Assessing the Quality of Bank Loan Ratings

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Abstract

As opposed to the public debt market, the ultimate users of bank loan ratings, lenders, may prefer inflated ratings to reduce their risk-weighted assets. By exploiting variation in borrower information asymmetry, and thus rating agencies' ability to acquiesce to lender demands, we provide evidence of whether ratings assigned on private bank loans are reliable indicators of borrower distress. We find that bank loan ratings are systematically biased upwards for bank borrowers with greater information asymmetry. We also find that bank loan ratings are less responsive to changes in underlying credit conditions for borrowers with greater information asymmetry, implying that rating agencies stray away from hard information when formulating ratings for these borrowers. In addition, ratings and ratings changes for high information asymmetry borrowers are less predictive of subsequent loan default. The Basel Accords allow banks to condition capital allocation on borrowers' credit ratings. Our study cautions against this practice.

Keywords: credit risk; credit rating agency; market information; private firms; catering

JEL Classifications: K00, G24, M40

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I. INTRODUCTION

Aside from their role in facilitating valuation and contracting in the public debt market, ratings produced by leading credit rating agencies (e.g., Moody's Investors Service (Moody's), Standard & Poor's (S&P), and Fitch Ratings (Fitch)) are often used in the private debt market. For instance, ratings are used as covenants in performance pricing grids (Asquith et al., 2005; Kraft, 2015). Ratings are also used by financial regulators to help determine bank capital adequacy. The Basel Accords on Capital Adequacy (particularly Basel II and III) enhanced the role of credit ratings in the bank loan market by allowing banks to condition regulatory capital on borrowers' credit ratings. In countries that have adopted the Basel capital adequacy norms, this encourages firms that rely upon bank funding to obtain credit ratings.[1] In this study, we assess the quality of credit ratings assigned to bank loans by exploiting variation in the ability of rating agencies to cater to the demands of banks and their borrowers.

In contrast to the public debt market, the primary users of bank loan ratings (commercial banks) may prefer inflated ratings. Specifically, the Basel Accords allow banks to hold less capital against loans that have higher ratings (i.e., closer to AAA). Despite their increased importance in the functioning of bank supervision and regulation, whether or not these loan-specific ratings are reliable benchmarks of borrower health remains an open question. The growing overhang of problem assets in developing economy banking sectors suggest that quality of bank loan ratings may be cause for concern for regulatory bodies.[2]

In an ideal experiment, we would like to compare ratings of publicly traded bonds and privately issued loans – with similar seniority and covenants – for the same firm at the same point in time. Unfortunately, to the best of our knowledge, no such large panel dataset is publicly available. To overcome this challenge, we take advantage of features in our institutional setting that allow us to generate variation in the ability of rating agencies to acquiesce to issuer and lender

[1]This is significant as countries that adhere to the Basel Accords are likely to account for the bulk of worldwide gross domestic product, and thus constitute the majority of private and public debt financing.

[2]As case in point, the Reserve Bank of India has started to conduct audits of major rating agencies in India to determine the overall quality of bank loan ratings. See "Reserve Bank to Hold Joint Audit of Credit Rating Agencies with SEBI", *The Economic Times*, July 20, 2018

preferences for inflated ratings. Specifically, information availability in the public domain may diminish rating agencies' ability to produce inflated ratings. This availability of information is likelier to be concentrated in firms that have publicly traded securities. These firms have prices, which are observed by market participants, as well as coverage from other information intermediaries such as sell-side analysts (we refer to these firms as *listed* firms). Conversely, rating agencies may face less constraints in catering to lenders and borrowers when borrowers lack publicly quoted security prices or have sparse coverage from third party sources (we refer to these firms as *unlisted* firms). If this dichotomy in information availability makes it easier for rating agencies to cater to unlisted firms relative to listed firms, then we expect unlisted firms' ratings to be more inflated, less sensitive to changes in underlying financial condition, and less predictive of future default.

Prior theoretical research supports our contention that credit rating agencies may selectively produce poor quality ratings. For example rating quality may be poor when reputational penalties are limited (Bolton et al., 2012; Bar-Isaac and Shapiro, 2013; Piccolo and Shapiro, 2017). The dearth of market information – and consequently market scrutiny – is one instance where the aforementioned trade-off can result in poorer quality summary measures of bank loan quality.

We conduct our analysis using Indian data to take advantage of several institutional features. The first notable feature is the availability of a large sample of bank loan ratings. Subsequent to India adopting the Basel capital adequacy norms, the number of Indian firms with bank loan ratings increased dramatically (see Figures 2 & 4). As of 2017, roughly 5,000 firms were rated, with the largest growth in coverage occurring for unlisted firms. The second advantage of utilizing an Indian setting is the availability of loan ratings and financial statements for both listed and unlisted firms. In India, all firms above certain size thresholds are required to file financial statements with regional Company Registrars. Thus, through a third-party data collection service, we have access to a wide cross section of unlisted (i.e., private) and listed (i.e., public) firms' financial statements from different industries, time periods, and geographies.[3] This is in contrast

[3]We note that each state in India has its own Registrar, and each Registrar is responsible for the firms domiciled within its respective state.

to the U.S. market, where firms that do not have publicly listed equity or publicly traded bonds are not required to file financial statements with a Registrar.

