bond characteristics, including duration, issue size, trading volume, and coupon rate, and firm characteristics, including cash flow to debt, revenue and earnings growth rate, profit margins, and operating leverage. Standard errors are two-way clustered by issuer and analyst. \*, \*\*, and \*\*\* denote statistical significance at 10%, 5%, and 1%.

	Specification 1				Specification 2				Specification 2 with controls			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
A × Yield Spread	21.760*** [3.82]	12.884** [2.66]	17.034*** [3.26]	12.951** [2.56]	19.794*** [3.28]	11.695** [2.32]	16.096** [2.74]	12.301** [2.27]	17.197*** [2.86]	12.576** [2.27]	16.702*** [2.92]	12.018* [2.05]
BBB × Yield Spread	1.966 [1.05]	1.189 [1.02]	0.938 [0.56]	0.650 [0.52]								
A	-0.601*** [-4.34]	-0.547*** [-4.57]	-0.625*** [-4.53]	-0.568*** [-4.69]	-0.601*** [-4.34]	-0.547*** [-4.57]	-0.625*** [-4.53]	-0.568*** [-4.69]	-0.616*** [-3.94]	-0.570*** [-3.80]	-0.660*** [-4.02]	-0.571*** [-3.70]
Yield Spread					1.966 [1.05]	1.189 [1.02]	0.938 [0.56]	0.650 [0.52]	-2.543 [-0.78]	-0.405 [-0.19]	-1.432 [-0.68]	-2.382 [-1.60]
Time FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Industry FE	N	Y	N	Y	N	Y	N	Y	N	Y	N	Y
Analyst FE	N	N	Y	Y	N	N	Y	Y	N	N	Y	Y
Controls	N	N	N	N	N	N	N	N	Y	Y	Y	Y
Observations	104,061	104,061	95,617	95,617	104,061	104,061	95,617	95,617	96,059	96,059	89,042	89,042
R Square	0.132	0.203	0.179	0.223	0.132	0.203	0.179	0.223	0.190	0.238	0.226	0.264

Table 4. Recommendation and EDF

This table presents two complementary OLS regression specifications. The first quantifies how EDF risk shape analyst recommendations across A-rated and BBB-rated firms. The second tests whether sensitivities of recommendations to EDF risk differ significantly between two rating categories.

$$\text{Rec}_{i,t} = \alpha + \beta_1 \text{EDF}_{i,t}^{g=A} + \beta_2 \text{EDF}_{i,t}^{g=BBB} + \mathbf{1}\{g_{i,t} = A\} + \mathbf{X}_{i,t} + \varepsilon_{i,t},$$

$$\text{Rec}_{i,t} = \alpha + \beta_1 \text{EDF}_{i,t}^{g=A} + \beta_2 \text{EDF}_{i,t} + \mathbf{1}\{g_{i,t} = A\} + \mathbf{X}_{i,t} + \varepsilon_{i,t},$$

where the dependent variable  $\text{Rec}_{i,t}$  is the analyst recommendation for bond  $i$  at time  $t$ , coded  $-1$  = Underweight,  $0$  = Neutral,  $+1$  = Overweight.  $g$  indicates the bond's rating group, which can be  $A$  or  $BBB$ .  $\text{EDF}_{i,t}$  is the firm's expected default frequency. Controls  $\mathbf{X}_{i,t}$  include bond characteristics, including duration, issue size, trading volume, and coupon rate, and firm characteristics, including cash flow to debt, revenue and earnings growth rate, profit margins, and operating leverage. Panel A reports estimates that include only EDF, and Panel B includes both yield spreads and EDF jointly. Standard errors are two-way clustered by issuer and analyst. \*, \*\*, and \*\*\* denote statistical significance at 10%, 5%, and 1%.

	Specification 1				Specification 2				Specification 2 with controls			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
A $\times$ EDF	1.139** [2.27]	0.871** [2.34]	0.733* [1.86]	0.819** [2.14]	0.964** [2.71]	0.659** [2.11]	0.688* [1.91]	0.671* [1.95]	1.478*** [3.55]	1.088*** [2.91]	1.188*** [2.91]	1.226*** [3.29]
BBB $\times$ EDF	0.174 [0.49]	0.212 [0.70]	0.045 [0.12]	0.148 [0.47]								
A	-0.940*** [-6.79]	-0.779*** [-5.03]	-0.848*** [-4.80]	-0.802*** [-5.00]	-0.940*** [-6.79]	-0.779*** [-5.03]	-0.848*** [-4.80]	-0.802*** [-5.00]	-1.264*** [-6.07]	-1.030*** [-5.14]	-1.151*** [-6.20]	-1.111*** [-6.35]
EDF					0.174 [0.49]	0.212 [0.70]	0.045 [0.12]	0.148 [0.47]	-0.238 [-0.79]	0.386 [1.62]	-0.056 [-0.16]	0.133 [0.42]
Time FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Industry FE	N	Y	N	Y	N	Y	N	Y	N	Y	N	Y
Analyst FE	N	N	Y	Y	N	N	Y	Y	N	N	Y	Y
Controls	N	N	N	N	N	N	N	N	Y	Y	Y	Y
Observations	104,061	104,061	95,617	95,617	104,061	104,061	95,617	95,617	96,059	96,059	89,042	89,042
R Square	0.139	0.208	0.179	0.227	0.139	0.208	0.179	0.227	0.201	0.252	0.233	0.278

Table 5. Performance of Portfolios Sorted on Rating and Recommendation

This table reports summary statistics, average excess returns, and alphas for 3-by-2 portfolios sorted by analyst recommendations and bond ratings. At the end of each month  $t$ , bonds are sorted based on their current-month analyst recommendations and held for three months from  $t + 1$  to  $t + 3$ . Summary statistics are bond-month characteristics observed at month  $t$ . Alphas are estimated by regressing portfolio excess returns on the CAPM and the Fama–French bond factors. Newey and West (1987) t-statistics with two lags are shown in bracket.

Panel A: Bond-month level variables									
		Underweight	Neutral	Overweight					
A	# of bonds	376.75	549.78	113.55					
	Rating	A+	A	A					
	Time to maturity (yrs)	10.79	12.51	14.24					
	Yield spread (%)	0.8	0.96	1.07					
	Yield (%)	2.72	2.98	3.15					
	Ret (%)	0.36	0.36	0.38					
	Trading volume_log (%)	16.11	16.11	15.74					
	Offering amount_log (%)	13.25	13.27	13.14					
BBB	# of bonds	123.88	836.01	316.44					
	Rating	BBB	BBB	BBB					
	Time to maturity (yrs)	10.12	10.76	10.91					
	Yield spread (%)	1.5	1.63	1.61					
	Yield (%)	3.37	3.54	3.51					
	Ret (%)	0.3	0.49	0.52					
	Trading volume_log (%)	16.26	16.37	16.47					
	Offering amount_log (%)	13.19	13.29	13.33					
Panel B: Excess return and alpha									
		Equal Weighted				Value Weighted			
		UW	N	OW	OWUW	UW	N	OW	OWUW
A	Excess return	0.333***	0.375**	0.433**	0.100	0.332***	0.363**	0.433**	0.102*
		[2.74]	[2.51]	[2.57]	[1.63]	[2.69]	[2.49]	[2.60]	[1.67]
	$\alpha_{FF}$	0.050	0.021	0.058	0.008	0.037	0.006	0.056	0.019
		[1.38]	[0.55]	[1.16]	[0.21]	[1.11]	[0.15]	[1.00]	[0.40]
	$\alpha_{CAPMB}$	-0.055	-0.107*	-0.092	-0.036	-0.062	-0.109*	-0.084	-0.021
	[-1.07]	[-1.78]	[-1.30]	[-0.86]	[-1.17]	[-1.82]	[-1.09]	[-0.42]	
BBB	Excess return	0.451***	0.474***	0.536***	0.085	0.450***	0.484***	0.549***	0.099**
		[3.31]	[3.30]	[3.56]	[1.65]	[3.09]	[3.20]	[3.46]	[2.17]
	$\alpha_{FF}$	0.125*	0.129*	0.183**	0.058	0.094	0.113	0.167**	0.073*
		[1.85]	[1.75]	[2.43]	[1.42]	[1.50]	[1.59]	[2.29]	[1.78]
	$\alpha_{CAPMB}$	0.015	0.0035	0.039	0.023	-0.026	-0.010	0.025	0.051
	[0.41]	[0.09]	[1.08]	[0.66]	[-0.78]	[-0.26]	[0.69]	[1.41]	

Table 6. Textual risk and objective risk

This table presents OLS regression results examining how analysts' textual expressions of risk relate to firms' expected default frequency (EDF). Columns (1)-(4) use the LLM-generated risk score derived from analyst comments as the dependent variable, while columns (5)-(8) utilize the frequency of uncertain words (following Loughran and McDonald, 2011) as an alternative measure of perceived risk. The main independent variables include EDF interacted with rating-group indicators (A-rated and BBB-rated bonds) and an A-rating dummy. Columns (1), (3), (5), and (7) control for time fixed effects only, whereas columns (2), (4), (6), and (8) include both time and industry fixed effects. Robust standard errors clustered at the issuer level are reported in brackets. \*, \*\*, and \*\*\* denote statistical significance at 10%, 5%, and 1%.

