Bank Internal Credit Ratings Bias and Borrower Financial Reporting Quality

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October 2025

ABSTRACT: There is regulatory concern that banks optimistically bias their internal borrower credit ratings under Basel's internal ratings-based (IRB) approach to minimize required regulatory capital. This concern has led some countries to implement restrictions on the use of the IRB approach, while other countries continue to debate their path forward. Using new data on banks' internal borrower credit ratings, we first find evidence of discontinuities that suggest optimistic bias at salient thresholds in the ratings distribution. Next, we provide evidence that the discontinuities are less pronounced for public borrowers relative to private borrowers, and for public borrowers with better financial reporting quality. Using firm-year measures from an implied credit-ratings model, we find that both optimistic ratings bias and ratings dispersion across banks are reduced for borrowers with better financial reporting quality. Collectively, our results suggest that borrower financial reporting quality facilitates bank examiner detection of internal ratings bias and may therefore be an important factor to consider in the current international regulatory debate concerning limitations on the use of the IRB approach.

Keywords: financial reporting quality, internal ratings-based (IRB) approach, bank capital, bank regulatory reporting, credit ratings, probability of default

JEL Codes: G21, M40, M41, M48

We gratefully acknowledge comments from Chih Huei (Debby) Banks, Richard Carrizosa, Aytekin Ertan (discussant), Yadav Gopalan, Hyunjin Kim (discussant), Arthur Morris, K. Ramesh, Ling Zhou, and workshop participants at the University of New Mexico, 2025 AAA Annual Meeting, and the 2025 Northwestern Debt Markets Conference. We appreciate financial support from the Carol and John Cochran Accounting Department Research Grant.
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1. Introduction

The Basel Accords introduced a regulatory-based capital framework that requires banks with riskier assets to maintain higher capital. The Basel II Accord introduced an "internal ratings-based approach" (IRB) where approved banks estimate a borrower's probability of default and assign an internal credit rating, which then determines required regulatory bank capital levels.[1] A bank's approval to use the IRB approach is granted based on a long list of factors that are *internal* to the bank (e.g., the quality of internal systems). While banks' access to private information and superior monitoring skills should allow them to estimate a borrower's default probability more accurately, banks also have incentives to maintain high capital levels. Recent international literature has provided evidence that banks on average underestimate borrowers' default probability (e.g., Behn et al., 2022; Plosser and Santos, 2018), which leads to an optimistic bias in their internal borrower credit ratings, thereby requiring less regulatory capital. Consistent with this evidence, regulators in some countries have already implemented limitations on the use of the IRB approach, while other countries are actively debating the issue (Schroeder, 2024).[2]

In the United States, federal banking agencies conduct a thorough examination of each bank at least annually (Code of Federal Regulations, Title 12 §337.12). Banks must maintain all necessary information to analyze each commercial credit, including the borrower's historical and current financial statements (Federal Reserve Board 2023, §2010.1, p. 3). During these examinations, bank examiners review credit files, including borrower financial statements, and perform credit analysis to evaluate the accuracy of default probability estimates, loan grading, and the corresponding ratings (Federal Reserve Board 2023, §2001.1, p. 2). In various settings, extant

[1] We describe how internal credit ratings map into regulatory capital levels, along with the estimation of risk parameters, in Section 2.

[2] For example, the European Union's Basel III revision took effect on January 1, 2025, which significantly limits banks' use of the IRB approach. The timeline for implementation of the revision in the United Kingdom and United States remains uncertain.

literature documents that better financial reporting quality is associated with improved ability to estimate firm default risk (e.g., Beaver et al., 2012). Accordingly, it is plausible that better borrower financial reporting quality makes it easier for regulators to assess the accuracy of banks' internal credit ratings. This logic forms our central research question: Is borrower financial reporting quality associated with the extent to which banks optimistically bias their internal borrower credit ratings?

We use U.S. borrowing firm data from Credit Benchmark, which gathers internal probability of default estimates for a large sample of borrowers from multiple banks monthly, averages the default probability estimates, and maps the average default probability for each borrower-month into a "consensus" credit rating that closely follows the Standard & Poor's credit rating scale.[3] For confidentiality purposes, Credit Benchmark discloses each borrower's consensus rating and the dispersion in ratings across all contributing banks without revealing the individual default probability estimates provided by each contributing bank or the names of the banks. We examine our research question using two alternative approaches to measure bank internal ratings bias (a distributional approach and a firm-year measure based on a comparison of the Credit Benchmark ratings to model-based implied credit ratings) and two approaches to capture borrower financial reporting quality (public vs. private firm classification and firm-year financial-statement-based measures, including divergence scores and abnormal accruals).

Using a sample of public and private borrowers, our distributional approach (e.g., Burgstahler and Dichev, 1997) finds that the Credit Benchmark ratings distribution is not smooth and shows clear discontinuities that are consistent with bias around salient rating thresholds. First,

[3] Both S&P and Credit Benchmark use the following 21-point rating scale: AAA (lowest default probability), AA+, AA, AA−, A+, A, A−, BBB+, BBB, BBB−, BB+, BB, BB−, B+, B, B−, CCC+, CCC, CCC−, CC, and C (highest default probability).

there is a significant discontinuity at BBB+, consistent with banks managing their internal ratings around FDIC guidelines that suggest a material jump in the estimated probability of default in moving from A- to BBB+ ratings. Second, there is a significant discontinuity at the investment-grade threshold BB+, consistent with banks responding to existing rules that require regulatory reporting that classifies exposures as either investment versus non-investment grade (e.g., the Shared National Credit or SNC program).

We then examine whether these discontinuities are more pronounced for private borrowers relative to public borrowers. Public borrowers supply verifiable financial reports that are available to all market participants and regulators alike and generally have higher financial reporting quality than private firms (Hope et al., 2013), which would allow banks less discretion in their default probability estimation (Plosser and Santos, 2018). In contrast, private borrowers' financial information is less widely available and generally exhibits lower reporting quality, potentially giving banks greater latitude in their internal credit assessments. Consistent with this reasoning, we find evidence that these discontinuities are indeed larger for private borrowers than for public borrowers.

We next analyze the scaled magnitudes of these discontinuities (Glaum et al., 2004) using a sample of public borrowers sorted by quintiles of a firm-year measure of financial reporting quality (i.e., financial statement divergence scores). The data show a clear pattern where the scaled magnitudes around both discontinuities increase when moving from the best to the worst financial reporting quality. This visual inspection reinforces the inference that better borrower financial reporting quality decreases optimistic bias in internal bank credit ratings.

We move beyond distributional analyses and provide a more granular analysis by estimating bank internal credit ratings bias for each borrower at the firm-year level. Specifically, we compute a firm-year measure of internal ratings bias as the difference between the consensus Credit Benchmark rating and the implied credit rating following the methodology of Baghai et al., (2014). We then regress this bias measure on alternative firm-year measures of financial reporting quality based on both financial statement divergence scores (e.g., Amiram et al., 2015) and two variations of abnormal accruals models (e.g., Badertscher et al., 2023; Dichev and Owens, 2025). Across all measures, we find that better borrower-level financial reporting quality is associated with less bank internal ratings bias, which directly highlights the role of borrower reporting quality in mitigating the potential underreporting of borrower default probability by banks to regulators.

Another indication of optimistic ratings bias could come from deviation in a bank's rating for a particular borrower relative to the consensus rating of other banks. Given the structure of the Credit Benchmark data, we cannot observe individual bank ratings. However, we can observe the dispersion in a borrower's rating across contributing banks, which should be positively correlated with the extent to which there is individual bank deviation from the consensus. We indeed find that the dispersion in ratings across banks is negatively associated with a borrower's financial reporting quality, consistent with the notion that reporting quality mitigates banks' optimistic ratings bias.

Our study extends the literature on bias in bank internal ratings. Prior studies examine whether borrower default probability estimates are consistent among banks (Firestone and Rezende, 2016). Other studies investigate how bank incentives affect their internally generated ratings. For instance, Behn et al. (2022) and Berg and Koziol (2017) use data from the German credit registry and show that banks have incentives to manipulate their internal ratings to reduce their regulatory capital requirements. Plosser and Santos (2018) obtain similar inferences using a sample of syndicated loans in the US market. We extend these prior studies by identifying where optimistic biases in ratings distributions are most likely to be concentrated (i.e., around salient thresholds related to capital adequacy).

More importantly, we extend the literature that documents the role of borrower financial reporting quality in preventing opportunistic bias by lenders. It is well established that better borrower financial reporting quality reduces information asymmetry between lead arrangers and participant lenders in syndicated loans, ostensibly by reducing the ability of the lead arranger to present an optimistically biased evaluation of borrower credit risk (e.g., Ball et al., 2008). In contrast to that literature, we *directly* measure the degree of lenders' bias within their internal credit ratings and document a direct association between this optimistic bias and borrower financial reporting quality.

Our study is also relevant for the international regulatory debate about the appropriateness of the IRB approach in future Basel revisions. Our evidence suggests that, in addition to assessing internal bank factors, regulators could consider external (e.g., borrower-side) factors that may affect banks' ability to bias their ratings on an exposure-by-exposure basis.

2. Background and Motivation

2.1. Basel and the IRB approach

The Bank for International Settlements (BIS) houses the Basel Committee on Banking Supervision (BCBS), which is the primary standard-setting body for bank regulation. The BCBS's mission is to improve financial stability, particularly by focusing on capital adequacy. The committee issues recommendations that bank regulators of individual countries implement.[4] In 1988, the BCBS introduced the Basel I Accord, which was the first attempt to require banks to hold more capital to absorb losses from risky assets. Basel I called for a minimum ratio of capital

[4] BCBS develops recommendations known as the Basel Accords, which several countries (including the United States) follow to regulate banks.

to risk-weighted assets of 8%.[5] For purposes of determining risk weights on various bank assets (i.e., the denominator of the capital adequacy ratio), Basel I classified bank assets into four categories—government securities (e.g., Treasury bills), loans supported by government-sponsored entities (e.g., Fannie Mae), residential mortgages, and commercial loans. Within each category, risk weights were equally applied regardless of differential credit risk posed by different assets within the category. For example, under Basel I, a bank holds the same level of capital for a corporate loan, whether rated A or BBB+. This uniform approach was a major limitation of Basel I. As a result, actual portfolio credit risk and capital adequacy ratios were weakly correlated.

Although Basel I did not require banks to do so, banks had the need to classify loans into finer categories for internal purposes (e.g., approval decisions and loan pricing). In doing so, banks generally adopted rating scales modeled after those used by bond rating agencies (Hyndman, 1996), with a particular focus on the S&P rating scale (the agency with the most corporate ratings). The development of more sophisticated financial products, including syndicated loans and structured finance, further incentivized banks to refine their internal rating systems.