Despite these India-specific institutional features, we stress that our results can be generalized to other settings such as other emerging markets as well as to the United States.[4] First, two of the three rating agencies in our sample are affiliates of S&P and Moody's. Hence, they employ rating technologies that are similar to their U.S. parents. Second, India has certain economic characteristics that are similar to other emerging markets. For instance, the ratio of private credit-to-GDP is 0.3 in India, versus a world average of 0.418. In addition, India's creditor rights index value is 2.0, versus a world average of 1.787 (Djankov et al., 2007). Lastly, as previously discussed, overall reliance on credit ratings has increased over time (Partnoy, 2010). Therefore, the opportunity for banks and firms to benefit from unlisted firms' inflated credit ratings is potentially a global concern.

Our data provider is Prowess, an online data repository that is maintained by the Center for Monitoring the Indian Economy (CMIE). As alluded to previously, Prowess collects information from disparate, regional Company Registrars to compile a yearly panel dataset of all Indian firms above certain size thresholds. Prowess also collects information on borrowers' ratings, including the ratings that are assigned at loan contract inception. We use information provided by Prowess to first compare the level of bank loan ratings for listed and unlisted firms. If rating agencies acquiesce to the demands of lenders and borrowers, then we expect the ratings for unlisted firms to be systematically biased upwards. Consistent with this prediction, we find that bank loan ratings for unlisted firms are roughly 0.42 notches more favorable, on average, relative to bank loan ratings issued to firms with more robust information environments.[5] This is in contrast to the existing evidence from the U.S. wherein Badertscher et al. (2018) find that the bond ratings of unlisted firms are *less favorable* on average than those of listed firms.[6]

[4]While the Dodd-Frank Act does not require regulators to use credit ratings when calculating banks' capital adequacy, conversations with Federal Reserve personnel suggest that ratings are still widely used for this purpose.

[5]A one notch rating difference equates to the difference between consecutive letter ratings (i.e., A and A+ on S&P's rating scale).

[6]We stress that our definition of "unlisted" differs from the definition of "private" in Badertscher et al. (2018). In our sample unlisted firms have no security prices outstanding, whereas private firms have bond prices and yields

Another role for credit ratings is to accurately summarize and reflect significant changes in firm financial condition. To examine the quality of bank loan ratings along this dimension, we compare the sensitivity of loan ratings to changes in underlying predictors of borrower distress for listed and unlisted firms. If lenders are conflicted in their desire for ratings that accurately represent firm financial condition, we expect bank loan ratings to be more sticky for a given change in underlying financial performance for unlisted firms especially if the change is for the worse. Consistent with this prediction, we find that bank loan ratings for unlisted firms are less sensitive to predictors of financial performance relative to firms that are publicly traded. As an example, we find that rating agencies downgrade bank loan ratings by one notch when listed firms increase *Leverage* by 34 basis points, on average. However, a similar increase in *Leverage* for unlisted firms only decreases bank loan ratings by 0.42 notches. This result suggests that rating agencies place less emphasis on "hard information", such as verifiable financial indicators of borrower health, particularly in the case of unlisted firms.

Another way to capture the quality of bank loan ratings is to study the frequency with which they are changed over a given time period. We find that bank loan ratings for unlisted borrowers are downgraded less often than the ratings for listed borrowers, while no such asymmetry exists for upgrades. Lastly, we examine the ability of bank loan ratings to predict future default. We find that bank loan rating levels and transitions for listed bank borrowers have a greater sensitivity to future default, relative to bank loan ratings of unlisted borrowers. Alternatively stated, bank loan ratings (and more importantly transitions) for listed borrowers convey more information about subsequent defaults. Collectively, our results show that while unlisted borrowers have *more favorable* credit ratings, these ratings do not accurately reflect the underlying credit conditions of the borrowers, especially when external reputational concerns are low.

We stress that our tests are subject to two important identification concerns. Firms can choose their listed status, which is likely to impact multiple aspects of their performance. As a result, listed firms may be different from unlisted firms along many unobserved dimensions. We tackle

outstanding in Badertscher et al. (2018).

this concern in two different ways. First, we test multiple predictions of our hypothesis. We show that while unlisted firms on average have more favorable ratings, their ratings are less responsive to deterioration in financial condition, they experience fewer downgrades and that their ratings are less informative about future defaults. Thus, any correlated omitted factor should be able to explain all findings in our various tests in order to invalidate to our main hypothesis. Second, we conduct a number of robustness tests. Most of our results are robust to the inclusion of firm fixed effects and thus are unaffected by unobserved time-invariant firm characteristics. Furthermore, our evidence of higher ratings among unlisted firms is present in the subsample of firms that transition from being unlisted to being listed. We find that the actual ratings of unlisted firms in this subsample are higher than their predicted ratings. We also find that our results are robust to matching the listed and unlisted firms on observable characteristics.

Another concern with our analysis is that firms that obtain unfavorable ratings may choose not to disclose their ratings. If this happens disproportionately among unlisted firms, then this could bias our tests towards finding higher ratings for unlisted firms. To alleviate this concern, we repeat our main tests after including predicted ratings for all borrowers that experience increases in bank debt greater than ten percent in a given year but do not have ratings outstanding. We find that our results are robust to the possible nondisclosure of poor credit ratings.