	Risk score				Uncertain text			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
A $\times$ EDF	0.663 [1.19]	0.907** [2.18]	-0.997* [-1.99]	-0.700* [-1.71]	2.115** [2.77]	2.186 [1.12]	-4.685*** [-2.88]	-3.009** [-2.43]
BBB $\times$ EDF	1.660*** [3.16]	1.607*** [4.68]			6.800*** [4.24]	5.195*** [3.66]		
EDF			1.660*** [3.16]	1.607*** [4.68]			6.800*** [4.24]	5.195*** [3.66]
A	0.737** [2.44]	0.677** [2.56]	0.737** [2.44]	0.677** [2.56]	2.067** [2.56]	1.655** [2.61]	2.067** [2.56]	1.655** [2.61]
Time FEs	Y	Y	Y	Y	Y	Y	Y	Y
Industry FEs	N	Y	N	Y	N	Y	N	Y
N	99,942	99,942	99,942	99,942	99,942	99,942	99,942	99,942
R <sup>2</sup>	0.049	0.091	0.049	0.091	0.287	0.434	0.287	0.434



Table 7. Recommendation, perceived risk and future risk materialization

This table reports logit regression results examining whether analysts' textual expressions of risk and uncertainty help predict future credit events. The dependent variable is an indicator equal to one if the issuer experiences a credit downgrade within three, six, or twelve months (DG), or defaults within three years (DF), and zero otherwise. Columns (1)-(4) use recommendation as explanatory variables. Columns (5)-(8) use the LLM-generated risk score from analyst comments as the main explanatory variable. Columns (9)-(12) utilize the frequency of uncertain words (following Loughran and McDonald, 2011) as an alternative measure of perceived risk. Both measures are interacted with rating-group indicators (A-rated and BBB-rated bonds). All regressions control for time fixed effects. Robust standard errors clustered at the issuer level are reported in brackets. \*, \*\*, and \*\*\* denote statistical significance at 10%, 5%, and 1%.

	DG(3m)	DG(6m)	DG(12m)	DF(3y)	DG(3m)	DG(6m)	DG(12m)	DF(3y)	DG(3m)	DG(6m)	DG(12m)	DF(3y)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
A $\times$ Rec	-0.175 [-0.84]	-0.154 [-0.76]	-0.181 [-0.88]	0.754*** [3.32]								
BBB $\times$ Rec	-0.566*** [-3.48]	-0.515*** [-3.30]	-0.365** [-2.43]	-0.254 [-0.84]								
A $\times$ Risk score					0.336*** [3.17]	0.251*** [2.68]	0.221** [2.53]	0.814*** [4.19]				
BBB $\times$ Risk score					0.347*** [3.92]	0.254*** [3.14]	0.216*** [3.02]	0.161 [0.61]				
A $\times$ Uncertain text									0.180*** [4.02]	0.139*** [3.71]	0.135*** [4.08]	0.254*** [3.50]
BBB $\times$ Uncertain text									0.063** [2.25]	0.063* [1.95]	0.046 [1.35]	0.039 [0.35]
A	-0.088 [-0.49]	-0.078 [-0.44]	-0.005 [-0.03]	2.071*** [5.02]	-0.021 [-0.11]	-0.011 [-0.06]	0.063 [0.34]	3.401*** [6.68]	-0.301 [-1.21]	-0.150 [-0.62]	-0.126 [-0.51]	1.231* [1.77]
Time FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	100,129	100,214	100,235	58,619	100,129	100,214	100,235	58,619	100,129	100,214	100,235	58,619
Pseudo R <sup>2</sup>	0.062	0.059	0.045	0.114	0.075	0.066	0.052	0.115	0.069	0.062	0.049	0.139

Table 8. Recommendations and textual risk

This table reports results from OLS regressions examining the relationship between analysts' textual expressions of risk and their bond recommendations. The dependent variable is the numerical recommendation score assigned by analysts, where higher values correspond to more favorable recommendations. Columns (1)-(4) measure perceived risk using the LLM-generated risk score, while columns (5)-(8) use the frequency of uncertain words (following Loughran and McDonald, 2011). These risk measures are interacted with rating-group indicators (A-rated and BBB-rated bonds). yield spreads are also interacted similarly and included as controls. All regressions control for time fixed effects, and columns (2), (4), (6), and (8) further include industry fixed effects. Robust standard errors clustered at the issuer level are shown in brackets. \*, \*\*, and \*\*\* denote statistical significance at 10%, 5%, and 1%.

Dep variable: Recommendation								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
A $\times$ Risk score	0.049 [0.91]	0.041 [0.83]	0.044 [0.84]	0.038 [0.78]				
BBB $\times$ Risk score	-0.144** [-2.30]	-0.127* [-1.80]	-0.151** [-2.41]	-0.131* [-1.86]				
A $\times$ Uncertain text					0.031 [1.43]	0.029 [1.53]	0.026 [1.29]	0.027 [1.43]
BBB $\times$ Uncertain text					-0.012 [-1.16]	-0.002 [-0.16]	-0.013 [-1.26]	-0.003 [-0.28]
A	-0.003 [-0.02]	-0.070 [-0.53]	-0.157 [-1.21]	-0.164 [-1.15]	-0.562*** [-3.66]	-0.543*** [-4.29]	-0.714*** [-4.03]	-0.637*** [-4.02]
Controls	N	N	Y	Y	N	N	Y	Y
Time FEs	Y	Y	Y	Y	Y	Y	Y	Y
Industry FEs	N	Y	N	Y	N	Y	N	Y
N	99,942	99,942	99,942	99,942	99,942	99,942	99,942	99,942
R <sup>2</sup>	0.130	0.206	0.144	0.211	0.127	0.203	0.140	0.207

Table 9. Yield spreads, yield tone, and recommendations

This table reports results of OLS regressions. Panel A regresses yield tone on option-adjusted yield spreads, an A-rating indicator, and their interactions. Yield tone is an LLM-derived measure of analysts' qualitative assessments of bond yield spreads, coded from -1 (tight) to 0 (neutral) to +1 (wide). Panel B regresses analyst recommendations (-1 = Underweight, 0 = Neutral, +1 = Overweight) on yield tone. All specifications include month fixed effects, and columns (2), (4), (6), and (8) add industry fixed effects. Standard errors are clustered by issuer and analysts. \*, \*\*, and \*\*\* denote statistical significance at 10%, 5%, and 1%.

Panel A: Yield spreads and yield tone

	Dep variable: Yield tone							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
A × Yield Spread	28.689*** [4.33]	29.856*** [4.39]	22.949*** [3.37]	24.493*** [3.93]	14.094** [2.49]	15.517** [2.75]	8.005 [1.44]	9.736* [1.86]
BBB × Yield Spread	14.595*** [5.19]	14.339*** [5.32]	14.944*** [5.41]	14.757*** [5.72]				
Yield Spread					14.595*** [5.19]	14.339*** [5.32]	14.944*** [5.41]	14.757*** [5.72]
Risk score		-0.166*** [-5.31]		-0.163*** [-4.71]		-0.166*** [-5.31]		-0.163*** [-4.71]
A	-0.468*** [-4.32]	-0.445*** [-3.89]	-0.438*** [-3.37]	-0.405*** [-2.97]	-0.468*** [-4.32]	-0.445*** [-3.89]	-0.438*** [-3.37]	-0.405*** [-2.97]
Time FE	Y	Y	Y	Y	Y	Y	Y	Y
Industry FE	N	Y	N	Y	N	Y	N	Y
Observations	38,311	38,311	38,310	38,310	38,311	38,311	38,310	38,310
R Square	0.117	0.171	0.164	0.214	0.117	0.171	0.164	0.214

Panel B: Yield tone and recommendation

	Dep variable: Recommendation			
	(1)	(2)	(3)	(4)
A × Yield Tone	0.323*** [5.00]	0.285*** [4.66]	0.046 [0.66]	0.043 [0.68]
BBB × Yield Tone	0.276*** [6.88]	0.241*** [6.02]		
A	-0.343*** [-5.08]	-0.343*** [-5.53]	-0.343*** [-5.08]	-0.343*** [-5.53]
Time FE	Y	Y	Y	Y
Industry FE	N	Y	N	Y
Observations	38,311	38,310	38,311	38,310
R Square	0.295	0.378	0.295	0.378