As banks developed more sophisticated internal rating scales, Basel II (released in 2004 and subsequently amended) incorporated these internal ratings. Specifically, Basel II introduced two main methods for determining risk weights in capital requirement calculations: the "standardized approach" and the "internal ratings-based" (IRB) approach. The standardized approach employs fixed weights like Basel I but introduces additional categories. In contrast, the IRB approach requires banks to use their own internal default probability estimates to assess the credit risk in their loan portfolios. The IRB model provides two options for measuring credit risk: the foundation approach (F-IRB) and the advanced approach (A-IRB). Both the F-IRB and A-IRB

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[5] The risk-based capital ratio is the ratio of regulatory capital to risk-weighted assets (RWA). Riskier assets have greater weights, which increases RWA and decreases the ratio.

require banks to estimate borrower probability of default and the exposure at default (EAD). Under the F-IRB, banks follow supervisory rules for other inputs, including loss given default (LGD) and maturity of the exposure, whereas the A-IRB requires banks to estimate these other inputs.

In the United States, regulators require the largest banks (those with consolidated assets of $250 billion or more, or at least $10 billion in on-balance-sheet foreign exposure) to adopt the IRB approach and allow other institutions to adopt this approach voluntarily (Federal Reserve Board 2017). According to the Code of Federal Regulations (12 CFR § 217), to qualify for the IRB approach, banks must satisfy certain minimum requirements related to various factors, including rating system design and operations, corporate governance, use of internal ratings for risk management practices, and validation of internal estimates. Under the IRB model, banks map borrower default probability onto their internal rating scales.[6] Loans with lower internal ratings (which reflect a higher default probability) have greater weights and increase risk-weighted assets, thereby decreasing risk-based capital ratios. Specifically, the effect of default probability on capital requirements (K) can be seen in the following risk weight function (12 CFR § 217.131):

$$K = \left[LGD * N\left[\frac{N^{-1}(PD) + \sqrt{R} * N^{-1}(0.999)}{\sqrt{1-R}} \right] - LGD * PD \right] * \left[\frac{1 + (M - 2.5) * b}{1 - 1.5 * b} \right] \qquad (1)$$

where PD is the one-year probability of default of the borrower (which is specific to the borrowing firm's characteristics and is not based on loan features or guarantees), LGD is loss given default, M is the effective maturity, N is the cumulative distribution function for a standard normal variable, and N^{-1} is the inverse cumulative distribution function for a standard normal variable. R is a correlation parameter and b is a maturity adjustment, both of which are themselves functions of

[6] In general, banks do not assign a specific default probability to each borrower. Instead, banks assign the borrower to a rating category that has an associated default probability.

PD. While banks estimate *PD* and other risk parameters, limitations exist.[7] To summarize, Eq. (1) shows that capital requirements are an increasing function of borrower default probability.

Basel III was published in 2010 in response to the factors that led to the 2007-2009 financial crisis. While Basel III increased capital adequacy requirements, it did not initially change the IRB methodology. A new iteration of these regulations, alternatively referred to as Basel 3.1 or Basel IV, aims to make significant changes to the way banks calculate risk-weighted assets. Basel IV arose, in part, due to concerns that the discretion permitted under the IRB approach allows banks to underestimate the riskiness of their portfolios. Accordingly, Basel IV proposes to constrain the use of internal models by imposing a floor such that capital does not fall below 72.5% of the amount that would be required under the standardized approach.

The implementation of these Basel revisions is being handled differently across countries. The European Union implemented new rules effective January 1, 2025 that significantly limit banks' use of internal ratings-based (IRB) approaches for credit risk and implement the 72.5% "output floor." In the United Kingdom, implementation of Basel revisions has been delayed from January 2026 to January 2027, citing uncertainty around U.S. implementation timing and competitiveness considerations.[8] The U.S. implementation timeline remains unclear. The current U.S. proposal replaces the IRB approach entirely with a new standardized approach for credit risk, requiring banks to use regulator-prescribed formulas instead of their own internal models.[9]

[7] For example, there is a minimum PD input floor of three basis points under Basel II, which was increased to five basis points under Basel III.

[8] https://www.bankofengland.co.uk/news/2025/january/the-pra-announces-a-delay-to-the-implementation-of-basel-3-1.

[9] https://www.deloitte.com/content/dam/assets-zone3/us/en/docs/services/risk-advisory/2023/us-advisory-deloitte-basel-iii-endgame-august-2023.pdf.

2.2. Regulatory supervision

Banks are subject to regulatory supervision to ensure compliance with established rules and regulations. In the U.S., federal banking agencies conduct thorough examinations of each bank at least annually (Code of Federal Regulations, Title 12 §337.12). For commercial loans, banks must maintain complete credit files, including the borrower's historical and current financial statements (Federal Reserve Board 2023, §2010.1, p. 3). During examinations, bank examiners review credit files (including borrower financial statements) and perform credit analyses to evaluate the accuracy of default probability estimates, loan grades, and corresponding ratings (Federal Reserve Board 2023, §2001.1, p. 2).

In addition to examinations, banks are also subject to review through the Shared National Credit (SNC) program. This program, governed by bank regulatory agencies (the Federal Reserve, the Federal Deposit Insurance Corporation, and the Office of the Comptroller of the Currency), gathers data on large loans. The program currently focuses on syndicated loans of $100 million or more, as well as loans involving participation from three federally supervised institutions, though some entities must report all syndicated loans. Banks submit their internal credit ratings to the SNC program, including the classification of investment grade or non-investment grade, along with other data requirements.[10] Because bank rating scales may differ across banks (Treacy and Carey, 2000), banks must submit a Concordance Mapping form that maps their internal rating scale to the investment grade or non-investment grade classification. The data collected through the SNC program is treated as *examination data* and is shared among the regulatory agencies.[11]

[10] Precisely, banks report their internal credit ratings in the "Bank Internal Credit/Obligor Rating" field. Other SNC data requirements include obligor-specific metrics related to leverage and repayment capacity. It collects identifying information about borrowing firms, such as their name, location, tax ID, CUSIP, and legal entity identifier (LEI). It also gathers credit-related information, including the type of credit (e.g., revolving line of credit), the purpose of the credit (e.g., working capital), the committed amount, and the outstanding amount.

[11] Reporting entities submit data requirements to the eSNC data system (https://bsr.frb.gov/my.policy) using XML files.

To sum up, banks' internal ratings play a crucial role in determining their capital requirements when using the IRB approach, as described in Section 2.1. Due to their importance, bank examiners assess the accuracy of these internally generated ratings during bank examinations and through the SNC program, with particular attention to whether loans are classified as investment grade or non-investment grade. Importantly for our study, in making these assessments, bank examiners rely in part on a review of borrowers' historical financial statements.

2.3. Related literature

Existing literature provides evidence that banks engage in capital management strategies. Both Beatty et al. (1995) and Ahmed et al. (1999) find that banks use loan loss provisions to reduce expected regulatory costs associated with violating capital requirements. Beatty and Liao (2014) discuss how accounting numbers are manipulated in the banking industry in response to capital requirements and other bank financial reporting incentives. Barth et al. (2017) find that banks use realized gains on available-for-sale securities to increase regulatory capital. Owens and Wu (2015) provide evidence of real activities management where banks temporarily reduce short-term borrowings around financial reporting dates to reduce perceived riskiness, particularly when capital adequacy is relatively low. Demerjian et al. (2023) provide further evidence of lender capital management, in that lenders with lower regulatory capital issue loans with lower covenant strictness because borrower covenant violations may trigger reductions in regulatory capital.

Existing literature has also examined bias in banks' internal credit ratings and has provided some initial evidence consistent with the underestimation of risk to maintain capital levels. Using data from the United States syndicated loan market, Firestone and Rezende (2016) document varying default probability estimates among banks for the same borrower. They also find that default probability estimates are generally lower for larger loans, suggesting that banks have incentives to underestimate default probability to save on regulatory capital when the benefits are more substantial. Plosser and Santos (2018) also note variations in internally generated risk estimates among banks within the same loan syndicate. They observe that banks with low capital adequacy tend to report systematically lower default probability estimates.[12]

Other studies obtain consistent evidence in the European context. Using German credit registry data, Behn et al. (2022) show that banks report lower default probability estimates under the IRB approach (which links internal ratings to regulatory capital) than the standardized approach (which does not use internal ratings as inputs to capital computations). Berg and Koziol (2017) find that banks with lower capital ratios report lower default probability estimates for the same borrowers compared to other banks with lending relationships to those borrowers, indicating that IRB discretion is used to reduce regulatory capital costs.

In motivating our research question, we also rely on literature which establishes that better financial reporting quality makes it easier to understand a firm's underlying economics in general, and credit risk in particular (e.g., Beaver et al., 2012). In our setting, because bank examiners review borrower financial statements as part of their supervisory assessments, this translates into the prediction that better borrower financial reporting quality will make it easier for bank examiners to detect (and therefore mitigate) banks' optimistic internal ratings bias. This prediction is consistent with evidence that higher quality financial reporting constrains managerial discretion and reduces optimistic bias in financial estimates (Chen et al., 2011; Dechow et al., 2011). Following this logic, we investigate whether a borrower's financial reporting quality affects the extent to which banks engage in capital management by underestimating borrower default

[12] Plosser and Santos (2018) also find that the association between downward bias in borrower default probability estimates and regulatory capital is attenuated for public borrowers relative to private borrowers. This is consistent with their hypothesis that because public companies provide "hard" verifiable financial reports to all market participants, banks have less discretion in estimating the probability of default for public firms relative to private firms.

probability. Specifically, we not only consider differential effects between public and private borrowers (e.g., Hope et al., 2013; Plosser and Santos, 2018), but also whether variation in financial reporting quality among public borrowers is associated with the magnitude of banks' bias in internal default probability estimates.

3. Sample Selection

We obtain internal bank ratings data from Credit Benchmark, which is a dataset that has recently been introduced into the accounting literature (Lourie et al., 2024). Credit Benchmark collects borrower credit risk assessments from different financial institutions, including the world's largest banks.[13] Specifically, Credit Benchmark collects one-year forward-looking borrowing firm default probability estimates from banks that maintain relationships (mostly lending) with the borrowing firms. Credit Benchmark averages the default probabilities from the contributing banks and reports monthly consensus internal bank ratings for each borrowing firm using the S&P rating scale.[14] Appendix B shows how the Credit Benchmark consensus rating is derived for an example entity. In the example, five banks contribute default probability estimates (20, 30, 40, 50, and 60 basis points), where the average default probability is 40 bps. This average maps into a BBB- rating, which has a lower bound of 30 bps and an upper bound of 48 bps.