We also conduct several tests to explore specific alternative hypotheses. We examine if the financial characteristics of unlisted firms are inherently less informative about future financial performance relative to those of listed firms. When we examine the sensitivity of future firm sales to current financial characteristics, we find no systematic significant differences between listed and unlisted firms in our sample. Thus, our primary findings do not appear to be due to differences in the informativeness of listed versus unlisted firms' financial statements. We also examine whether our primary results are influenced by the amount of non-rating revenue the rating agencies generate for each issuer, as well as the profitability of business groups to which issuers belong.[7] Our primary inferences remain unchanged to these alternate specifications.

[7] We thank Baghai and Becker (2018) for providing us with their non-rating revenue data.

While prior research examines the impact of obtaining bank loan ratings on firm investment policy (Sufi, 2009), our paper is the first to examine the properties of bank loan ratings. Furthermore, prior research stresses that the ultimate users of public debt ratings (i.e., bondholders) may unambiguously prefer accurate credit ratings in order to appropriately price the default risk of publicly traded bonds. In contrast, our results indicate that lenders may be conflicted in their desire for accurate ratings and may even demand poorer quality ratings for their more informationally opaque borrowers. Given this, our study highlights a previously undocumented pressure rating agencies face with regard to certain ratings. In addition, while rating agencies claim that they apply consistent methodologies across both geographies and firms (Ganguin and Bilardello, 2005; Standard & Poor's, 2001), our results suggest that rating properties vary *within* asset classes.

Our study also extends prior research that examines the rating quality of listed versus unlisted firms. For instance, Badertscher et al. (2018) suggest that U.S. private firms with bonds traded in the secondary market receive less favorable ratings than listed firms due to the former's limited capital market access. In contrast, the unlisted firms in our sample have no traded securities or coverage by other information intermediaries. In our setting, pressure by lenders for inflated bank loan ratings appears to dominate the effect of limited capital market access in influencing the rating properties of unlisted firms.

Our findings suggest implications for both regulators and market participants. Specifically, our results show that linking bank capital allocation to unlisted firms' credit ratings can prove problematic. For instance, while our results may suggest a positive role for inflated credit ratings, in that banks can fund more projects by holding less equity, these projects may actually be of lower innate credit quality. This reliance on potentially inflated credit ratings may help explain the sharp increase in non-performing assets among state owned Indian banks.[8]

II. BACKGROUND AND HYPOTHESIS DEVELOPMENT

Background on the Indian Credit Rating Market

[8]See "India's RBI warn on rise in bad loans", *Financial Times*, June 29, 2016.

India's credit rating industry began in 1987 when The Credit Rating Information Services of India (CRISIL) was created, which is now partially owned by S&P. While other firms were created over time, the "Big Three" credit rating agencies consist of CRISIL, the Investment Information and Credit Rating Agency of India Limited (ICRA), which was founded in 1991 and is now partially owned by Moody's, and CARE Ratings of India (CARE), which was founded in 1993.

As affiliates of S&P and Moody's, both CRISIL and ICRA, respectively, operate in a manner similar to that of their U.S. parents. Specifically, both firms employ the issuer-pay compensation model and attempt to assess firms' overall credit risk "through the economic cycle." The latter suggests that changes in firms' or securities' assigned credit ratings are applied over the longest maturity structure possible for a given firm or security. This is done in an effort to reduce unnecessary ratings volatility.

More importantly, credit rating agencies can help facilitate investment decisions by helping credit rating users achieve balance in their risk-return profiles, while also assisting issuers in obtaining lower-cost financing than would otherwise be available. In this regard, credit rating agencies act as agents that can help allocate capital and price risk appropriately. This is particularly relevant for our setting as the Basel Accords recommend that external ratings be obtained for calibrating regulatory capital requirements. Therefore, risk weightings are assigned to banks' exposures based on each exposure's assigned credit rating. This is not insignificant as even though the Basel Accords do not require banks to obtain credit ratings for all issued loans, unrated loans are likely to be assigned higher risk weights, which in some instances can exceed 100 percent. Given this, obtaining a favorable credit rating can reduce bank capital allocation for the loan, as well as the interest rate charged on the loan.

Hypothesis Development

While credit rating agencies' stated methodologies note that corporate debt securities are evaluated consistently across issuers, industries, and asset classes (Ganguin and Bilardello, 2005; Standard & Poor's, 2001), and that their reputations are their most valuable asset (Cantor and

Packer, 1995; Covitz and Harrison, 2003), prior research casts doubt on some of these claims. For instance, rating agencies may alter their catering propensities during periods of economic growth versus contraction (Bolton et al., 2012; Bar-Isaac and Shapiro, 2013), or when perceived reputation risks (Piccolo and Shapiro, 2017) or monitoring incentives vary (Bonsall et al., 2015). In addition, Kraft (2015), Baghai and Becker (2018), Griffin and Tang (2012), and Griffin et al. (2013) provide evidence of inflated ratings in different contexts. These studies suggest that rating agencies can strategically alter their rating methodologies sporadically for listed firms.