Table 10. Recommendation and yield spread: catering to client

The first four columns report OLS estimates of  $\beta_1$  from the following specification:

$$\text{Rec}_{i,t} = \alpha + \beta_1 \text{YieldSpread}_{i,t}^{g=A} + \beta_2 \text{YieldSpread}_{i,t} + \mathbf{1}\{g_{i,t} = A\} + \mathbf{X}_{i,t} + \varepsilon_{i,t}.$$

where columns (1) and (2) focus on the sample without any client relationship and columns (3) and (4) focus on the sample with client relationship. Columns (5) to (10) report OLS estimates of  $\beta_7$  from the following specification:

$$\begin{aligned} \text{Rec}_{it} = & \alpha_0 + \beta_1 \mathbf{1}\{g_{i,t} = A\} + \beta_2 \text{YieldSpread}_{it} + \beta_3 \text{YieldSpread}_{i,t}^{g=A} + \beta_4 M_{i,t} + \beta_5 M_{i,t}^{g=A} + \beta_6 (M_{i,t} \times \text{YieldSpread}_{it}) \\ & + \beta_7 (M_{i,t} \times \text{YieldSpread}_{i,t}^{g=A}) + FE + u_{it}. \end{aligned}$$

where  $\text{Rec}_{it}$  is analyst  $j$  recommendation for bond  $i$  in month  $t$ ,  $A_i$  equals one for A-rated bonds and zero for BBB-rated bonds,  $\text{Spread}_{it}$  is the bond's yield spread, and  $M_j$  is a dummy for the client relationship. It can be manager, broker, or others. All represents all these three types of client relationships. The reported coefficient is  $\beta_7$ , the triple interaction  $A \times \text{Spread} \times \text{Relationship}$ , which indicates how the A-minus-BBB spread slope varies with the client relationship. All regressions include the full vector of bond and firm controls, time fixed effects  $\gamma_t$ , and, where indicated, industry fixed effects  $\gamma_{\text{industry}}$ . Standard errors are two-way clustered by issuer and analyst. \*, \*\*, and \*\*\* denote statistical significance at 10%, 5%, and 1%.

	Non-client		Client		Separate		Whole		Past & Future	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
A $\times$ Yield Spread	16.650** [2.47]	12.464* [2.03]	11.673** [2.58]	1.411 [0.39]						
A $\times$ Yield Spread $\times$ Relationship(all)							-2.468 [-0.32]	-4.178 [-0.60]	-1.244 [-0.16]	-2.422 [-0.34]
A $\times$ Yield Spread $\times$ Relationship(IB)					-2.861 [-0.35]	-4.958 [-0.67]				
A $\times$ Yield Spread $\times$ Relationship(broker)					-3.203 [-0.49]	4.612 [0.70]				
A $\times$ Yield Spread $\times$ Relationship(fin. interests)					27.462 [1.25]	35.547* [1.80]				
Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Time FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Industry FE	N	Y	N	Y	N	Y	N	Y	N	Y
Observations	82,776	82,776	13,283	13,283	96,059	96,059	96,059	96,059	96,059	96,059
Adj. R <sup>2</sup>	0.182	0.232	0.266	0.395	0.193	0.240	0.192	0.240	0.196	0.243

Table 11. Recommendation and yield spread: catering to investor demand

The first two columns focus on the merged sample of bond analyst reports with eMAXX holding data and report OLS estimates of  $\beta_1$  from the following specification:

$$\text{Rec}_{i,t} = \alpha + \beta_1 \text{YieldSpread}_{i,t}^{g=A} + \beta_2 \text{YieldSpread}_{i,t} + \mathbf{1}\{g_{i,t} = A\} + \mathbf{X}_{i,t} + \varepsilon_{i,t}.$$

Columns (3) to (8) report OLS estimates of  $\beta_7$  from the following specification:

$$\begin{aligned} \text{Rec}_{it} = & \alpha_0 + \beta_1 \mathbf{1}\{g_{i,t} = A\} + \beta_2 \text{YieldSpread}_{it} + \beta_3 \text{YieldSpread}_{i,t}^{g=A} + \beta_4 M_{i,t} + \beta_5 M_{i,t}^{g=A} + \beta_6 (M_{i,t} \times \text{YieldSpread}_{it}) \\ & + \beta_7 (M_{i,t} \times \text{YieldSpread}_{i,t}^{g=A}) + FE + u_{it}. \end{aligned}$$

where  $\text{Rec}_{it}$  is analyst  $j$  recommendation for bond  $i$  in month  $t$ .  $A_i$  equals one for A-rated bonds and zero for BBB-rated bonds.  $\text{Spread}_{it}$  is the bond's yield spread.  $M_{i,t} = 1$  if insurers' par holdings of bond  $i$  at time  $t$  are at least  $k$  times mutual-fund holdings, for thresholds  $k \in \{2, 5, 10\}$ ; otherwise  $M_{i,t} = 0$ . The coefficient of interest,  $\beta_7$ , measures how the A–BBB spread slope changes when the insurer-to-mutual-fund holdings ratio exceeds  $\kappa$ , relative to when it does not. A positive  $\beta_7$  indicates a larger A–BBB slope gap under insurer dominance. All regressions include the full vector of bond and firm controls, time fixed effects  $\gamma_t$ , and, where indicated, industry fixed effects  $\gamma_{\text{industry}}$ . Standard errors are two-way clustered by issuer and analyst. \*, \*\*, and \*\*\* denote statistical significance at 10%, 5%, and 1%.

	Merged		Two times		Five times		Ten times	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
A × Yield Spread	17.606*** [3.08]	10.567** [2.61]						
A × Yield Spread × Insurance/Mutual(two times)			-8.048 [-0.83]	0.263 [0.04]				
A × Yield Spread × Insurance/Mutual(five times)					-3.344 [-0.40]	2.172 [0.30]		
A × Yield Spread × Insurance/Mutual(ten times)							-0.208 [-0.03]	4.875 [0.70]
Controls	Y	Y	Y	Y	Y	Y	Y	Y
Time FE	Y	Y	Y	Y	Y	Y	Y	Y
Industry FE	N	Y	N	Y	N	Y	N	Y
Observations	20,440	20,439	20,440	20,439	20,440	20,439	20,440	20,439
Adj. R <sup>2</sup>	0.190	0.244	0.192	0.246	0.192	0.245	0.192	0.245

Table 12. Characteristics of matched A and BBB firms

This table reports the characteristics of matched A and BBB firms. Each month, an A (A-, A, A+) non-utility firm is matched to the BBB (BBB-, BBB, BBB+) firm that is closest in terms of log assets, book leverage, market leverage, EDF, Cash to assets, Z-Score, and PPE to assets. Distance is defined as the absolute difference between the log-odds of the propensity scores obtained from the logit model, and a BBB candidate is accepted as the nearest neighbor only when the distance lies within a caliper of 0.35. Utility firms are matched in the same way except that Z-score is omitted. The full sample contains 3,265 A and 5,287 BBB firm-month observations. The matched sample consists of 1,556 A-rated firm-month observations matched to 846 unique BBB-rated firm-month observations. The sample period is from September 2013 to January 2023. \*, \*\*, and \*\*\* denote statistical significance at 10%, 5%, and 1%.

	Full sample			Matched sample		
	A	BBB	$\Delta$	A	BBB	$\Delta$
Assets	10.760	9.974	0.787***	10.507	10.519	-0.012
Book leverage	0.488	0.505	-0.017***	0.498	0.501	-0.003
Market leverage	0.262	0.300	-0.038***	0.223	0.229	-0.006
EDF	0.510	0.583	-0.073***	0.520	0.520	0.000
Cash/Asset	0.090	0.069	0.022***	0.110	0.105	0.005
Z-Score	1.155	0.786	0.368***	1.056	1.046	0.011
PPE/Asset	0.389	0.392	-0.003***	0.272	0.263	0.009
ROA	0.018	0.012	0.006***	0.019	0.019	0.000
PM	0.110	0.067	0.043***	0.097	0.100	-0.003
Sales growth	0.016	0.047	-0.031***	0.017	0.024	-0.008
Earnings growths	0.114	0.062	0.052*	0.074	0.091	-0.017
CF/PPE	0.290	0.259	0.031***	0.354	0.352	0.001

Table 13. Recommendation formation in matched A and BBB firms

This table presents regression of testing whether the sensitivity of recommendations to each credit signal differs significantly between the matched A and BBB firms. The matching is by time and industry. The regression specification is

$$Rec_{i,t} = \alpha + \beta_1 YieldSpread_{i,t}^{g=A} + \beta_2 YieldSpread_{i,t} + \mathbf{1}\{g_{i,t} = A\} + \mathbf{X}_{i,t} + \varepsilon_{i,t},$$

where the dependent variable  $Rec_{i,t}$  is the analyst recommendation for bond  $i$  at time  $t$ , coded  $-1$  = Underweight,  $0$  = Neutral,  $+1$  = Overweight.  $YieldSpread_{i,t}$  is the bond's yield spread over the yield of treasuries in the same maturity and expressed in decimal yield units. \*, \*\*, and \*\*\* denote statistical significance at 10%, 5%, and 1%.