Credit Benchmark "does not express any view on individual models, nor does it modify the contributed data in any way" (Credit Benchmark report: Credit Risk IQ – In Depth). Credit Benchmark shares its consensus ratings with the contributing banks and other Credit Benchmark data subscribers. Credit Benchmark only reports consensus ratings for a borrowing entity if three or more financial institutions contribute default probability estimates. Given this requirement,

[13] The data includes internal credit ratings reported by at least seven global systemically important banks (G-SIBs).
[14] The Credit Benchmark scale (which is based on S&P) is AAA, AA+, AA, AA−, A+, A, A−, BBB+, BBB, BBB−, BB+, BB, BB−, B+, B, B−, CCC+, CCC, CCC−, CC, C, and D. Investment grade is BBB- or better, and non-investment grade (also known as speculative grade and high yield) is BB+ or worse.

Credit Benchmark ratings generally cover large corporations, including publicly traded and privately held firms across the globe. All participating banks use the IRB method for regulatory capital purposes. One key limitation of the data is that Credit Benchmark maintains the confidentiality of the contributing bank names; accordingly, individual bank-level analyses are not possible with these data.

Table 1 summarizes our sample construction. The Credit Benchmark data reports 2,520,154 *monthly* consensus borrower ratings from May 2015 to July 2023. Given that rating changes are relatively infrequent, we aggregate the monthly data to the firm-year level to avoid inflating the number of observations and t-statistics in our analyses.[15] To do so, we keep only the most recent monthly Credit Benchmark consensus rating for a given firm year, resulting in 293,076 yearly ratings corresponding to 72,897 unique borrowers. We further restrict our sample to firms domiciled in the United States, resulting in 69,868 yearly ratings corresponding to 16,585 unique borrowers. Throughout our discussion, we refer to this sample of United States firms as the *full sample*. The full sample is further subdivided into 59,075 yearly ratings for 14,947 private firms (*private sample*) and 10,793 yearly ratings for 1,638 public firms (*public sample*). We will use these samples to pursue our distributional analysis of internal bank ratings.

Our analyses of firm-year financial reporting quality and internal ratings bias require additional data. Credit Benchmark uses the legal entity identifier (LEI) to identify each firm. For the public sample, we use Refinitiv Workspace to find the central index key (CIK) associated with each LEI, resulting in CIK matches for 1,329 (out of 1,638) firms. For the unmatched firms, we manually search for CIKs on the SEC EDGAR website.[16] Refinitiv and the manual search lead to CIKs for 1,537 public firms (101 firms are unmatched). We then use the CIK to merge our sample

[15] We report summary statistics on rating changes in Table 2 and discuss rating dynamics below.
[16] The website can be accessed at https://www.sec.gov/edgar/search-and-access

with Compustat data, which are necessary to compute our measures of borrower financial reporting quality and implied credit ratings. We further combine the data with stock market measures from Beta Suite by WRDS (also necessary to compute implied credit ratings), leading to a sample of 3,654 yearly ratings for 934 unique firms, hereafter referred to as the *implied ratings sample*.

Table 2 Panel A presents basic descriptive statistics for Credit Benchmark ratings for the full, public, private, and implied ratings samples. In the full sample, the average (median) rating is 10.15 (10), corresponding to BBB-, consistent with Lourie et al. (2024). As reported, 33% of firm-year ratings experienced a change relative to the prior year, where 16% (17%) of observations experienced a year-over-year downgrade (upgrade). The descriptive statistics for the other samples are similar.

Table 2 Panel B reports rating frequencies for all samples. In general, the frequency distributions are not smooth. In the full sample, the number of firms rated BB+ (the highest non-investment grade) is low relative to its next two adjacent ratings (BBB- and BB). The discontinuity attenuates for the public sample and increases for the private sample. We observe another dip in the distribution for the BBB+ rating relative to the neighboring ratings (A- and BBB) for the full sample. We formally examine this initial evidence in the next section.

Panel C of Table 2 reports frequencies of year-over-year Credit Benchmark rating changes. For the full sample, 12.35% of firm-years experience an upgrade of one rating notch, and 3.07% of two rating notches. Regarding downgrades, 10.19% experience a one-notch downgrade and 3.12% experience a two-notch downgrade. Rating changes of three or more notches are infrequent. The general pattern is similar across the private and public samples. The implied ratings sample shows 17.00% (10.84%) upgrades (downgrades) by one notch.

Panel D of Table 2 reports Credit Benchmark coverage by industry. The most rated industries are financials, industrials, consumer services and goods, oil and gas, healthcare, utilities, technology, and basic materials. All other industries each represent approximately 2% or less of the sample.

4. Bank Internal Ratings Distributional Analysis

The logic of our distributional approach to identifying internal ratings bias is grounded in the non-linear relationship between borrower credit ratings and risk-weighted capital requirements. In certain ranges of the ratings distribution, a one-unit upgrade has a nominal impact on required risk weights (see Appendix C)—in this case, incentives to optimistically bias the rating will be minimal. Conversely, at other points in the ratings distribution—such as near the "investment grade" threshold—a one-unit rating upgrade can significantly affect the required risk weights. We conjecture that banks are more likely to optimistically bias a borrower's rating when the rating is on the border of a material risk-weighting threshold.

4.1. Public versus private borrowers

Figure 1 displays histograms of Credit Benchmark ratings (as tabulated in Table 2 Panel B). Panel A of Figure 1 displays the ratings distribution for the *full sample* (which includes both private and public United States firms). We plot investment grades (BBB- or better) in light gray and non-investment grades (BB+ or worse) in dark gray. A visible discontinuity exists around the investment grade threshold, where a relatively large (small) number of firms are just above (below) the investment grade threshold. There is also a noticeable discontinuity around A- and BBB+, with a relatively large (small) number of observations having an A- (BBB+) rating. This latter discontinuity is noteworthy because the A- to BBB+ rating transition separates firms with a strong payment capacity from firms with an adequate payment capacity (Cantor and Packer 1997), and results in a material increase in risk weights in the IRB risk-weight function (see Appendix C). Panels B and C present corresponding histograms for the *public sample* and *private sample*, respectively. Visually, the public sample distribution appears to be smoother than the private sample distribution. For comparison, in Panel D of Figure 1, we display a histogram of the implied S&P ratings (*ImpliedSPRating*) from the implied ratings sample—as shown, the distribution of implied ratings is smooth.

In Table 3, we formally report tests of the statistical significance of these two discontinuities. Under smoothness assumptions, the number of observations in a rating bucket approximates the average of the two adjacent ratings. We assess the statistical significance of discontinuities in the ratings distribution following Burgstahler and Dichev (1997). Precisely, the standardized difference in a rating bucket is the difference between the actual number of observations and the expected number of observations (where the expected number is the average of the adjacent ratings) divided by the estimated standard deviation of the difference.[17] We also report measures of scaled magnitudes of the differences (italicized in parentheses) following Glaum et al. (2004).[18] With respect to the investment-grade discontinuity, for the full sample, the BBB- standardized difference is 11.87, which indicates that the number of observations rated BBB- (i.e., the lowest rating with an investment-grade classification) is statistically higher than the average of both adjacent ratings at the 1% level ($p<0.01$). The BB+ standardized difference is -43.00, which indicates that the number of observations rated BB+ (i.e., the highest rating with a non-investment-grade classification) is statistically lower than the average of the adjacent ratings

[17] We compute the standard deviation following Beaver et al. (2007), who revise Burgstahler and Dichev's test for a more conservative measure of standardized differences.
[18] Specifically, for the scaled magnitude measure, we divide the difference between the number of observations on either side of the rating threshold by the total number of observations in the two ratings. This measure ranges between -1 and 1, where values closer to zero indicate no discontinuity and positive (negative) values indicate an unusually large (small) number of observations.

($p<0.01$). Together, this evidence is consistent with banks optimistically biasing their internal ratings such that more borrowers than expected are rated just above the investment-grade threshold. There is similar evidence of statistical discontinuities around the investment-grade threshold for both the private and public samples, although the magnitude and significance of the standardized differences are greater in the private sample. Similar evidence exists for the discontinuity at the A-/BBB+ threshold.

To summarize, this distributional analysis reveals two significant discontinuities in the internal bank ratings distribution, which is consistent with concentrations of optimistic internal bank ratings bias at these points. In each case, there is an unusually large (small) number of observations in the rating category just above (below) a threshold that results in a material adverse impact on bank regulatory capital requirements. That these discontinuities are smaller for public borrowers relative to private borrowers, combined with the stylized fact that public firms have better financial reporting quality than private firms (e.g., Hope et al., 2013), is consistent with borrower financial reporting quality playing a role in the extent to which banks can bias their internal ratings.

4.2. Public borrowers' financial reporting quality

We next examine these distributional discontinuities as a function of borrowing firm financial reporting quality, which we can measure only for public firms. As our primary measure of financial reporting quality, we compute *FSDScore* following the methodology of Amiram et al. (2015). In short, *FSDScore* is based on statistical deviations from the theoretical distribution of numbers that one would expect to observe in a firm's financial statements, where higher values of *FSDScore* indicate lower financial reporting quality. One advantage of *FSDScore* as a measure of financial reporting quality is that there is no obvious reason why a measure based only on properties of naturally occurring numerical distributions would be correlated with innate firm characteristics, which mitigates endogeneity concerns (e.g., Badertscher et al., 2023).

We analyze the scaled magnitudes (measured using the methodology in Glaum et al., 2004, described in section 4.1) of the significant discontinuities around the A-/BBB+ and BBB-/BB+ rating thresholds using our public sample sorted by *FSDScore* quintiles, where observations in *FSDScore* quintile 1 (quintile 5) have the best (worst) financial reporting quality.[19] Figure 2 Panel A (Panel B) displays the results of this analysis for the BBB-/BB+ (A-/BBB+) discontinuity. The vertical axis measures the magnitude of the discontinuity, and the horizontal axis shows the five *FSDScore* quintiles. The data show a clear pattern where the scaled magnitudes around both discontinuities increase when moving from the lowest to the highest quintile of *FSDScore* (i.e., from the best to the worst financial reporting quality). This visual inspection reinforces our inference that better borrower financial reporting quality decreases optimistic bias in internal bank credit ratings.