In contrast to the United States, the public debt market in India is small. According to the Reserve Bank of India (RBI), the primary regulator of financial institutions, non-financial public limited Indian firms raised about 27.14 billion Indian Rupees (or roughly $400 million) through public bond issues in 2016 (Reserve Bank of India, 2016). As a result, the main originators of debt (as well as the main consumers of ratings) are commercial banks. In contrast to public debt investors, commercial banks may be more conflicted with respect to their demand for bank loan ratings that accurately reflect underlying firm performance. While higher quality ratings may enable Indian lenders to monitor borrower performance, ratings that are biased upwards may allow banks to skirt risk-weighting rules. For instance, lenders can condition capital on borrowers' stated credit quality; thus inflated ratings allow banks to hold less capital towards the loans that they underwrite. Indian banks, in particular, might find this situation favorable, since many banks in India are capital constrained.[9] The higher ratings will also allow the banks to provision less against expected loan losses, since provisioning itself may be a function of firms' credit ratings. Thus, banks may have incentives to encourage ratings inflation. Prior research supports this contention as banks in other countries may also share this tendency to allocate less capital and provide less for future loan losses (Balin, 2010).

The RBI, on the other hand, is primarily concerned with the ability of bank loan ratings to accurately reflect borrower repayment risk. Lower information asymmetry about borrowers will allow the RBI, among others, to better evaluate the quality of bank loan ratings. In contrast,

[9]Most Indian banks are majority Government owned (see LaPorta et al., 2002) and have found it difficult to raise equity due to Government budget constraints (see Acharya and Subramanian (2016)).

the RBI and other external parties may find it more difficult to assess the quality of bank loan ratings for unlisted borrowers due to their opacity. This opacity reduces external parties' ability to evaluate any differences in their assessments of unlisted borrowers' creditworthiness versus those of the credit rating agencies. If this is the case in our setting, credit rating agencies may be more likely to acquiesce to lenders' desires for more favorable credit ratings for loans provided to unlisted firms relative to listed firms, given the dearth of information available with regard to the former relative to the latter. Therefore, decreased oversight from the market would predict that ceteris paribus, unlisted firms will have higher (i.e., more favorable) credit ratings than listed firms. In addition, because market participants will have less incentive or find it more difficult to obtain or verify unlisted firms' financial characteristics, lower market scrutiny would also imply that unlisted firms' credit ratings will be less sensitive to credit quality as reflected in audited financial statements.

Rating agencies may not acquiesce to lenders' desires for more favorable ratings for unlisted firms if market participants believe that listed firms' ratings are already inaccurate or if banks value accurate and reliable credit ratings. Similarly, while difficult, market participants can obtain from a Registrar the necessary data to evaluate differences between their assessments of firms' credit risk and those of the rating agencies. Such actions could prevent rating agencies from providing inflated ratings to unlisted firms.

III. DATA AND SAMPLE SELECTION

Data

We obtain the data to conduct our empirical tests from Prowess, a data warehouse maintained by the Center for Monitoring the Indian Economy (CMIE), which has been used by a number of prior studies on Indian companies, including Aghamolla and Li (2018), Bertrand et al. (2002), Gormley et al. (2012), Gopalan et al. (2007), and Baghai and Becker (2018). Prowess provides access to annual financial statement information, industry classifications, auditor relationships, as well as whether firms have publicly traded stock outstanding (i.e., their listed status). Prowess covers between 2,000 to 6,000 listed and unlisted firms with total assets plus sales of at least 40 million Indian Rupees (or roughly $600,000 using a 67 Indian Rupees-to-U.S. Dollar conversion rate) annually (Gopalan et al., 2016b).

In addition to detailed firm-level balance sheet and income statement information, Prowess records the credit ratings assigned to a firm by major credit rating agencies in India. We focus on the three largest credit rating agencies: CARE, CRISIL, and ICRA. These agencies rate most of the debt in the Indian market. Furthermore, CRISIL and ICRA are affiliates of S&P and Moody's, respectively. While CARE does not have an active partner in the United States, it does have the second largest market share in India.

Indian firms often have credit ratings for various types of debt instruments, such as structured products, term loans, term deposits, and corporate debt. For our analyses, we focus on credit ratings of bank loans for which the rating scale closely matches that of the long-term debt scale in the United States. Specifically, we look only at debt instruments with the following labels: "Long term loans", "Medium term loans", "Term loans", and "Working capital loans".

Since no active secondary market exists for bank debt in India, rating agencies are likely to rely on non-market information to infer unlisted firms' creditworthiness. From the ratings for individual securities, we construct a panel dataset with one observation per firm-month-year for the time period during which the firm receives ratings from at least one of the three rating agencies. We consolidate ratings for each time period by taking the mean rating assigned to the firm by the three rating agencies. In the end, our goal is to create firm-level ratings observations similar to those in the Standard & Poor's/Compustat ratings database.[10] We transform the ratings into an ordinal scale, with the highest rated debt ("AAA" on S&P's scale) equal to 20 and the lowest rated debt ("D") equal to 1.[11]

For each loan, Prowess records the security's rating amount and rating. Other features of the loan, such as its associated covenants, interest rates, or restrictions, are not readily available. Furthermore, while Prowess records lending relationships between commercial banks and borrow-

[10]For added robustness, we also perform our main analyses at the firm-year and security-month-year levels.