Dep. Variable: Recommendation						
	(1)	(2)	(3)	(4)	(5)	(6)
A $\times$ Yield Spread	9.553** [2.82]	10.063*** [3.06]	10.063*** [3.06]			
Yield Spread	9.189*** [3.08]	15.045*** [3.65]	15.045*** [3.65]			
A $\times$ EDF				0.906 [1.10]	0.904 [1.09]	0.904 [1.09]
EDF				2.407*** [3.94]	2.388*** [3.87]	2.388*** [3.87]
A	-0.412*** [-5.42]	-0.394*** [-5.22]	-0.394*** [-5.22]	-0.835* [-1.91]	-0.826* [-1.86]	-0.826* [-1.86]
Bond control	N	Y	Y	N	Y	Y
Pair FE	Y	Y	Y	Y	Y	Y
Analyst FE	N	N	Y	N	N	Y
N	9,692	9,556	9,556	9,692	9,556	9,556
R <sup>2</sup>	0.540	0.546	0.546	0.556	0.560	0.560



Table 14. Supportive evidence of categorical thinking: Number of financial concepts

This table reports the regression results examining the level of detail analysts provide in their notes, specifically measuring how many financial concepts analysts mention. Columns (1)-(3) use the total number of financial concepts in each analyst note as the dependent variable. Columns (4)-(6) focus only on the factual description sections, while columns (7)-(9) isolate the subjective, forward-looking parts of the notes. Columns (10)-(12) analyze the likelihood that analysts omit factual descriptions entirely, presenting the probability that notes contain only subjective predictions without any accompanying factual information. \*, \*\*, and \*\*\* indicate significance at the 10%, 5%, and 10% level, respectively.

Dep var: Num of concepts in	Whole comment			Fact. description			Sub. prediction			Prob of no fact.		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
main												
A	-2.011*** [-4.95]	-0.684*** [-3.55]	-0.331* [-2.04]	-1.024*** [-3.78]	-0.205 [-1.60]	0.001 [0.01]	-0.986*** [-5.82]	-0.479*** [-3.76]	-0.333*** [-3.22]	0.497** [2.05]	0.539* [1.95]	0.375 [1.27]
EDF			5.032** [2.75]			2.950** [2.25]			2.082*** [3.78]			-2.234** [-2.42]
Time FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FEs	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Observations	89,803	89,803	89,803	89,803	89,803	89,803	89,803	89,803	89,803	88,668	87,380	87,380
R Square	0.276	0.456	0.467	0.145	0.308	0.317	0.321	0.440	0.446			

Table 15. Future downgrade, default, upgrade and Recommendation

This table investigates the predictive power of analyst recommendations for future downgrades or defaults using the following regression specification:

$$\text{Downgrade}_{i,t+3} = \alpha + \beta_1 \cdot \text{Rec}_{i,t} \times \sum_{g \in G} \text{RatingGroup}_g + \beta_2 \cdot \text{RatingGroup Dummy}_g + \gamma_t + \epsilon_{i,t}$$

$\text{Downgrade}_{i,t+3}$ , is an indicator that equals one if any of the three rating agencies (S&P, Fitch, and Moody's) downgrade the bond  $i$  within the next 3 months after the recommendation. Columns (1) to (4) focus on the future downgrades in the next 3 months, and columns (5) to (8) look at the future downgrades in the next six months. In columns (8) to (12), the dependent variable Default equals one if the bond defaults within the next three years, and zero otherwise. Standard errors are clustered at the firm level and reported in brackets below the coefficients. \*\*\*, \*\*, and \* indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Logit reg - Downgrade and Default									
	DG(3m)			DG(6m)			DF		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
A × Rec	-0.206 [-0.99]	-0.344 [-1.41]	-0.375 [-1.64]	-0.179 [-0.89]	-0.317 [-1.31]	-0.352 [-1.55]	0.755*** [3.34]	0.616** [2.55]	0.585** [2.48]
BBB × Rec	-0.559*** [-3.49]	-0.592*** [-3.62]	-0.582*** [-3.46]	-0.517*** [-3.36]	-0.545*** [-3.51]	-0.548*** [-3.37]	-0.253 [-0.84]	-0.303 [-0.95]	-0.246 [-0.70]
A	-0.065 [-0.36]	0.070 [0.41]	0.388** [2.19]	-0.064 [-0.36]	0.069 [0.41]	0.385** [2.29]	2.072*** [5.03]	2.259*** [5.60]	2.562*** [6.28]
EDF		3.730** [2.21]	2.570 [1.64]		3.550** [2.21]	2.494* [1.67]		4.097*** [3.27]	3.600*** [2.98]
Yield spread			42.112*** [6.24]			44.186*** [5.86]			30.509*** [2.60]
Time FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	104,285	104,285	104,285	104,374	104,374	104,374	59,143	59,143	59,143
Pseudo R <sup>2</sup>	0.063	0.074	0.090	0.063	0.075	0.093	0.114	0.126	0.130

Panel B: Logit reg - Upgrade								
	Upgrade(3m)				Upgrade(6m)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
A × Rec	0.712*** [3.47]	0.721*** [3.42]	0.740*** [3.63]	0.741*** [3.56]	0.714*** [3.49]	0.724*** [3.44]	0.741*** [3.64]	0.744*** [3.58]
BBB × Rec	0.133 [0.68]	0.135 [0.70]	0.135 [0.70]	0.136 [0.71]	0.138 [0.71]	0.140 [0.72]	0.140 [0.73]	0.141 [0.73]
A	0.065 [0.35]	0.053 [0.28]	-0.063 [-0.32]	-0.064 [-0.32]	0.079 [0.43]	0.067 [0.35]	-0.045 [-0.23]	-0.047 [-0.23]
EDF		-0.289 [-0.29]		-0.056 [-0.05]		-0.293 [-0.29]		-0.070 [-0.06]
Yield spread			-21.101*** [-2.99]	-20.954*** [-2.73]			-20.485*** [-2.87]	-20.303*** [-2.62]
Time FEs	Y	Y	Y	Y	Y	Y	Y	Y
Observations	101,807	101,807	101,807	101,807	101,896	101,896	101,896	101,896
Pseudo R <sup>2</sup>	0.114	0.114	0.116	0.116	0.114	0.114	0.115	0.115

Panel C: Logit reg - A- and BBB+: Downgrades and Upgrades

	Downgrade(3m)				Upgrade(3m)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
A- $\times$ Rec	-0.268 [-0.93]	-0.299 [-0.98]	-0.316 [-1.09]	-0.334 [-1.10]	0.687*** [2.91]	0.687*** [2.87]	0.696*** [2.95]	0.697*** [2.93]
BBB+ $\times$ Rec	-0.532** [-2.17]	-0.541** [-2.15]	-0.586** [-2.28]	-0.589** [-2.26]	0.301 [0.76]	0.301 [0.76]	0.316 [0.81]	0.316 [0.80]
BBB+	-0.453* [-1.82]	-0.453* [-1.81]	-0.523** [-2.08]	-0.521** [-2.07]	-0.750** [-2.23]	-0.750** [-2.23]	-0.717** [-2.13]	-0.717** [-2.13]
EDF		1.250 [0.77]		0.899 [0.60]		-0.016 [-0.01]		0.060 [0.05]
Yield spread			36.074*** [3.13]	34.258*** [3.05]			-24.478 [-1.55]	-24.544 [-1.53]
Time FEs	Y	Y	Y	Y	Y	Y	Y	Y
Observations	28,551	28,551	28,551	28,551	22,138	22,138	22,138	22,138
Pseudo R <sup>2</sup>	0.096	0.098	0.103	0.104	0.132	0.132	0.134	0.134

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# Internet Appendix

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Sep 2025

## IA.A LLM Prompts and Examples

### Prompt 1: Perceived risk score

#### USER PROMPT:

Forget all previous instructions. You are a financial economics expert reading corporate bond research notes.