5. Firm-Year Internal Ratings Bias and Borrower Financial Reporting Quality

5.1. Research design

Using our implied ratings sample, we estimate the degree of internal bank ratings bias in a given borrower-year by computing the difference between the borrower's consensus internal bank rating and its implied S&P rating, where we compute implied S&P ratings based on firm fundamentals using the methodology in Baghai et al. (2014). Importantly, we estimate bias by comparing internal bank ratings with a smoothed model-based implied rating, rather than with actual (potentially biased) S&P ratings.[20] Specifically, we first obtain estimated coefficients

[19] To maximize the number of observations, we use our public sample for which we have available *FSDScore*.
[20] Studies point out conflicts of interest related to S&P and other large traditional rating agencies' issuer-pay model, which can lead to bias in issuer-paid ratings. The Baghai et al. (2014) model assumes that the ratings are solely based

(untabulated) from the following firm-year regression model using all observations for the sample period 2015 to 2023 (to maintain consistency with our Credit Benchmark sample period) with necessary data at the intersection of Compustat, S&P Credit Ratings, and Beta Suite by WRDS:

$$\begin{aligned} SPRating_{i,t} = {} & \beta_0 + \beta_1 InterestCoverage_{i,t} + \beta_2 Profitability_{i,t} + \beta_3 BookLeverage_{i,t} + \beta_4 Size_{i,t} \\ & + \beta_5 DebttoEBITDA_{i,t} + \beta_6 I.DebttoEBITDA_{i,t} + \beta_7 ProfitabilityVol_{i,t} \\ & + \beta_8 CashtoAssets_{i,t} + \beta_9 ConvDebttoAssets_{i,t} + \beta_{10} RentExptoAssets_{i,t} \\ & + \beta_{11} PPEtoAssets_{i,t} + \beta_{12} CAPEXtoAssets_{i,t} + \beta_{13} Beta_{i,t} + \beta_{14} IdioRisk_{i,t} \\ & + IndustryFE + TimeFE + \varepsilon_{i,t} \end{aligned} \tag{2}$$

where *i* and *t* denote firm and year, respectively. *SPRating* is the S&P senior unsecured credit rating for a firm-year. Following the typical approach in the literature, we convert the alphabetic S&P rating scale to a numeric scale ranging from 1 (corresponding to AAA) to 21 (corresponding to C), where lower numbers indicate lower risk (i.e., better credit quality).[21] We then apply the estimated coefficients from Eq. (2) to a broader sample of firms (including firms without available ratings but with available firm characteristics) to obtain implied S&P ratings for each borrower (*ImpliedSPRating*).

Following prior literature (e.g., Bonsall et al., 2024), we estimate internal bank credit ratings bias as the difference between the internal bank rating (similarly converted to a numeric scale where lower values indicate lower risk) and the implied S&P rating:

$$RatingDifference_{i,t} = ImpliedSPRating_{i,t} - InternalBankRating_{i,t} \tag{3}$$

on quantitative analysis. This methodology's output is a smoothed distribution of implied ratings, which mitigates concerns that, in some cases, S&P's revenue model affects the rating process.

[21] In robustness checks, we estimate Eq. (2) alternately using a sample of S&P ratings when the agency is more likely to provide better assessments (following Badoer et al., 2019), Egan Jones ratings (EJR), and the more conservative rating between S&P and EJR.

Positive (negative) values of *RatingDifference* indicate that banks understate (overstate) borrower risk relative to the implied rating, where the magnitude reflects the degree of disagreement.[22]

Next, we regress the firm-year internal bank ratings bias proxy on measures of the borrower's financial reporting quality (*FRQ*) using OLS:

$$RatingDifference_{i,t} = \beta_0 + \beta_1 FRQ_{i,t} + \sum \beta_n Controls_{i,t} + TimeFE + \varepsilon_{i,t} \quad (4)$$

where *RatingDifference* is as defined above, and our primary *FRQ* measure is *FSDScore*, as described above. We also consider two alternative *FRQ* measures based on abnormal accruals models: *AbAccruals* (e.g., Badertscher et al., 2023) and *PosDurTotAcc* (Dichev and Owens, 2025). Eq. (4) uses the same controls as shown in Eq. (2) and additionally controls for the number of banks contributing to the consensus rating (*NBanks*).

We also replace the dependent variable in Eq. (4) with a measure of the dispersion in internal bank ratings (i.e., an alternate way to detect internal bank ratings bias) to provide evidence of whether financial reporting quality is linked with lower internal bank rating dispersion. *RatingDispersion* is the standard deviation of all internal bank ratings for a specific firm-year and is calculated using a minimum of three different bank ratings. We estimate the following OLS model to measure the degree to which financial reporting quality inhibits individual bank managers from deviating their ratings from the average consensus bank rating.

$$RatingDispersion_{i,t} = \beta_0 + \beta_1 FRQ_{i,t} + \sum \beta_n Controls_{i,t} + TimeFE + \varepsilon_{i,t} \quad (5)$$

5.2. Descriptive statistics

Table 4 presents descriptive statistics for the implied ratings sample, which includes 3,654 firm-years with available Credit Benchmark ratings, S&P implied ratings, and fundamentals. The

[22] For example, if *ImpliedSPRating* equals 11 (corresponding to BB+) and *InternalBankRating* equals 10 (corresponding to a rating of BBB-, which indicates lower risk than BB+), *RatingDifference* equals 1.

average (median) *RatingDifference* is 0.88 (1.00), indicating that, on average, banks' internal ratings are more optimistic than the S&P-implied ratings by approximately one rating notch. The average (median) *RatingDispersion* is 0.54 (0.50), with the distribution indicating that the first percentile equals 0.10. This indicates that for most borrower firm-years in our sample, lenders exhibit some disagreement concerning one-year-ahead forward-looking probability of default estimates. Regarding our main proxy for financial reporting quality, the average *FSDScore* is 0.03 with a standard deviation of 0.01, consistent with the distribution reported in Amiram et al. (2015).

5.3. Empirical results

Table 5 reports results from the estimation of Eq. (4), which documents the association between our three alternative measures of *FRQ* (*FSDScore*, *AbAccruals*, and *PosDurTotAcc*) and *RatingDifference* (i.e., the difference between the implied S&P rating and the Credit Benchmark rating). Note that *RatingDifference* increases in value as optimistic bias increases, and each *FRQ* proxy increases in value as financial reporting quality decreases. Therefore, a positive coefficient on an *FRQ* proxy indicates that a decrease in financial reporting quality is associated with an increase in optimistic bias. As reported in Columns (1)-(3), inferences are the same across all alternative measures of borrower financial reporting quality. Accordingly, we will focus on Column (1) for discussion (*FSDScore*).

The association between *FSDScore* and *RatingDifference* is positive and statistically significant (coefficient 10.014; t-statistic 2.46), which indicates that internal bank ratings are less optimistically biased when the borrower has better financial reporting quality. In terms of economic significance, a one standard deviation increase in *FSDScore* (worse financial reporting quality) corresponds to an approximate 11.4% increase in *RatingDifference*. This evidence suggests that better borrower financial reporting quality constrains lenders' ability to underreport borrower default probability. We interpret this finding as evidence that better borrower financial reporting quality enables bank examiners to more easily detect ratings bias, which in turn constrains banks' ability to optimistically bias their internal ratings for capital management purposes.

In Table 6, we present the results from estimating Eq. (4) after replacing the dependent variable with alternative measures of internal bank ratings bias that use different proxies for implied credit ratings.[23] Recall that our primary *RatingDifference* measure uses all available S&P ratings as inputs to the Baghai et al. (2014) model to estimate implied ratings. However, the fact that some S&P ratings may themselves be biased due to conflicts of interest inherent in the issuer-pay model may introduce error into the estimation of implied ratings. To address this concern, we re-estimate the Baghai et al. (2014) implied ratings model using (alternatively) (1) S&P ratings that are not more favorable than EJR (i.e., investor-paid) ratings, as S&P ratings that are more favorable than EJR ratings may have low quality (Badoer et al., 2019); (2) the more conservative (i.e., less favorable) rating between S&P and EJR; and (3) EJR ratings, which prior literature shows are informative (e.g., Beaver et al., 2006; Bruno et al., 2016). Across all alternatives, our inferences remain consistent.

Table 7 reports results from our analysis of internal bank rating dispersion (i.e., Eq. 5). As reported, there is a positive association between *FSDScore* and the dispersion in internal bank ratings (*RatingDispersion*) across all contributing banks (coefficient 1.213; t-statistic 2.19).[24] This is again consistent with poor borrower financial reporting quality enabling an individual bank to

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[23] Moving forward, we will limit our analyses to *FSDScore* as the measure of financial reporting quality.
[24] Inferences are consistent if we additionally include Credit Benchmark rating fixed effects (untabulated coefficient 1.350; t-statistic 2.55).

bias its internal rating, which manifests as a deviation from the average consensus bank rating (leading to higher rating dispersion).

As a caveat, we note that there may be a concern that the results reported in Table 7 reflect a reduction in uncertainty rather than a reduction in bias. For example, Akins (2018) presents evidence that better financial reporting quality in a rated firm is associated with less disagreement among traditional credit rating agencies, which he attributes to uncertainty reduction. Applying that logic to our setting, it is possible that better borrower financial reporting quality reduces disagreement (i.e., uncertainty) among the contributing banks' internal ratings, which would also yield the Table 7 results. To mitigate the concern that our collective findings reflect the effect of financial reporting quality on uncertainty rather than bias, we repeat our Table 5 (i.e., Eq. 4) analysis after replacing the dependent variable with the absolute value of *RatingDifference* (i.e., |*RatingDifference*|). We obtain an insignificant coefficient estimate (untabulated) on *FSDScore* (coefficient 3.073; t-statistic 0.99), which supports our bias reduction interpretation. That is, better borrower financial reporting quality is associated with a decrease in the extent to which bank internal ratings are *optimistic* relative to the implied S&P rating—financial reporting quality is *not* associated with a decrease in the extent to which bank internal ratings *deviate* (in any direction) from the implied S&P rating.

6. Conclusion

Existing international literature provides evidence that banks' incentives related to capital adequacy lead to optimistic bias in their internal credit risk ratings for borrowers through discretion permitted by the "internal ratings-based approach" (IRB) (e.g., Behn et al., 2022; Plosser and Santos, 2018). This bias has led regulators to debate limitations on banks' use of the IRB approach in their implementation of the Basel III reform. We investigate whether better borrower financial reporting quality enables examiners to better detect and prevent instances of optimistic bias in banks' internal borrower ratings.

Using a sample of bank internal default probability estimates for U.S. borrowing firms, we first provide evidence by pursuing a distributional approach (e.g., Burgstahler and Dichev, 1997). We find that the internal bank ratings distribution shows clear discontinuities that indicate internal ratings bias is concentrated around rating thresholds that have material regulatory capital implications, including the investment-grade threshold. Further, we provide evidence that these discontinuities are more pronounced for private borrowers than for public borrowers, and for public borrowers with relatively poor financial reporting quality.