[11]The long-term credit rating scale in India only contains 20 notches, versus the 22 notches present in the U.S. debt market. Indian ratings forego "CCC+", "CCC", "CCC-", and "CC"; they use "C+", "C", and "C-" instead.

ers, we cannot perform analyses that take into consideration bank financial condition for several reasons. First, lending relationships are recorded between commercial bank and borrowing firm. Ratings are assigned at the security level and do not have any identifiers for which bank originated the loan. Second, while Prowess does collect financial information on commercial banks, their bank-related data and ratios are sparsely populated.

We make several data sampling choices to restrict the population of firms in our sample of Prowess firm-year observations from 1991 to 2017. Specifically, we exclude all financial firms (NIC codes: 641 - 663) as these firms' credit risk characteristics differ materially from industrial firms (Morgan, 2002; Livingston et al., 2007) , firms owned wholly or partially by the government or governmental agency, as well as firm-year observations for which either total assets or total sales are not positive, and values for any one of interest expense, total income, and PBITDA are missing. Our final panel dataset consists of average ordinal credit ratings by firm-month-year, matched to firms' most recent audited financial statements.

An added feature of the Indian bank loan market is that some financial institutions require borrowers to provide credit enhancements.[12] Given their opaque nature, banks may disproportionately require these enhancements for unlisted firms than for listed firms. To the extent to which enhancements are found more often for unlisted firms and that enhancements may bias ratings upwards for such borrowers, we exclude all ratings of structured obligations from our analyses. Furthermore, while the presence of credit enhancements may explain the more favorable ratings of unlisted firms, they are less likely to explain some of our subsequent results, such as the differential sensitivity of ratings changes prior to default.[13]

Sample Selection

Table 1 provides summary statistics of the key variables we use in our analysis. We have a total

[12]Loans with these enhancements are often referred to as "structured obligations" by the rating agencies.

[13]In addition, the role of credit enhancements in helping lenders recover funds in case of borrower distress in India is questionable due to its weak contract enforcement regime (Gopalan et al., 2016a). The recent well publicized default by Kingfisher Airlines is a case in point. Although the promoter, Mr. Vijay Mallaya, had provided personal guarantees for some of the loans, his move to the U.K has prevented the banks from enforcing the personal guarantee to recover their money. This suggests that even if present, such personal guarantees may not significantly result in more favorable bank loan ratings.

of 21,576 (227,925) firm-year (firm-month-year) observations in our sample. We model bank loan ratings as a function of variables used in prior work (e.g., Baghai et al. 2014): *Leverage*, *Debt-to-Earnings*, *Cash*, *Interest Coverage*, *Profitability*, *PP&E*, *Size*, *CRA Coverage*, and *Group Membership*. We describe the construction of each variable in detail in Appendix A. To prevent outliers from biasing our results, we winsorize all variables of interest at the 1% level.

From Table 1, the mean value of *Rating* is 11.61, which corresponds roughly to "BBB". In contrast, Gopalan et al. (2014) find an average rating of 10.40 (roughly "BBB-" using their rating scale) for a sample of U.S. firms with long-term credit ratings.[14] Indian firms in our sample have leverage comparable to that of U.S. firms. For instance, the average *Leverage* in our sample is 0.38, while the average leverage among U.S. firms featured in Compustat is 0.30. The mean *Interest Coverage* for our sample is 7.27, lower than the U.S. average of 9.36 found in Gopalan et al. (2014). Firms in our sample are also profitable, with a mean *Profitability* equal to 0.18. Furthermore, Indian firms in our sample have higher *PP&E* as compared to U.S. firms. The mean *PP&E* for our sample is 0.51, while the mean value for the same variable in the U.S. sample is 0.37. On average, firms in our sample are only covered by 1 rating agency at any given time. This stands in contrast with the market for bond ratings in the United States, in which Moody's and S&P have a practice of automatically rating most corporate credits (Cantor and Packer, 1995). In addition, roughly thirty percent of the firm-year observations in our sample are members of large family owned business groups (similar to conglomerates in the U.S.). We control for this corporate structure throughout our analyses since access to the group's internal capital may provide an additional source of financial strength, resulting in improved creditworthiness.[15]

Table 2 reports the mean differences for the variables that we use in our analysis for listed and unlisted firms. We find that on a univariate basis, on average listed firms have bank loan ratings that are 1.55 notches more favorable than unlisted firms. This difference is statistically significant at the 0.01 level. More specifically, listed (unlisted) firms receive an average rating equivalent

[14] Gopalan et al. (2014) use an inverse rating scale where less favorable credit ratings are assigned higher values (AAA = 1).