**TASK:** Extract only explicitly stated information from the provided context. Do NOT infer or add information.

#### CONTEXT:

{comment}

Respond strictly with a valid JSON object matching the schema below:

#### Questions:

**Q1:** List **ALL** explicitly stated financial or economic concepts related to risk and performance in the company's securities, operations, business, or financials.

- Don't miss any relevant information from the context.
- Provide a comma-separated list of noun phrases (each  $\leq 3$  words) or nouns.
- Do not infer, generate, or add information beyond what is explicitly stated.
- If none exist, answer "N/A".

**Q2:** Provide the subset of Q1 concepts that signal **HIGHER risk or WORSE performance**.

- Answer "N/A" if none exist.

**Q3:** Provide the subset of Q1 concepts that signal **LOWER risk or BETTER performance**.

- Answer "N/A" if none exist.

**Q4:** Provide the subset of Q1 concepts that appear **RISK-NEUTRAL**.

- Answer "N/A" if none exist.

#### Note for Q2–Q4:

- Q2, Q3, and Q4 must be **mutually exclusive**; no concept may appear in more than one list.

**Q5:** Based on the provided context, evaluate the company's overall risk profile using the scale below. Provide only the corresponding number:

- +4: Extreme Risk
- +3: High Risk
- +2: Moderate Risk
- +1: Mild Risk
- 0: Neutral
- −1: Mild Safety

–2: Moderate Safety

–3: High Safety

–4: Extreme Safety

**Required Output Format:**

```
{"Q0": ANSWER, "Q1": ANSWER, "Q2": ANSWER, "Q3": ANSWER, "Q4": ANSWER,
"Q5": ANSWER}
```

Figure A1. Prompt 1: Perceived risk score

**Prompt 2: Yield mention and tone**

Forget all previous instructions. You are a financial economics expert reading corporate bond research notes.

**Return exactly the following JSON format:**

```
{"Q1": 0 or 1, "Q2": -1, 0, 1, or "N/A"}
```

**Q1: Does the paragraph explicitly mention yield or spread?**

- Answer 1 if yes, 0 if no.
- Include synonyms or related terms: : *yield, yields, spread, spreads, basis points, bp, carry, valuation, rich, cheap, etc.*

**Q2: If Q1 = 1, classify the yield sentiment**

- 1 if yield is described positively (e.g. attractive, wide, compelling, etc).
- 0 if tone is neutral or fair.
- –1 if yield is described negatively (e.g. tight, compressed, unattractive, etc).
- If Q1 = 0, output "N/A".

**Context**

<<<

{comment}

>>>

Figure A2. Prompt 2: Identify yield mention and tone

**Prompt 3: Decompose comments into factual and subjective content and identify financial concepts**

**Instruction:** Forget all previous instructions. You are a financial economics expert analyzing corporate bond research reports. You will receive an analyst’s commentary on corporate bonds. Your task is to extract either factual information or the analyst’s subjective views from the provided context.

**Context:**

{comment}

Answer the following two questions based solely on the provided context. Respond strictly in JSON format:

**Q1: Factual information extraction**

- Extract only explicitly stated factual information related to the company's securities (bonds, stocks, characteristics), operations, business, or financials.
- Include only publicly known or already realized information.
- Do not include opinions, forecasts, predictions, or subjective statements.
- Do not infer, assume, omit, or add information beyond explicit statements.
- Provide your response as a concise natural-language paragraph. If no factual information exists, respond "N/A".

**Q2: Subjective prediction summarization**

- Summarize only subjective statements, forecasts, predictions, or opinions explicitly made by the analyst regarding the company's securities, operations, business, or financials.
- Exclude any factual information already covered in Q1.
- Do not infer, assume, omit, or add information beyond explicit statements.
- Begin your response explicitly with: "The analyst believes...".
- Provide your response as a concise natural-language paragraph. If no subjective statements exist, respond "N/A".

**Q3:** From Q1 of factual information, list **ALL** explicitly stated financial or economic concepts related to risk and performance in the company's securities, operations, business, or financials.

- Don't miss any relevant information from the context.
- Provide a comma-separated list of noun phrases (each  $\leq 3$  words) or nouns.
- Do not infer, generate, or add information beyond what is explicitly stated.
- If none exist, answer "N/A".

**Q4:** From Q3 of subjective information, list **ALL** explicitly stated financial or economic concepts related to risk and performance in the company's securities, operations, business, or financials.

- Don't miss any relevant information from the context.
- Provide a comma-separated list of noun phrases (each  $\leq 3$  words) or nouns.
- Do not infer, generate, or add information beyond what is explicitly stated.
- If none exist, answer "N/A".

**Required Output Format:**

```

{
    "Q1": ANSWER,
    "Q2": ANSWER,
    "Q1": ANSWER,
    "Q2": ANSWER
}

```

Figure A3. Prompt 3: Decompose comments into factual and subjective contents and identify financial concepts

General Electric (GE) on 08/14/2018:
<p><b>Raw comment:</b></p> <p><i>"We recommend a Neutral on GE. GE bond spreads trade much wider than other single A industrials which we view as appropriate given the significant changes underway at the company and related uncertainty and execution risk, weak outlook for important end markets – power, transportation and energy – and elevated leverage. The company outlined its strategic plan in June which includes the spin-off of its Healthcare business and exit from its Baker Hughes JV over the next 2 to 3 years. The company targets &lt; 2.5x adjusted net debt/EBITDA and long-term ratings at single A. Risks to our recommendation include change in underlying business trends and credit metrics, and if proceeds from asset disposals are mostly returned to shareholders versus a balanced approach."</i></p> <p><b>Factual description summarized by LLM:</b></p> <p>"The company's GE bond spreads trade wider than other single A industrials. The company has outlined its strategic plan in June, which includes the spin-off of its Healthcare business and exit from its Baker Hughes JV over the next 2 to 3 years. The company targets &lt; 2.5x adjusted net debt/EBITDA and long-term ratings at single A. The company operates in end markets such as power, transportation, and energy. The company has elevated leverage."</p> <p><b>Subjective prediction summarized by LLM:</b></p> <p>"The analyst believes that a Neutral recommendation is appropriate for GE. The analyst views the company's current situation as having significant changes underway, related uncertainty, and execution risk. The analyst also views the weak outlook for the company's end markets as a concern. The analyst considers the risks to the recommendation to include changes in underlying business trends and credit metrics, and if proceeds from asset disposals are mostly returned to shareholders versus a balanced approach."</p> <p><b>Financial economic concepts extracted by LLM: factual content:</b></p> <p>significant changes, underlying business trends, credit metrics, asset disposals, execution risk, end markets, weak outlook, changes in business, balanced approach</p> <p><b>Financial economic concepts extracted by LLM: subjective content:</b></p> <p>significant changes, execution risk, weak outlook, changes in business</p>

Figure A4. Example of comment summarization from prompt 3

Table A1. Illustrative Analyst Comments and Risk Scores

The table presents examples of comments, corresponding recommendations, and the perceived-risk score assigned by the LLM. The LLM identifies and scores the paragraph's overall stance toward credit risk on a scale from  $-4$  (extreme safety) to  $+4$  (extreme risk). Ellipses indicate omitted text without reordering or altering content. Pink words are about risk and blue words are about safety.