We next construct a borrower-year measure of bank internal ratings bias using an implied ratings model, and again find that better borrower financial reporting quality is associated with less bank internal ratings bias and reduced ratings dispersion across banks. Collectively, this evidence is consistent with borrower financial reporting quality limiting banks' ability to bias their internal borrower credit ratings.

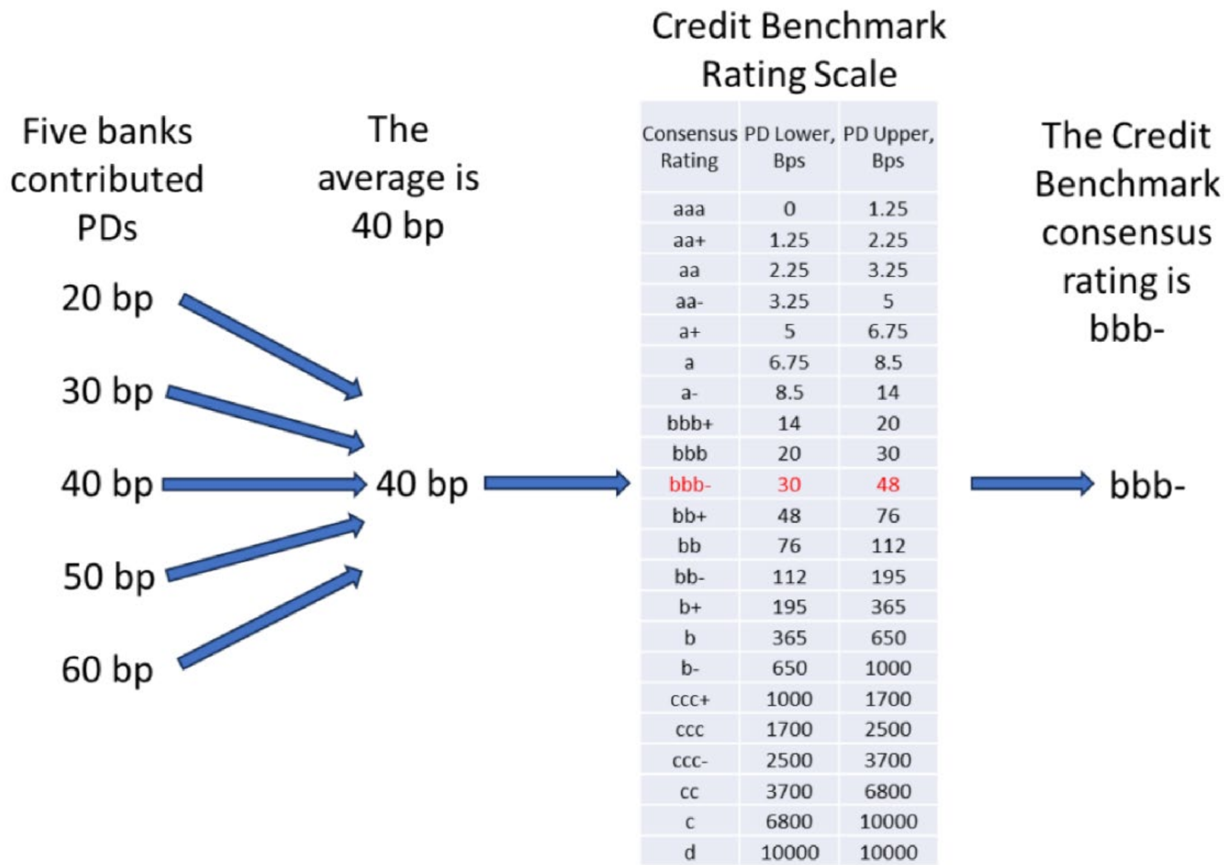
In general, our study extends the literature that examines the role of financial reporting quality in constraining managerial opportunism. More specifically, our findings have important implications for the ongoing international regulatory debate about the IRB approach. Our results suggest that regulators evaluating which bank exposures should be eligible for IRB treatment might consider not only internal bank factors but also borrower-side characteristics that affect the potential for ratings manipulation. Specifically, borrower financial reporting quality appears to be a constraint on banks' ability to optimistically bias their internal credit ratings.

Appendix A – Variable Definitions

Dependent Variables and Related	
$RatingDifference_{i,t}$	The difference between the model-implied S&P rating and the Credit Benchmark rating for borrower *i* in year *t* (i.e., *ImpliedSPRating* minus *InternalBankRating*). Sources: Credit Benchmark, S&P Credit Ratings, Compustat, Beta Suite by WRDS
$RatingDispersion_{i,t}$	The relative standard deviation of the individual bank ratings that are inputs to the consensus Credit Benchmark rating (*InternalBankRating*), computed as the standard deviation divided by the consensus rating. Source: Credit Benchmark
$ImpliedSPRating_{i,t}$	Borrower *i*'s model-based implied S&P rating for year *t*, calculated using our Eq. (2) which follows the methodology in Baghai et al. (2014). Source: S&P Credit Ratings, Compustat, Beta Suite by WRDS
Financial Reporting Quality Variables	
$AbAccruals_{i,t}$	Borrower *i*'s discretionary accruals (Jones 1991) at the end of year *t*, computed as follows: $\frac{Accruals_{i,t}}{Assets_{i,t-1}} = \beta_0 + \beta_1 \frac{1}{Assets_{i,t-1}} + \beta_2 \left[\frac{(\Delta Sales_{i,t} - \Delta Receivables_{i,t})}{Assets_{i,t-1}} \right] + \beta_3 \frac{PPE_{i,t}}{Assets_{i,t-1}} + \beta_4 ROA_{i,t} + \beta_5 SalesGrowth_{i,t} + \varepsilon_{i,t}$ Source: Compustat
$FSDScore_{i,t}$	Borrower *i*'s financial statement divergence (FSD) score based on year *t* financial statements, following Amiram et al. (2015). Source: Compustat
$PosDurTotAcc_{i,t}$	Borrower *i*'s positive-duration total accruals in year *t*, computed as the residual from a pooled firm-year (within-industry) regression of total accruals, on operating cash flow, investing cash flow, and financing cash flow, following Dichev and Owens (2025). Source: Compustat
Control Variables	
$Beta_{i,t}$	Borrower *i*'s beta, computed using a Fama and French 3-factor model with monthly returns and a minimum estimation window of 12 months, not exceeding 24 months. Source: Beta Suite by WRDS
$BookLeverage_{i,t}$	Borrower *i*'s year *t* debt in current liabilities and long-term debt divided by total assets. Source: Compustat
$CAPEXtoAssets_{i,t}$	Borrower *i*'s capital expenditures divided by total assets in year *t*. Source: Compustat
$CashtoAssets_{i,t}$	Borrower *i*'s cash divided by total assets in year *t*. Source: Compustat
$ConvDebtoAssets_{i,t}$	Borrower *i*'s convertible debt divided by total assets in year *t*. Source: Compustat
$DebttoEBITDA_{i,t}$	Borrower *i*'s debt in current liabilities and long-term debt divided by EBITDA in year *t*. Source: Compustat
$I.DebttoEBITDA_{i,t}$	An indicator variable that equals one if *DebttoEBITDA* is negative, otherwise zero. Source: Compustat

IdioRisk$_{i,t}$	Borrower *i*'s volatility of the difference between realized returns and expected returns based on a Fama and French 3-factor model with monthly returns and a minimum estimation window of 12 months, not exceeding 24 months. Source: Beta Suite by WRDS
InterestCoverage$_{i,t}$	Borrower *i*'s EBITDA divided by interest expense in year *t*. Source: Compustat
PPEtoAssets$_{i,t}$	Borrower *i*'s fixed assets net of accumulated depreciation divided by total assets in year *t*. Source: Compustat
Profitability$_{i,t}$	Borrower *i*'s EBITDA divided by revenues in year *t*. Source: Compustat
ProfitabilityVol$_{i,t}$	Standard deviation of borrower *i*'s current quarter profitability and prior four quarters. Source: Compustat
RentExptoAssets$_{i,t}$	Borrower *i*'s rent expense divided by total assets in year *t*. Source: Compustat
Size$_{i,t}$	The natural log of the borrower *i*'s total assets in year *t*. Source: Compustat
Credit Benchmark Variables	
InternalBankRating$_{i,t}$	Borrower *i*'s most recent monthly Credit Benchmark consensus numeric rating in year *t*, where the rating scale mirrors the S&P rating scale. Source: Credit Benchmark
NBanks	The number of banks contributing ratings to the Credit Benchmark consensus. Source: Credit Benchmark

Appendix B – Credit Benchmark Rating for an Example Entity



Consensus Rating	PD Lower, Bps	PD Upper, Bps
aaa	0	1.25
aa+	1.25	2.25
aa	2.25	3.25
aa-	3.25	5
a+	5	6.75
a	6.75	8.5
a-	8.5	14
bbb+	14	20
bbb	20	30
bbb-	30	48
bb+	48	76
bb	76	112
bb-	112	195
b+	195	365
b	365	650
b-	650	1000
ccc+	1000	1700
ccc	1700	2500
ccc-	2500	3700
cc	3700	6800
c	6800	10000
d	10000	10000

This is an example of how Credit Benchmark derives a borrower's rating (source: Credit Benchmark).