[15] In untabulated analysis, we also control for the average profitability of other firms in the group and find that our inferences remain unchanged to this alternate specification.

to BBB+ (BBB-) on S&P's rating scale, both of which are investment-grade. Once we control for known credit rating determinants, listed firms actually receive less favorable ratings than unlisted firms. In our sample, unlisted (listed) firms are upgraded 17 percent (14 percent) relative to all unlisted (listed) ratings changes. Conversely, unlisted (listed) firms are downgraded 14 percent (16 percent) relative to all unlisted (listed) ratings changes. In a univariate setting, the differences in downgrade (upgrade) propensities between unlisted and listed firms are statistically significant at the 0.01 level. The univariate evidence on rating changes is consistent with our primary hypothesis that credit rating agencies cater to lenders by recording more favorable ratings changes to informationally opaque borrowers. We find that unlisted firms have higher leverage as compared to listed firms (mean *Leverage* of 0.40 as compared to 0.33, respectively), and that this difference is statistically significant at the 0.01 level. While the leverage of listed firms in our sample is roughly similar to that of listed firms in the U.S., the leverage of unlisted firms in our sample is substantially lower than that of U.S. private firms with public debt outstanding (0.67) (see Givoly et al., 2010). The evidence in Table 2 suggests that significant differences exist between listed and unlisted firms in our sample. However, overall we find that both sets of firms are large, profitable, and are assigned relatively strong bank loan ratings.

Column (3) of Table 3 displays summary statistics for our sample of individual securities that eventually default (i.e., receive a "D" rating). One year prior to default, these issues have an average rating of 8.43, which is between BB and BB-. As these firms financial performance deteriorates, their ratings progressively decline. One month prior to default, they have an average rating of 7.73, which is between a BB- and B+. When we separately look at the issues of listed and unlisted firms we find an interesting pattern. During the one year prior to default, while the average ratings of unlisted firms' decrease from 8.17 to 7.65 (column (4)), a 0.52 notch decline, those of listed firms' decline from 9.21 to 7.99 (column (5)), a 1.22 notch downgrade. Thus, unlisted firms' experience fewer and less severe downgrades before they default as compared to listed firms. Consistent with this pattern, our subsequent analyses show that defaults of unlisted firms are less sensitive to ratings and rating changes pre-default.

From columns (4) and (5) of Table 3, we also find that ratings decline by approximately six to seven notches in the one month prior to default, on average. This appears to be a steep fall and it also indicates that there are likely to be very few issues with ratings between BB- and D. These descriptive statistics are supported by graphical evidence shown in Figures 1(a) and 1(b) which display the histograms of issue-level bank loan ratings of issues that eventually default. It is interesting to note that this pattern is not unique to the Indian market; the distribution of entity-level credit ratings of U.S. issuers from Standard & Poor's/RatingsXpress behave in a similar pattern. We believe this can occur for multiple reasons: 1) rating agencies' willingness to cater to borrowers, 2) rating agencies being surprised by events of default, and 3) the proliferation of ratings-based covenants in loan agreements that specify "technical" defaults at rating levels greater than "D" (i.e., "C+" or "C-"). In the presence of such covenants, if a firm is assigned a "C" rating, it is likely to trigger a technical default, which can give the lender the right to call the debt, in turn forcing the rating agency to lower the rating all the way to "D". Future research should explore the implications of the significant change in ratings at the lower end of the speculative-grade spectrum.

IV. RESEARCH DESIGN AND EMPIRICAL RESULTS

Ratings and Listed Status

Ratings Levels

As mentioned in our hypothesis development, we predict that bank loan ratings for high information asymmetry borrowers will be systematically biased upwards relative to bank borrowers with low information asymmetry. We test this prediction using the following OLS model:

$$
\begin{aligned}
Rating_{i,t} = {} & \beta_{1t} \times Unlisted_{i,t-1} + \beta_2 \times Leverage_{i,t-1} + \beta_3 \times Debt-to-Earnings_{i,t-1} + \\
& \beta_4 \times Cash_{i,t-1} + \beta_5 \times \textit{Interest coverage}_{i,t-1} + \beta_6 \times Profitability_{i,t-1} + \\
& \beta_7 \times PP\&E_{i,t-1} + \beta_8 \times Size_{i,t-1} + \beta_9 \times CRA\ Coverage_{i,t-1} + \\
& \beta_{10} \times Group\ Membership_{i,t-1} + \theta_{Ind,y} + \rho_z + \epsilon_{i,t}
\end{aligned}
\tag{1}
$$

Specifically, we amend Baghai et al. (2014) and model credit ratings as a function of $\frac{Borrowings}{Assets}$ (*Leverage*), $\frac{Borrowings}{PBITDA}$ (*Debt-to-Earnings*)[16] , $\frac{Cash}{Assets}$ (*Cash*), $\frac{PBITDA}{Int.Expense}$ (*Interest Coverage*), $\frac{PBITDA}{Sales}$ (*Profitability*), $\frac{PP\&E}{Assets}$ (*PP&E*), $Log(Assets)$ (*Size*), the number of rating agencies covering a firm (*CRA Coverage*), and whether a firm is part of a family owned business group (*Group Membership*), where *i* indexes firms, *t* indexes time in year-month and *y* indexes the year. As mentioned previously, we match firms' bank loan ratings with their most recent fiscal year-end financial information. We control for industry-year fixed effects, in addition to auditor fixed effects.[17] The latter controls for potential heterogeneity in accounting quality across firms via the identity of the auditor. These fixed effects are represented by the variables $\theta_{Ind,y}$ and ρ_z respectively, where z represents the auditor. We cluster standard errors by firm and year throughout our analyses, unless otherwise specified (Petersen, 2009; Gow et al., 2010).