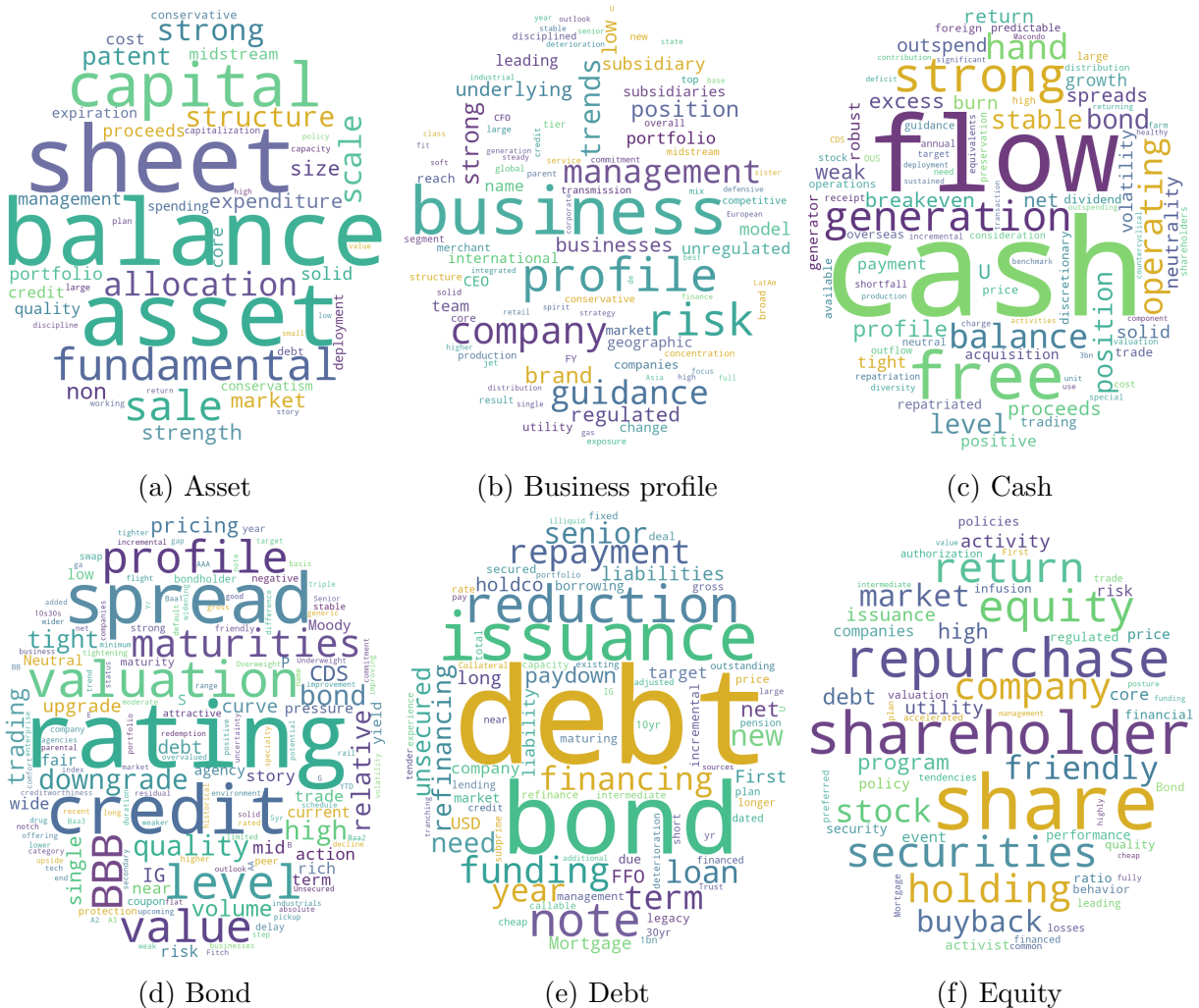
Issuer	Rating	Comments	Rec.	Risk Score
KO	A	...Stable, high-quality credit ...broad global operations with leading brands and market shares....Recent investments ...add to product diversification ...	N	-3 (High safety)
DTE	BBB	...DTE ...will likely remain supportive ..DTE has improved its balance sheet and management has committed to maintaining solid BBB ratings with strong credit metric targets. The company ...alleviate credit investors concern and ...adequately managed its ...business, which has historically been an overhang for some investors.	OW	-2 (Mod. safety)
GE	A	...relatively wide spreads ...reflecting GE's elevated leverage and business headwinds ...GE ...de-risk and de-lever its balance sheet, and this remains a top management priority. Cash generation has been better than expected ...Risks ...include change in underlying business trends and credit metrics and downward rating actions.	N	0
GE	A	...bond spreads trade much wider than other A industrials, which we view as appropriate given ... the related uncertainty and execution risk. The company has ...a weak outlook ...and elevated leverage ...The company targets ...debt/EBITDA ...long-term ratings at single A. Risks include change in underlying business trends and credit metrics ...	N	2 (Mod. risk)
DuPont	BBB	Uncertainty around the spin, revenue headwinds, lukewarm operating profitability, and renewed pressure ... We believe investors should not rule out ... updated rating target (BB) ...downside in owning protection ...is largely limited to the roll(s).	UW	3 (High risk)



## IA.B Label Concepts

Figure A5. Word cloud of financial concepts

This panel presents the word cloud for each identified financial category. I adopt key categories emphasized by credit rating analysts: Business Profile, Leverage, Liquidity, Profitability, and firm-specific Events. Additionally, I include fundamental balance-sheet items (Asset, Cash, Debt, Equity), and concepts related to firm-level Growth, Credit/Bond Terms, and Risk considerations. Sector-level buckets isolate industry-specific drivers such as Regulation/Policy and Supply–Demand dynamics. Macro-level buckets distinguish top-down influences, including Monetary & Fiscal Policy and broader Country/Global Growth & Shocks. Any residual concepts that do not fit these categories fall under Other (not displayed). For each bucket, we drop stop-words, and the word size is proportional to frequency.



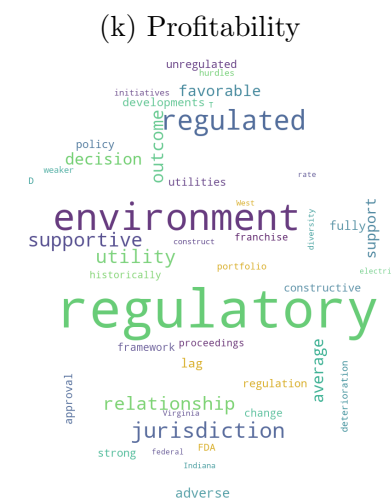
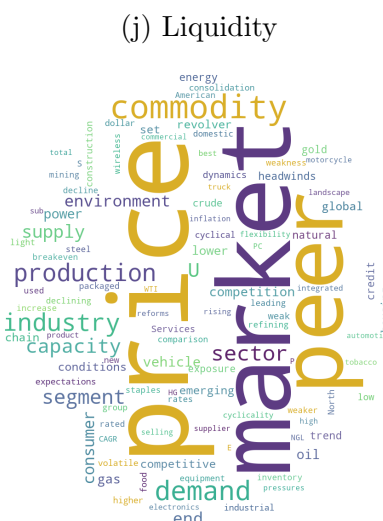
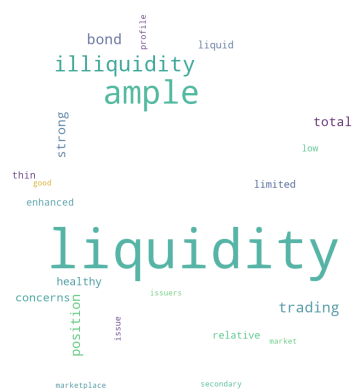
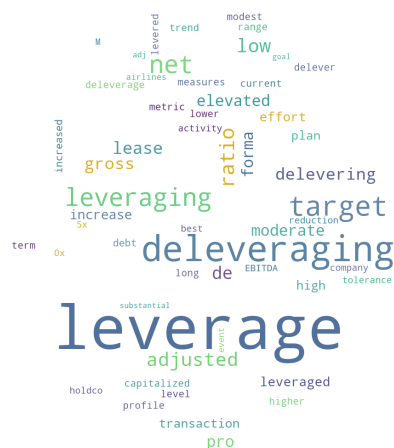
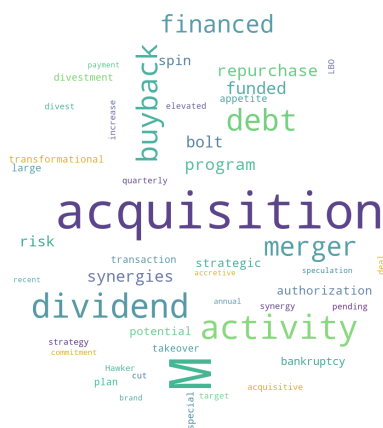
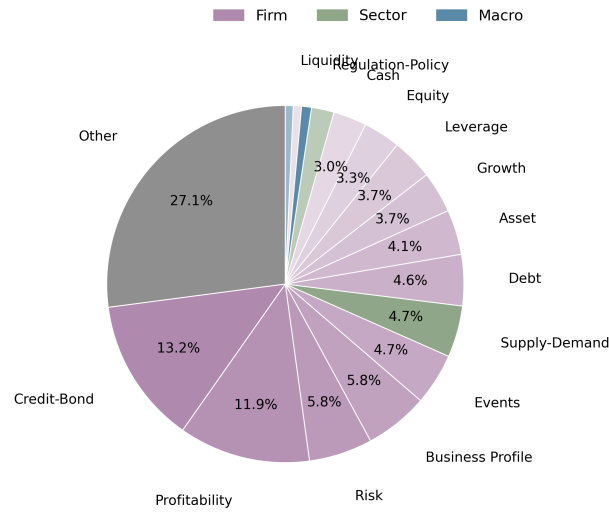




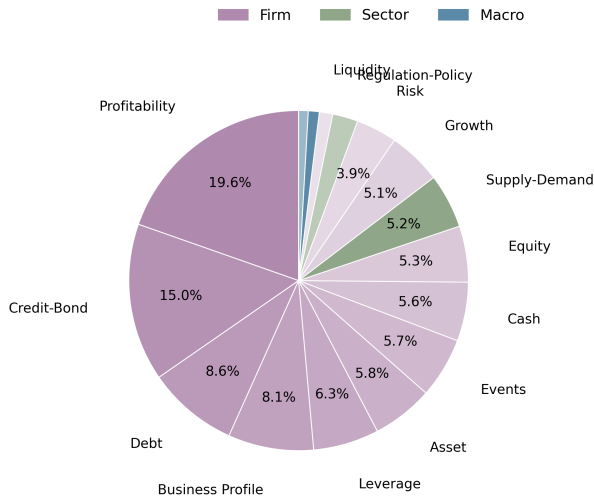
Figure A6. Distribution of financial concepts by factual vs subjective content

This figure shows the distribution of financial concepts discussed by analysts, separated by factual descriptions and subjective predictions. Panel (a) displays the overall distribution across all comments. Panels (b) and (c) separately illustrate the frequency of each concept within factual and subjective content, respectively. Financial concepts are further categorized into firm-level, sector-level, and macroeconomic factors.