Appendix C – Example of FDIC Risk Weights under Basel II

Table 2
Basel II Risk Weights are Proportional to Estimated LGD:
Commercial and Industrial Loan Risk Weights for 2.5-Year Maturity Loans With Varying LGDs

Initial S&P Rating	Cum. 1-Yr. Default Rate (%)[1,2]	LGD									
		10%	20%	30%	40%	45%	50%	60%	70%	80%	90%
AAA	0.03	3.28	6.56	9.84	13.13	14.77	16.41	19.69	22.97	26.25	29.53
AA+	0.03	3.28	6.56	9.84	13.13	14.77	16.41	19.69	22.97	26.25	29.53
AA	0.03	3.28	6.56	9.84	13.13	14.77	16.41	19.69	22.97	26.25	29.53
AA-	0.03	3.28	6.56	9.84	13.13	14.77	16.41	19.69	22.97	26.25	29.53
A+	0.03	3.28	6.56	9.84	13.13	14.77	16.41	19.69	22.97	26.25	29.53
A	0.05	4.45	8.90	13.35	17.80	20.03	22.25	26.70	31.15	35.60	40.05
A-	0.05	4.45	8.90	13.35	17.80	20.03	22.25	26.70	31.15	35.60	40.05
BBB+	0.12	7.46	14.92	22.38	29.84	33.57	37.30	44.76	52.22	59.68	67.14
BBB	0.22	10.50	21.00	31.49	41.99	47.24	52.49	62.99	73.49	83.99	94.48
BBB-	0.35	13.42	26.84	40.26	53.68	60.39	67.11	80.53	93.95	107.37	120.79
BB+	0.44	15.05	30.09	45.14	60.18	67.70	75.23	90.27	105.32	120.36	135.41
BB	0.94	21.12	42.25	63.37	84.49	95.05	105.61	126.74	147.86	168.98	190.10
BB-	1.33	24.16	48.31	72.47	96.63	108.70	120.78	144.94	169.09	193.25	217.41
B+	2.91	31.91	63.83	95.74	127.65	143.61	159.56	191.48	223.39	255.30	287.21
B	8.38	50.79	101.58	152.37	203.16	228.56	253.95	304.74	355.53	406.32	457.11
B-	10.32	56.51	113.02	169.54	226.05	254.30	282.56	339.07	395.58	452.10	508.61
CCC	21.94	81.70	163.40	245.10	326.81	367.66	408.51	490.21	571.91	653.61	735.31

Source: https://www.fdic.gov/archived-research/fyi-update-emerging-issues-banking; accessed 12/30/24

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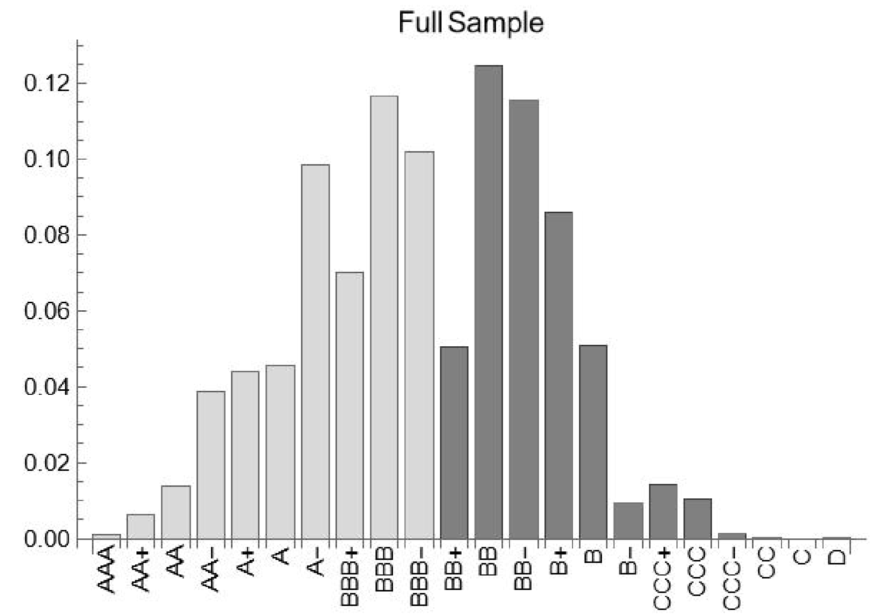
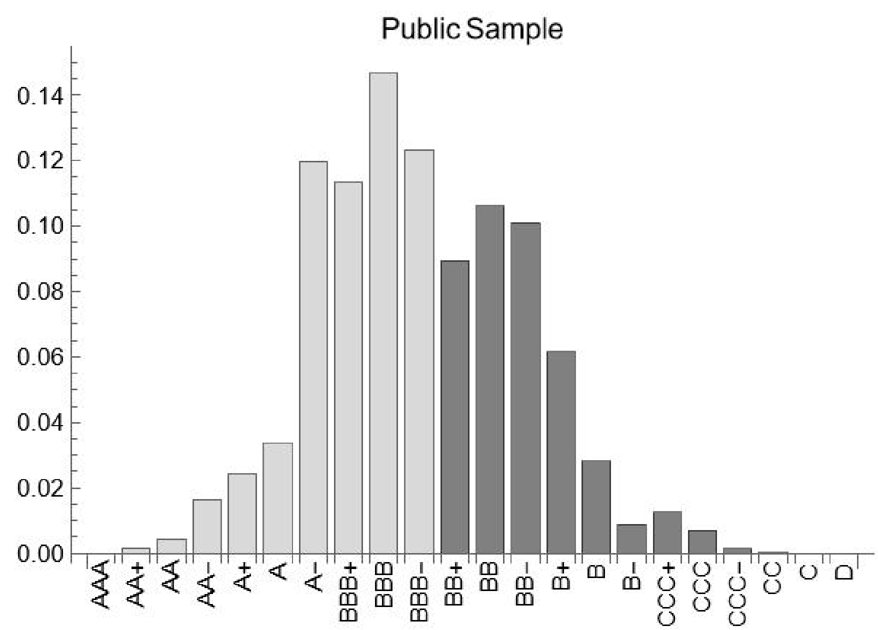
Figure 1 – Credit Benchmark Rating Distributions

Panel A shows Credit Benchmark ratings for the full sample. Panel B shows Credit Benchmark ratings for the public sample. Panel C shows Credit Benchmark ratings for the private sample. Panel D shows the distribution of *ImpliedSPRatings* used for the implied ratings sample. Light gray indicates investment-grade ratings, and dark gray indicates non-investment-grade ratings. The horizontal axis shows ratings, and the vertical axis shows relative frequencies.

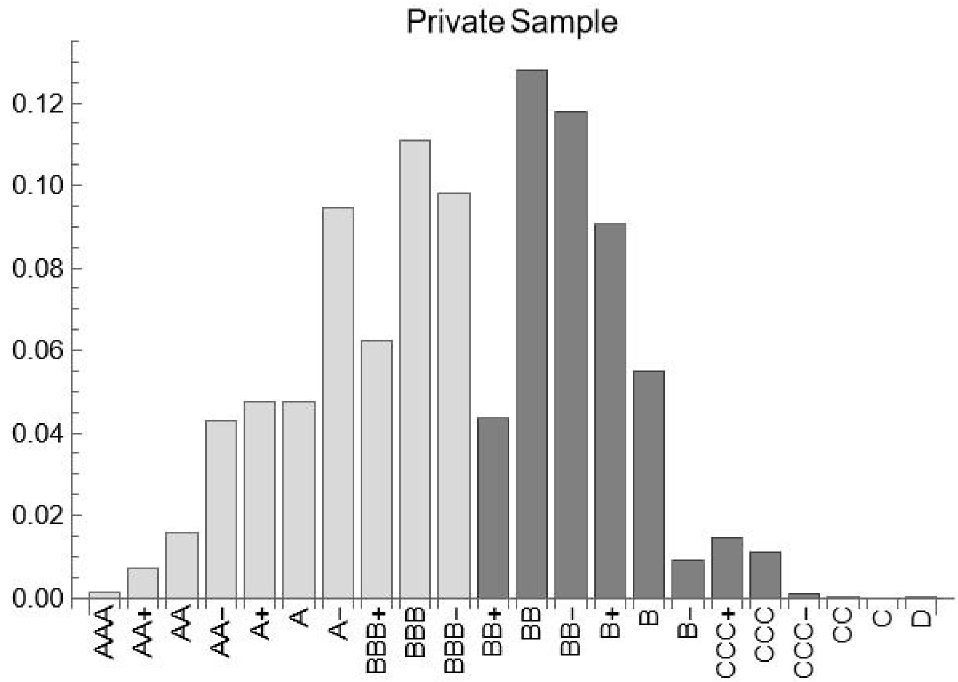
Panel A:



Panel B:



Panel C:



Panel D:

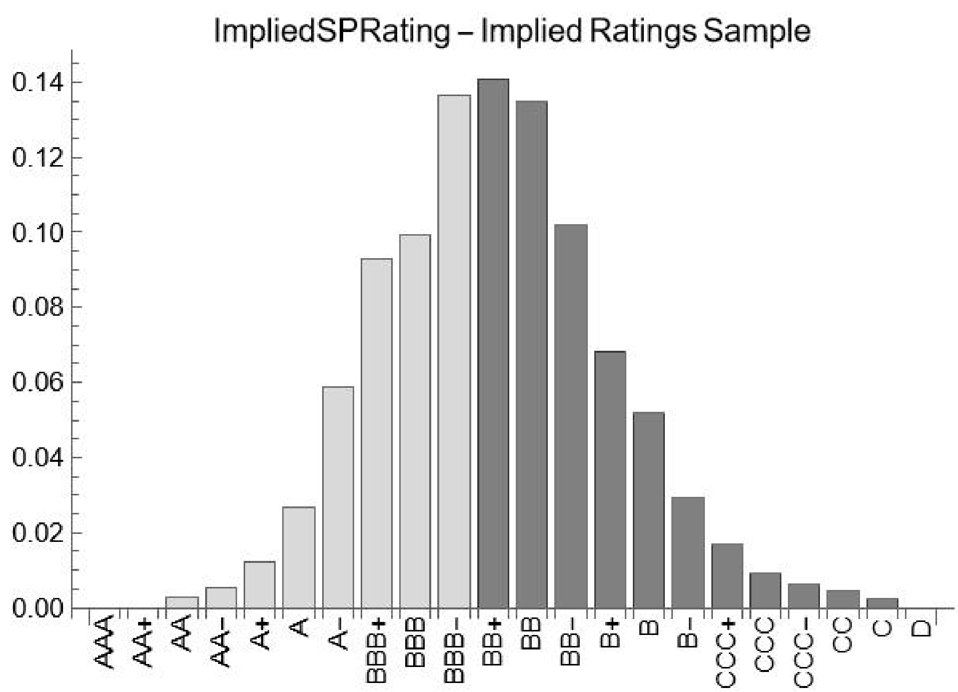
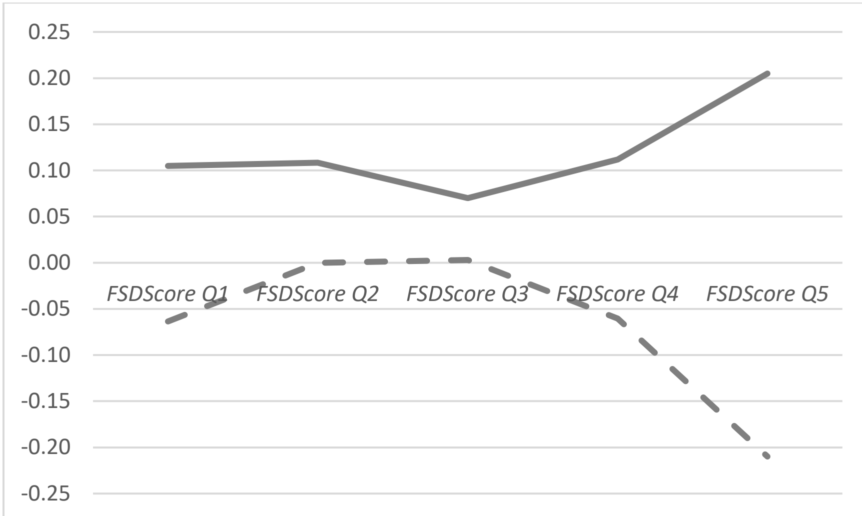