We present the results of estimating equation (1) at the firm-month-year level in column (1) of Table 4 Panel A. Consistent with our main hypothesis, we find that the coefficient on *Unlisted* is positive and statistically significant at the 0.01 level. Specifically, in column (1), we find that unlisted firms' bank loan ratings are on average 0.418 notches higher than those of comparable listed firms.[18] These results are consistent with rating agencies acquiescing to banks' desire for more favorable credit ratings for unlisted borrowers. Focusing on the coefficients on the control variables, we find that firms with lower leverage, firms with lower debt-to-earnings, and firms with higher interest coverage ratios have more favorable ratings. This is consistent with lower leverage, measured in different ways, being correlated with higher credit ratings. Furthermore, ceteris paribus, firms with more cash, more profitable firms, larger firms, firms rated by more credit rating agencies, and firms that are a part of a conglomerate also have more favorable ratings.

In column (3) we consolidate our observations at the firm-fiscal year level and repeat our

[16]PBITDA is defined as firm profits before interest, taxes, depreciation, and amortization

[17]We use 2-digit NIC codes to proxy for industry classification. NIC codes are industry-level codes assigned to firms by the Federal Government of India.

[18]These magnitudes are in-line with recent research which examines ratings inflation. For instance, Baghai and Becker (2018) suggest that Indian firms that pay rating agencies non-rating revenues are assigned ratings that are roughly 0.30 to 0.40 notches more favorable than firms that do not pay such fees.

analyses. Our dependent variable is the average rating for the fiscal year-end month.[19] The coefficient on *Unlisted* continues to be positive and statistically significant at the 0.01 level, while the magnitude of our main variable of interest, *Unlisted*, slightly declines. In columns (5) and (6), we repeat our analyses at the security level and find that, as before, unlisted firms receive more favorable ratings by 0.43 notches, on average. Collectively, these findings support our hypothesis that the quality of bank loan ratings deteriorate as external sources for verification decline.

Our tests are potentially subject to various identification issues. For instance, a firm's listed status is likely to impact multiple aspects of its behavior and performance; thus listed firms may be different from unlisted firms along unobserved dimensions. To alleviate this concern, we extend our primary analyses and examine firms that transition from unlisted to listed status (or vice versa) in Panel B of Table 4.[20] Specifically, we compare the average difference between actual and expected ratings (which we term as a borrower's *RatingsGap*) for the subset of firms that change their listing status during our sample period.

In order to calculate a transitioning firm's *RatingsGap*, we first estimate equation (1) when a transitioning firm is listed and obtain coefficient weights. We combine these "listed" weights with the financial ratios of those same firms when they are unlisted and calculate expected ratings. These expected ratings provide an approximate counterfactual for how a firm *should* be rated, given a more stringent rating model applied to listed firms.

We provide the *RatingsGap* based on this methodology in column (1) of Table 4 Panel B. We find that the average *RatingsGap* is 0.504 when firms are unlisted and that this difference is statistically significant at the 0.01 level. This result implies that the actual ratings of transitioning firms when they are unlisted are 0.504 notches higher than the rating implied by the expected rating that best fits transitioning firms when they were listed. In column (2), we repeat this analysis by utilizing the expected rating coefficients for when transitioning firms are unlisted and combine those weights with financial ratios for when transitioning firms are listed to create

[19]Most Indian companies end their fiscal year on March 31. Thus, we use the average rating as of March 31 as our dependent variable.

[20]Given the relatively small number of firms that transition between unlisted and listed status, we lack power to run our main tests with firm fixed effects.

expected ratings. Our findings are similar to those documented in column (1): when using a predicted rating when transitioning firms were unlisted, actual ratings for listed firms are less favorable (i.e., closer to "D"). Collectively, these findings suggest that credit rating agencies alter their rating methodologies once firms alter their listing status in a manner consistent with our main hypothesis.

From Table 2, we find that unlisted and listed firms differ along observable characteristics. A valid critique of our results is that these observable differences make linear controls inadequate and potentially bias the coefficient on *Unlisted*. To control for this possibility, we repeat our analyses from Panel A of Table 4 after initially matching unlisted and listed firms on observable dimensions. Specifically, for every unlisted firm-year in our sample, we use Mahalanobis distance to find a listed firm that is closest to the unlisted firm observation in terms of *Debt-to-Earnings* and *Profitability* within the same industry-year and *Size* quintile. We match unlisted and listed firms only on these variables because not only are they important determinants of credit ratings, but limiting the matching dimensions also ensures that we have a reasonable sample size. To improve the quality of the match, we match with replacement so that the same listed firm may be a match for more than one unlisted firm.

In Panel C of Table 4 we re-estimate equation (1) within the unlisted and listed matched sample. Consistent with our prior findings, unlisted firms continue to have more favorable ratings relative to listed firms. The magnitude of the effect is also similar to our estimates in Panel A of Table 4. This offers us assurance that linear controls do not bias the coefficients on *Unlisted* in Panel A of Table 4.