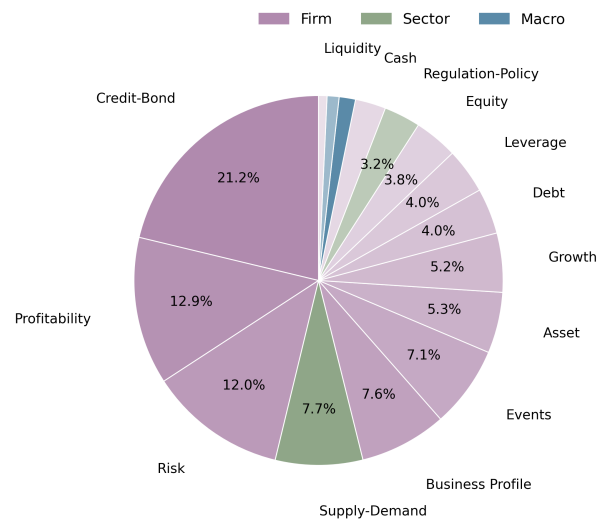
(a) All



(b) Factual description



(c) Subjective prediction



## IA.C Additional Empirical Analysis

Table A2. Summary Statistics: Firm and bond month level characteristics in the whole sample

The table provides descriptive statistics for issuers and bonds in the full sample. Panel A presents firm-month-level financial characteristics, including the number of bonds issued per firm and firm size. Panel B summarizes bond-month-level characteristics, such as credit rating, duration (in years), time to maturity (in years), credit spread, and monthly bond returns. We construct the full sample from the WRDS Corporate Bond Database for any month with at least one industry report, applying the same filters as the main sample: available credit ratings, credit spreads, and a time to maturity exceeding two years.

Panel A: Firm-month level variables								
	N	Mean	SD	1st	25th	50th	75th	99th
<i>IG report</i>								
Number of Bonds per Firm	28,658	8.09	9.93	1	2	5	10	51
Size (in million)	28,658	37,773.51	89,539.38	518.69	5,979.65	14,357.75	35,687.5	324,827.7
Panel B: Bond-month level variables								
<i>IG report</i>								
Credit Rating	231,723	20.52	1.94	18	19	20	22	28
Credit Rating	231,723			BBB-	BBB	BBB+	A	AA+
Duration (years)	230,384	7.97	4.67	1.91	4.07	6.73	12.06	18.32
Time to Maturity (years)	231,723	12.1	10.26	2.08	4.58	8	19.75	37.08
Credit Spread (%)	231,723	2.73	4.78	-10	0.46	2.62	5.23	13.73
Monthly Bond Return (%)	227,806	0.66	2.98	-6.31	-0.57	0.32	1.65	10.6

Table A3. EDF can predict downgrades and defaults in sample

This table examines the relationship between the EDF and future downgrades.  $n$  is the next 3, 6, 12 months. The granular rating groups include AAA/AA, A+, A, A-, BBB+, BBB, and BBB-. The regression specification is as follows:

$$\text{Downgrade}_{i,t+n} = \alpha + \beta_1 \text{EDF}_{i,t}^{g=A} + \beta_2 \text{EDF}_{i,t}^{g=BBB} + \mathbf{1}\{g_{i,t} = A\} + \text{Granular rating FE} + \varepsilon_{i,t}.$$

Panel A: OLS regression								
	DG(3m)		DG(6m)		DG(12m)		DF	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
A $\times$ EDF	0.097** [2.22]	0.091** [2.22]	0.152* [1.92]	0.142* [1.88]	0.184 [1.50]	0.171 [1.48]	0.052 [1.17]	0.045 [1.18]
BBB $\times$ EDF	0.187*** [3.82]	0.208*** [4.14]	0.399*** [5.24]	0.437*** [5.75]	0.552*** [5.17]	0.606*** [5.81]	0.040** [2.05]	0.041** [1.97]
A	0.039** [2.13]		0.099*** [3.22]		0.151*** [3.07]		0.008 [1.57]	
Time FEs	Y	Y	Y	Y	Y	Y	Y	Y
Rating FEs		Y		Y		Y		Y
Observations	125,214	125,214	125,476	125,476	125,556	125,556	125,566	125,566
R Square	0.027	0.029	0.047	0.050	0.051	0.057	0.011	0.025

Panel B: logit regression								
	DG(3m)		DG(6m)		DG(12m)		DF	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
A $\times$ EDF	2.483** [2.11]	2.362** [2.14]	2.027* [1.81]	1.921* [1.80]	1.503 [1.46]	1.430 [1.47]	5.359*** [5.00]	4.876*** [4.27]
BBB $\times$ EDF	5.376*** [3.91]	6.028*** [4.19]	6.173*** [5.57]	6.846*** [5.98]	5.203*** [5.27]	5.776*** [5.84]	13.423** [2.54]	14.302*** [3.37]
A	1.279** [2.06]		1.735*** [3.23]		1.545*** [3.19]		5.048*** [2.77]	
Time FEs	Y	Y	Y	Y	Y	Y	Y	Y
Rating FEs		Y		Y		Y		Y
Observations	125,214	125,214	125,476	125,476	125,556	125,556	88,545	75,126
R Square	0.071	0.077	0.079	0.085	0.065	0.072	0.096	0.18

Table A4. Recommendation and yield spread and EDF

This table joins yield spreads and EDF in the same regression to test whether one signal subsumes the other. The estimate captures the incremental weight analysts assign to each signal while holding the other signal constant. The first four columns show results of the joint model with both signals in the equation. Compared with the single-signal specifications, the pattern is stable. The interaction between EDF and the A rating remains positive, while the corresponding BBB interaction remains negative. The spread interaction is still strongly positive for A-rated bonds and economically negligible for BBB-rated bonds. The slight reduction in the credit-spread coefficient indicates that the spread and EDF share some information, but each still contributes distinctly to explaining recommendations once both are included. Columns (5)–(12) show that, with both EDF and the spread in the equation, the BBB-interaction terms for each signal remain negative and highly significant, only marginally smaller than in the single-signal panels. Adding industry and analyst fixed effects or bond controls leaves these gaps essentially intact. Including both EDF and the spread raises the within-pair R square by only a few percentage points, because each signal already captures most of the default-risk variation that matters once pair-month effects are removed. Across every specification the standalone BBB indicator carries a positive and significant coefficient.