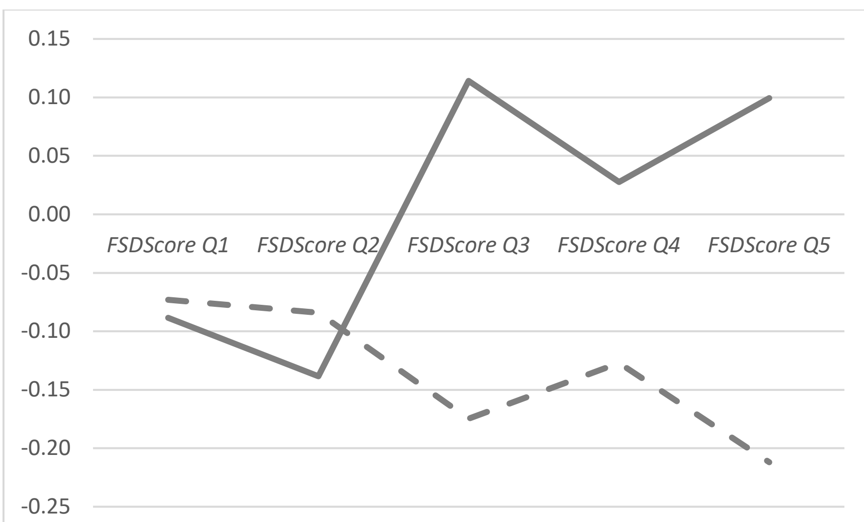
Figure 2 – Discontinuity Magnitudes

Panel A: Investment Grade Threshold



The solid curve (upper curve) shows the discontinuity magnitude computed based on the difference in the number of firms rated BBB- and BB+, all divided by the number of firms rated BBB- or BB+. The dashed curve (lower curve) shows the discontinuity magnitude computed based on the difference in the number of firms rated BB+ and BB, all divided by the number of firms rated BB+ or BB. The horizontal axis shows *FSDScore* quintiles, where quintile 1 represents the best financial reporting quality and quintile 5 represents the worst.

Panel B: A-/BBB+ Threshold



The solid curve (upper curve) shows the discontinuity magnitude computed based on the difference in the number of firms rated A- and BBB+, all divided by the number of firms rated A- or BBB+. The dashed curve (lower curve) shows the discontinuity magnitude computed based on the difference in the number of firms rated BBB+ and BBB, all divided by the number of firms rated BBB+ or BBB. The horizontal axis shows *FSDScore* quintiles, where quintile 1 represents the best financial reporting quality and quintile 5 represents the worst.

Table 1 – Sample Construction

This table presents the construction of the full sample, private sample, public sample, and implied ratings sample. The identifiers CIK, GVKEY, and LEI refer to the central index key, global company key, and legal entity identifier, respectively. *FSDScore* is the financial statement divergence score based on Amiram et al. (2015).

Sample Selection	Number of Firm-Year Observations	Number of Firms
Credit Benchmark Data	293,076	72,897
Keep United States observations	(223,208)	(56,312)
Full Sample	**69,868**	**16,585**
Private Sample	**59,075**	**14,947**
Public Sample	**10,793**	**1,638**
Less: observations without identifiers (CIK, GVKEY)	(734)	(101)
Less: observations without *FSDScore*	(1,947)	(311)
Less: observations without financial statement data	(1,249)	(77)
Less: observations without stock market measures	(3,209)	(215)
Implied Ratings Sample	**3,654**	**934**

Table 2 – Credit Benchmark Data Descriptive Statistics

Table 2 reports descriptive statistics on Credit Benchmark (CB) data for the full, public, private, and implied ratings samples, where we have converted CB monthly ratings into annual ratings. In Panel A, *InternalBankRating* is the CB numerical rating, which follows the S&P rating scale (e.g., 1 = AAA, 2 = AA+, etc.). *RatingChange* indicates whether a rating-year observation experienced a rating change relative to the prior year. *Downgrade* (*Upgrade*) indicates whether a rating-year observation experienced a downgrade (upgrade) relative to the prior year. Panel B reports CB rating frequencies. Panel C reports the frequency of CB rating changes. Panel D reports CB rating frequencies by industry categories. The full, public, private, and implied ratings samples contain firm-year observations.

Panel A: Credit Benchmark Rating Statistics

Variable	N	Mean	SD	P1	P25	P50	P75	P99
Full Sample								
InternalBankRating	69,868	10.15 (≈BBB-)	3.42	3 (AA)	8 (A-)	10 (BBB-)	13 (BB-)	18 (CCC)
RatingChange	69,868	0.33	0.47	0	0	0	1	1
Downgrade	69,868	0.16	0.36	0	0	0	0	1
Upgrade	69,868	0.17	0.38	0	0	0	0	1
Public Sample								
InternalBankRating	10,793	10.08 (≈BBB-)	2.89	4 (AA-)	8 (BBB+)	10 (BBB-)	12 (BB)	17 (CCC+)
RatingChange	10,793	0.38	0.49	0	0	0	1	1
Downgrade	10,793	0.18	0.38	0	0	0	0	1
Upgrade	10,793	0.20	0.40	0	0	0	0	1
Private Sample								
InternalBankRating	59,075	10.17 (≈BBB-)	3.51	3 (AA)	7 (A-)	10 (BBB-)	13 (BB-)	18 (CCC)
RatingChange	59,075	0.32	0.47	0	0	0	1	1
Downgrade	59,075	0.15	0.36	0	0	0	0	1
Upgrade	59,075	0.17	0.37	0	0	0	0	1
Implied Ratings Sample								
InternalBankRating	3,654	10.15 (≈BBB-)	2.84	4 (AA-)	8 (BBB+)	10 (BBB-)	12 (BB)	17 (CCC+)
RatingChange	3,654	0.39	0.49	0	0	0	1	1
Downgrade	3,654	0.17	0.37	0	0	0	0	1
Upgrade	3,654	0.23	0.42	0	0	0	0	1

Table 2, cont'd.

Panel B: Credit Benchmark Rating Frequencies

Credit Benchmark Numeric Rating	Credit Benchmark Scale	Full Sample		Public Firm Sample		Private Firm Sample		Implied Ratings Sample	
		Freq.	Percent	Freq.	Percent	Freq.	Percent	Freq.	Percent
1	AAA	77	0.11	0	0.00	77	0.13	0	0.00
2	AA+	432	0.62	17	0.16	415	0.70	6	0.16
3	AA	973	1.39	46	0.43	927	1.57	16	0.44
4	AA−	2,714	3.88	177	1.64	2,537	4.29	60	1.64
5	A+	3,073	4.40	260	2.41	2,813	4.76	99	2.71
6	A	3,175	4.54	362	3.35	2,813	4.76	123	3.37
7	A−	6,890	9.86	1,293	11.98	5,597	9.47	394	10.78
8	BBB+	4,908	7.02	1,223	11.33	3,685	6.24	356	9.74
9	BBB	8,141	11.65	1,587	14.70	6,554	11.09	521	14.26
10	BBB−	7,127	10.20	1,332	12.34	5,795	9.81	475	13.00
11	BB+	3,539	5.07	966	8.95	2,573	4.36	365	9.99
12	BB	8,714	12.47	1,145	10.61	7,569	12.81	424	11.60
13	BB−	8,062	11.54	1,091	10.11	6,971	11.80	382	10.45
14	B+	6,011	8.60	664	6.15	5,347	9.05	235	6.43
15	B	3,561	5.10	305	2.83	3,256	5.51	105	2.87
16	B−	641	0.92	95	0.88	546	0.92	38	1.04
17	CCC+	1,003	1.44	137	1.27	866	1.47	31	0.85
18	CCC	735	1.05	77	0.71	658	1.11	21	0.57
19	CCC−	81	0.12	15	0.14	66	0.11	3	0.08
20	CC	7	0.01	1	0.01	6	0.01	0	0.00
21	C	0	0.00	0	0.00	0	0.00	0	0.00
22	D	4	0.01	0	0.00	4	0.01	0	0.00
Total		69,868	100.00	10,793	100.00	59,075	100.00	3,654	100.00

Table 2, cont'd.

Panel C: Credit Benchmark Rating Changes Frequencies

Credit Benchmark Numeric Rating Change	Full Sample		Public Sample		Private Sample		Implied Ratings Sample	
	Freq.	Percent	Freq.	Percent	Freq.	Percent	Freq.	Percent
9 (Upgrade)	3	0.00	0	0.00	3	0.01	0	0.00
8 (Upgrade)	13	0.02	0	0.00	13	0.02	0	0.00
7 (Upgrade)	12	0.02	0	0.00	12	0.02	0	0.00
6 (Upgrade)	43	0.06	3	0.03	40	0.07	1	0.03
5 (Upgrade)	123	0.18	12	0.11	111	0.19	1	0.03
4 (Upgrade)	282	0.40	55	0.51	227	0.38	19	0.52
3 (Upgrade)	708	1.01	99	0.92	609	1.03	47	1.29
2 (Upgrade)	2,143	3.07	343	3.18	1,800	3.05	139	3.80
1 (Upgrade)	8,630	12.35	1,670	15.47	6,960	11.78	621	17.00
0	46,974	67.23	6,658	61.69	40,316	68.25	2,214	60.59
1 (Downgrade)	7,120	10.19	1,286	11.92	5,834	9.88	396	10.84
2 (Downgrade)	2,177	3.12	392	3.63	1,785	3.02	124	3.39
3 (Downgrade)	1,057	1.51	151	1.40	906	1.53	50	1.37
4 (Downgrade)	364	0.52	77	0.71	287	0.49	22	0.60
5 (Downgrade)	144	0.21	31	0.29	113	0.19	12	0.33
6 (Downgrade)	46	0.07	11	0.10	35	0.06	5	0.14
7 (Downgrade)	19	0.03	2	0.02	17	0.03	1	0.03
8 (Downgrade)	7	0.01	1	0.01	6	0.01	1	0.03
9 (Downgrade)	1	0.00	0	0.00	1	0.00	0	0.00
10 (Downgrade)	2	0.00	2	0.02	0	0.00	1	0.03
Total	69,868		10,793		59,075		3,654	

Table 2, cont'd.