	Specification 1				Specification 2				Specification 2 with controls			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
A × Yield Spread	18.115** [2.57]	10.570* [1.87]	15.282** [2.41]	10.673* [1.83]	16.470** [2.36]	9.421* [1.70]	14.163** [2.15]	9.895 [1.65]	12.354* [1.83]	7.634 [1.33]	12.356* [1.93]	6.718 [1.11]
BBB × Yield Spread	1.644 [1.02]	1.150 [1.16]	1.119 [0.86]	0.779 [0.73]								
Yield Spread					1.644 [1.02]	1.150 [1.16]	1.119 [0.86]	0.779 [0.73]	-1.046 [-0.35]	0.416 [0.22]	-0.302 [-0.15]	-1.209 [-0.88]
A × EDF	1.018** [2.09]	0.806** [2.15]	0.654* [1.72]	0.752* [1.98]	0.881** [2.65]	0.617* [1.98]	0.621* [1.77]	0.621* [1.80]	1.338*** [3.38]	1.014** [2.73]	1.067** [2.64]	1.141*** [3.01]
BBB × EDF	0.137 [0.39]	0.188 [0.62]	0.033 [0.09]	0.131 [0.41]								
EDF					0.137 [0.39]	0.188 [0.62]	0.033 [0.09]	0.131 [0.41]	-0.181 [-0.65]	0.399 [1.67]	-0.027 [-0.08]	0.161 [0.50]
A	-1.037*** [-7.46]	-0.839*** [-5.25]	-0.934*** [-5.07]	-0.862*** [-5.22]	-1.037*** [-7.46]	-0.839*** [-5.25]	-0.934*** [-5.07]	-0.862*** [-5.22]	-1.306*** [-6.73]	-1.061*** [-5.18]	-1.199*** [-6.74]	-1.133*** [-6.33]
Time FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Industry FE	N	Y	N	Y	N	Y	N	Y	N	Y	N	Y
Analyst FE	N	N	Y	Y	N	N	Y	Y	N	N	Y	Y
Controls	N	N	N	N	N	N	N	N	Y	Y	Y	Y
Observations	104,061	104,061	95,617	95,617	104,061	104,061	95,617	95,617	96,059	96,059	89,042	89,042
R Square	0.148	0.211	0.185	0.230	0.148	0.211	0.185	0.230	0.204	0.254	0.236	0.278

Table A5. Recommendation and yield spread and EDF

This table presents *ordered logit regression* specifications with time fixed effects. Columns (1) and (3) quantify how credit signals shape analyst recommendations across matched A- and BBB-rated firms. Columns (2) and (4) test whether the sensitivity of recommendations to each credit signal differs significantly between the two rating buckets. The dependent variable  $Rec_{i,t}$  is the analyst recommendation for bond  $i$  at time  $t$ , coded  $-1$  = Underweight,  $0$  = Neutral,  $+1$  = Overweight.  $YieldSpread_{i,t}$  is the bond's yield spread over the yield of treasuries in the same maturity and expressed in decimal yield units.  $EDF_{i,t}$  is the firm's expected default frequency. \*, \*\*, and \*\*\* denote statistical significance at 10%, 5%, and 1%.

	Dep var: recommendation			
	(1)	(2)	(3)	(4)
A $\times$ Yield Spread	75.495*** [4.10]	69.222*** [3.46]		
BBB $\times$ Yield Spread	6.273 [0.86]			
Yield Spread		6.273 [0.86]		
A $\times$ EDF			4.316** [2.04]	3.847* [1.93]
BBB $\times$ EDF			0.469 [0.35]	
EDF				0.469 [0.35]
A	-2.075*** [-6.80]	-2.075*** [-6.80]	-3.530*** [-3.23]	-3.530*** [-3.23]
Time FEs	Y	Y	Y	Y
Observations	104,534	104,534	104,534	104,534
Pseudo R <sup>2</sup>	0.074	0.074	0.079	0.079



Table A6. Textual risk, objective risk, and future risk materialization

This table reports OLS regression results examining whether analysts' textual expressions of risk and uncertainty help predict future credit events. The dependent variable is an indicator equal to one if the issuer experiences a credit downgrade within three, six, or twelve months (DG), or defaults within three years (DF), and zero otherwise. Panel A use LLM risk and Panel B use uncertain words.

Robust standard errors clustered at the issuer level are reported in brackets. \*, \*\*, and \*\*\* denote statistical significance at 10%, 5%, and 1%.

	DG(3m)		DG(6m)		DG(12m)		DF	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
A $\times$ textual risk	0.013*** [2.97]	0.012*** [3.03]	0.018*** [2.99]	0.017*** [3.11]	0.028*** [2.91]	0.027*** [3.29]	0.003 [0.96]	0.004 [0.99]
A $\times$ textual risk	0.014*** [3.95]	0.014*** [3.67]	0.020*** [3.10]	0.019*** [2.79]	0.027** [2.57]	0.025** [2.29]	-0.001 [-1.24]	0.000 [0.96]
A	-0.001 [-0.13]	0.003 [0.22]	-0.000 [-0.00]	0.011 [0.53]	0.010 [0.38]	0.032 [0.92]	0.007 [1.13]	0.004 [1.07]
Time FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FEs	No	Yes	No	Yes	No	Yes	No	Yes
Observations	89,587	89,587	89,661	89,661	89,677	89,677	89,413	89,405
R Square	0.030	0.036	0.039	0.054	0.045	0.072	0.010	0.045

	DG(3m)		DG(6m)		DG(12m)		DF	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
A $\times$ Uncertain text	0.010** [2.24]	0.011** [2.42]	0.013** [2.27]	0.015** [2.40]	0.019*** [3.05]	0.020*** [3.22]	0.003 [0.99]	0.004 [0.99]
A $\times$ Uncertain text	0.003 [1.45]	0.005** [2.09]	0.006 [1.31]	0.008* [1.87]	0.006 [1.03]	0.009 [1.60]	0.000 [0.75]	0.001 [1.03]
A	-0.015 [-1.51]	-0.014 [-1.16]	-0.014 [-0.64]	-0.004 [-0.14]	-0.019 [-0.63]	0.003 [0.08]	-0.001 [-0.29]	-0.003 [-0.72]
Time FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FEs	No	Yes	No	Yes	No	Yes	No	Yes
Observations	99,916	99,916	100,001	100,001	100,022	100,022	99,764	99,755
R Square	0.029	0.036	0.040	0.054	0.042	0.068	0.014	0.049

Table A7. Future returns, credit spreads, and EDF

This table presents two complementary regression specifications. The first quantifies how credit signals affect future returns across matched A- and BBB-rated firms. The second tests whether the sensitivity of future returns to each credit signal differs between the two rating buckets.

$$Ret_{i,t \rightarrow t+3} = \alpha + \sum_{g \in G} \beta_{1,g} CreditSpread_{i,t} G_{g,i,t} + \sum_{g \in G} \beta_{2,g} EDF_{i,t} G_{g,i,t} + \beta_3 D_{BBB,i,t} + \varepsilon_{i,t},$$

$$Ret_{i,t \rightarrow t+3} = \alpha + \beta_1 CreditSpread_{i,t} G_{BBB,i,t} + \beta_2 EDF_{i,t} G_{A,i,t} + \beta_3 D_{BBB,i,t} + \varepsilon_{i,t}.$$

where the dependent variable  $Ret_{i,t \rightarrow t+3}$  is the excess return for bond  $i$  at time  $t$  in excess of 1-month risk-free rate taken from Ken French's website.  $CreditSpread_{i,t}$  is the bond's yield spread over the yield of treasuries in the same maturity and expressed in decimal yield units.  $G_{g,i,t}$  indicates the bond's rating group, where  $g = A$  or  $BBB$ , and the interaction terms allow the sensitivity of recommendations to credit spreads to vary across rating groups.  $EDF_{i,t}$  is the firm's expected default frequency. The columns (1) to (6) report estimates for the full sample of firms excluding the financial and utility sectors. The columns (7) to (12) repeat the exercise for the matched samples. \*, \*\*, and \*\*\* denote statistical significance at 10%, 5%, and 1%.

	All sample						Matched sample					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
A × Yield Spread	0.079 [0.35]				0.083 [0.37]		0.288 [0.61]				1.123** [2.28]	
BBB × Yield Spread	1.106*** [3.20]	1.027*** [3.30]			1.121*** [3.17]	1.038*** [3.23]	0.730*** [2.74]	0.442 [1.18]			1.352*** [3.71]	0.229 [0.74]
Yield Spread		0.079 [0.35]				0.083 [0.37]		0.288 [0.61]				1.123** [2.28]
A × EDF			-0.006** [-2.02]		-0.004 [-1.19]				-0.026 [-1.25]		-0.008 [-0.74]	
BBB × EDF			0.016** [2.37]	0.022*** [2.74]	-0.009 [-1.13]	-0.005 [-0.64]			-0.037 [-1.23]	-0.011 [-0.27]	-0.006 [-0.56]	0.003 [0.24]
EDF				-0.006** [-2.02]		-0.004 [-1.19]				-0.026 [-1.25]		-0.008 [-0.74]
BBB	-0.014*** [-3.01]	-0.014*** [-3.01]	-0.010** [-2.50]	-0.010** [-2.50]	-0.011*** [-3.30]	-0.011*** [-3.30]	-0.008* [-1.95]	-0.008* [-1.95]	0.007 [0.33]	0.007 [0.33]	-0.005 [-0.96]	-0.005 [-0.96]
Time by Industry FE	Y	Y	Y	Y	Y	Y	N	N	N	N	N	N
Pair FE	N	N	N	N	N	N	Y	Y	Y	Y	Y	Y
Observations	343,865	343,865	343,865	343,865	343,865	343,865	16,090	16,090	16,090	16,090	8,881	8,881
R Square	0.570	0.570	0.542	0.542	0.570	0.570	0.673	0.673	0.668	0.668	0.630	0.630