Panel D: Credit Benchmark Rating Industry Frequencies

Credit Benchmark Industry	Full Sample		Public Sample		Private Sample		Implied Ratings Sample	
	Freq.	Percent	Freq.	Percent	Freq.	Percent	Freq.	Percent
Basic Materials	3,537	5.06	737	6.83	2,800	4.74	330	9.03
Community Groups	28	0.04	0	0.00	28	0.05	0	0.00
Consumer Goods	5,851	8.37	1,085	10.05	4,766	8.07	469	12.84
Consumer Services	9,181	13.14	1,615	14.96	7,566	12.81	685	18.75
Family Trusts	2	0.00	0	0.00	2	0.00	0	0.00
Financials	17,558	25.13	2,045	18.95	15,513	26.26	46	1.26
Government	1,130	1.62	7	0.06	1,123	1.90	0	0.00
Health Care	4,895	7.01	781	7.24	4,114	6.96	317	8.68
Industrials	11,152	15.96	1,830	16.96	9,322	15.78	790	21.62
Nonprofit Organizations	1,466	2.10	14	0.13	1,452	2.46	6	0.16
Oil & Gas	5,115	7.32	770	7.13	4,345	7.36	293	8.02
Other Non-Profit Organizations	140	0.20	0	0.00	140	0.24	0	0.00
Professional Associations	70	0.10	2	0.02	68	0.12	1	0.03
Religious Groups	131	0.19	0	0.00	131	0.22	0	0.00
Social Work & Charities	584	0.84	0	0.00	584	0.99	0	0.00
Technology	3,770	5.40	1,107	10.26	2,663	4.51	504	13.79
Telecommunications	738	1.06	117	1.08	621	1.05	47	1.29
Utilities	4,520	6.47	683	6.33	3,837	6.50	166	4.54
Total	69,868	100.00	10,793	100.00	59,075	100.00	3,654	100.00

Table 3 – Test of Discontinuities

This table reports statistics associated with internal bank ratings distribution discontinuities at two rating thresholds: BBB-/BB+ and A-/BBB+. The first number is the standardized difference (which essentially is a t-statistic) following Burgstahler and Dichev (1997), where *, **, *** denote two-tailed significance at the 0.10, 0.05, and 0.01 levels, respectively. The second number (italicized in parentheses) is a scaled magnitude measure following Glaum et al. (2004).

Sample	N	Standardized Difference (*Scaled Magnitude*)	
		BBB-	BB+
Full Sample	69,868	11.87*** (*0.34*)	-43.00*** (*-0.42*)
Private Firms	59,075	12.68*** (*0.39*)	-44.87*** (*-0.49*)
Public Firms	10,793	1.16 (*0.16*)	-6.13*** (*-0.08*)
		A-	BBB+
Full Sample	69,868	28.46*** (*0.17*)	-24.56*** (*-0.25*)
Private Firms	59,075	26.03*** (*0.21*)	-25.33*** (*-0.28*)
Public Firms	10,793	11.57*** (*0.03*)	-4.49*** (*-0.13*)

Table 4 – Implied Ratings Sample Descriptive Statistics

Table 4 presents descriptive statistics for the implied ratings sample. All variables are defined in detail in Appendix A.

Variable	N	Mean	SD	P1	P25	P50	P75	P99
InternalBankRating	3,654	10.15	2.84	4.00	8.00	10.00	12.00	17.00
RatingDifference	3,654	0.88	2.04	-4.00	0.00	1.00	2.00	6.00
RatingDispersion	3,654	0.54	0.25	0.10	0.40	0.50	0.70	1.30
FSDScore	3,654	0.03	0.01	0.01	0.02	0.03	0.03	0.05
AbAccruals	3,507	0.05	0.05	0.00	0.02	0.04	0.08	0.24
PosDurTotAcc	3,409	0.11	0.12	0.00	0.03	0.07	0.15	0.61
InterestCoverage	3,654	17.58	34.25	-11.88	4.86	9.00	16.80	262.00
Profitability	3,654	0.04	0.09	-0.37	0.01	0.05	0.08	0.26
BookLeverage	3,654	0.36	0.18	0.02	0.23	0.34	0.46	0.97
Size	3,654	8.74	1.44	5.81	7.65	8.66	9.72	12.46
DebttoEBITDA	3,654	3.04	5.15	-21.90	1.54	2.63	4.17	31.61
I.DebttoEBITDA	3,654	0.05	0.22	0.00	0.00	0.00	0.00	1.00
ProfitabilityVol	3,654	0.04	0.05	0.00	0.02	0.03	0.05	0.29
CashtoAssets	3,654	0.11	0.12	0.00	0.03	0.07	0.15	0.59
ConvDebttoAssets	3,654	0.02	0.07	0.00	0.00	0.00	0.00	0.44
RentExptoAssets	3,654	0.02	0.02	0.00	0.00	0.01	0.02	0.13
PPEtoAssets	3,654	0.29	0.24	0.02	0.10	0.20	0.43	0.89
CAPEXtoAssets	3,654	0.04	0.04	0.00	0.02	0.03	0.05	0.19
IdioRisk	3,654	0.08	0.04	0.03	0.05	0.07	0.09	0.26
Beta	3,654	1.11	0.65	-0.44	0.71	1.05	1.44	3.27
NBanks	3,654	6.18	3.27	4.00	4.00	4.00	7.00	18.00

Table 5 – Financial Reporting Quality and Internal Ratings Bias

This table presents regression results from the estimation of Eq. (4). *RatingDifference* is the difference between the Credit Benchmark consensus rating and model-implied S&P rating (Baghai et al. 2014). *FSDScore* is borrower *i*'s financial statement divergence (FSD) score, following Amiram et al. (2015). *AbAccruals* is a measure of borrower *i*'s "abnormal" accruals. *PosDurTotAcc* is borrower *i*'s positive-duration total accruals, following Dichev and Owens (2025). All other variables are defined in Appendix A. Intercepts and fixed effects are included in the estimation but not reported. *, **, *** denote two-tailed significance at the 0.10, 0.05, and 0.01 levels, respectively.

Column:	Pred. Sign	(1)	(2)	(3)
Dep. Var.:		*RatingDifference*	*RatingDifference*	*RatingDifference*
FSDScore	+	10.014**		
		(2.46)		
AbAccruals	+		3.494***	
			(4.88)	
PosDurTotAcc	+			0.600**
				(2.25)
InterestCoverage		-0.003*	-0.003*	-0.002
		(-1.73)	(-1.80)	(-1.34)
Profitability		1.542**	1.265*	1.866**
		(2.02)	(1.69)	(2.42)
BookLeverage		-0.222	-0.222	-0.285
		(-0.66)	(-0.64)	(-0.82)
Size		-0.684***	-0.702***	-0.684***
		(-12.86)	(-13.06)	(-12.46)
DebttoEBITDA		-0.003	-0.000	0.002
		(-0.20)	(-0.04)	(0.15)
I.DebttoEBITDA		-0.700*	-0.608*	-0.555
		(-1.93)	(-1.71)	(-1.53)
ProfitabilityVol		1.352	1.304	1.524
		(1.17)	(1.11)	(1.32)
CashtoAssets		-3.040***	-3.339***	-3.440***
		(-6.47)	(-6.94)	(-7.04)
ConvDebttoAssets		7.053***	6.928***	6.692***
		(9.25)	(9.19)	(8.67)
RentExptoAssets		-5.314*	-4.911*	-5.519*
		(-1.92)	(-1.77)	(-1.91)
PPEtoAssets		-1.758***	-1.554***	-1.641***
		(-4.01)	(-3.46)	(-3.68)
CAPEXtoAssets		10.754***	9.542***	10.291***
		(4.80)	(4.19)	(4.58)
IdioRisk		1.857	1.318	1.798
		(1.46)	(1.00)	(1.34)
Beta		-0.177***	-0.174***	-0.179***
		(-2.75)	(-2.69)	(-2.69)
NBanks		0.130***	0.137***	0.130***
		(6.57)	(6.63)	(6.53)
Fixed effects		Year, Industry	Year, Industry	Year, Industry
Observations		3,654	3,408	3,311
Adjusted R^2		0.367	0.363	0.354

Table 6 – Alternative Measures of Implied Credit Ratings

This table reports the association between *FSDScore* and alternative measures of internal bank ratings bias (i.e., *RatingDifference*) constructed using different measures of *ImpliedRating* in Eq. (3), where the different *ImpliedRating* measures are generated by alterations to the estimation of Eq. (2). *FSDScore* is borrower *i*'s financial statement divergence score, following Amiram et al. (2015). Column (1) estimates implied ratings using a sample of S&P ratings equal to or more conservative than EJR in Eq. (2). Column (2) estimates implied ratings using the lower (more conservative) rating between S&P and EJR as the dependent variable in Eq. (2). Column (3) computes implied ratings using EJR ratings as the dependent variable in Eq. (2).

Column:	Pred. Sign	(1)	(2)	(3)
		S&P does not overrate	Min SPR or EJR	Implied EJR
Dep. Var.:		*RatingDifference*	*RatingDifference*	*RatingDifference*
FSDScore	+	9.806**	9.297**	10.273***
		(2.41)	(2.28)	(2.55)
Borrower Controls		Yes	Yes	Yes
Fixed effects		Year, Industry	Year, Industry	Year, Industry
Observations		3,654	3,654	3,654
Adjusted R^2		0.493	0.419	0.461

Table 7 – Financial Reporting Quality and Internal Rating Dispersion

This table presents regression results from estimating Eq. (5). *FSDScore* is borrower *i*'s financial statement divergence (FSD) score, following Amiram et al. (2015). *RatingDispersion* is the relative standard deviation of Credit Benchmark ratings for borrower *i* in year *t* across all contributing banks. All other variables are defined in Appendix A. Intercepts and fixed effects are included in the estimation but not reported. *, **, *** denote two-tailed significance at the 0.10, 0.05, and 0.01 levels, respectively.

Column:	Pred. Sign	(1)
Dep. Var.:		*RatingDispersion*
FSDScore	+	1.213**
		(2.19)
InterestCoverage		-0.000***
		(-2.80)
Profitability		-0.007
		(-0.08)
BookLeverage		0.046
		(1.19)
Size		-0.016***
		(-3.02)
DebttoEBITDA		0.003*
		(1.69)
I.DebttoEBITDA		0.061
		(1.24)
ProfitabilityVol		0.338**
		(2.34)
CashtoAssets		0.095*
		(1.88)
ConvDebttoAssets		-0.018
		(-0.19)
RentExptoAssets		0.349
		(0.99)
PPEtoAssets		0.023
		(0.48)
CAPEXtoAssets		-0.434**
		(-2.04)
IdioRisk		0.351**
		(2.36)
Beta		0.013
		(1.46)
NBanks		0.006***
		(3.03)
Fixed effects		Year, Industry
Observations		3,654
Adjusted R^2		0.092