In contrast to the United States, firms in India can choose to not disclose their ratings. Figure 2, which displays the ratio of firms that have more than a 10% increase in bank debt and have at least one rating outstanding, shows why this could be problematic for our setting.. While both listed and unlisted firms may not disclose their ratings, unlisted firms appear to take advantage of this flexibility more often. Thus, it could be the case that only unlisted firms with favorable ratings disclose their ratings, which could bias our primary results. To alleviate this concern, we assign pseudo ratings to all (unlisted and listed) firms that experience a large increase in bank debt and repeat our analysis. We calculate pseudo ratings by estimating our baseline model outlined in equation (1) on all the listed firms with a rating. Using the coefficient estimates from this model, we impute a rating for all listed and unlisted firms within the same industry-year that experience a greater than 10% increase in bank loans outstanding and that do not have a credit rating.[21]

We include the firms with imputed ratings in our sample, repeat our tests, and present the results in Panel D of Table 4. Column (1) presents our results using industry-year fixed effects. While the coefficient on *Unlisted* is smaller than those reported in Panel A of Table 4, it is statistically significant below the 0.01 level. Column (2) presents our results after replacing industry-year fixed effects with firm and year fixed effects. Despite this restriction, we still find the coefficient on *Unlisted* to be positive and statistically significant below the 0.10 level.[22] We expect that our results using pseudo ratings will generate magnitudes on *Unlisted* that are smaller than our initial results in Panel A of Table 4, given that the potential ratings that were not disclosed were likely lower quality. These results provide further support that bank loan ratings issued to informationally opaque firms are likely biased upwards, thereby aiding lenders' capital constraints and borrowers' credit access. In all, these results are consistent with our main hypothesis.

Sensitivity of Ratings Changes to Financial Characteristics

We next examine the sensitivity of listed and unlisted firms' credit ratings to financial characteristics. To do so, we re-estimate an augmented version of equation (1) separately on the unlisted and the listed firm subsamples and compare the coefficients. Note that this method is equivalent to estimating a model with a full-set of interaction terms. Our methodology also allows for the coefficients on the control variables to vary for listed and unlisted firms. Since we are interested in the coefficients on time-varying financial characteristics, we include firm fixed effects, in addition to both year and auditor fixed effects in these tests. The inclusion of auditor fixed effects ensures that we control for an important determinant of the quality of audited financial statements.

We present our findings in Panel A of Table 5 at the firm-month-year level. We present the

[21] We re-assign predicted ratings below 1 and above 20 to 1 and 20, respectively.

[22] We are able to utilize firm fixed effects in this specification, given the increased variation in listed status by firm.

sensitivities of unlisted firms in column (1), of listed firms in column (2), and the difference between the coefficients in column (3). Consistent with our main hypothesis, we find that the bank loan ratings of unlisted firms are less sensitive to firm financial condition relative to those of listed firms. Furthermore, the differences we document are economically significant. For example, the value of the coefficient on *Leverage* is less negative for unlisted firms than it is for listed firms. This implies that while a 34 basis point increase in *Leverage* decreases listed firms' credit ratings by one notch (.34 $\times$ 2.927=1), the same increase in *Leverage* for unlisted firms only decreases their ratings by 0.42 notches (.34 $\times$ 1.249=0.42).

Note that while the univariate comparisons in Table 2 show that listed firms have higher ratings than unlisted firms, the results in Table 4 show that once we control for firm characteristics the opposite is true. The lower sensitivity of unlisted firms' ratings to financial characteristics documented in Table 5 help reconcile these seemingly contradictory findings. Unlisted firms in our sample have higher *Leverage*, higher *Debt-to-Earnings* and lower *Interest Coverage* (see Table 2). Therefore, if unlisted firms' ratings were as sensitive to financial condition as those of listed firms, given the former's "worse" financial condition, unlisted firms' ratings would on average be less favorable than what is reported herein. This is also evident in Panel B of Table 4 for the subsample of firms that transition during our sample period.

Similar to our results in Table 4, we also re-estimate our regressions at the firm-fiscal year level, as well as at the security level. We present these findings in Panels B and C of Table 5, respectively. We find that our results are consistent with those reported in Panel A of Table 5.

In addition to examining the sensitivity between reported financial ratios and ratings levels, we also examine whether listed firms' bank loan ratings changes are more sensitive to changes in firm distress predictors in Panel D of Table 5. Specifically, we regress $\triangle Rating_{i,t}$ on $\triangle Debt-to-Earnings_{i,t}$ and interact this main predictor with two indicator variables for whether the change in *Debt-to-Earnings* was positive or negative. In other words, we allow for differential sensitivity between changes in *Debt-to-Earnings* and $\triangle Ratings$ based upon improvement or deterioration in our predictor of interest. While we find that improvements and deteriorations in *Debt-to-Earnings* are incorporated into ratings changes for listed firm bank loan ratings, we find no such pattern for unlisted firm bank loan ratings. Collectively, these findings suggest that credit rating agencies alter the rigor of their quantitative analysis with respect to reported financial statement data in an effort to provide more favorable credit ratings to unlisted firms.

As a consequence of lower sensitivity to underlying financial condition, the distribution of ratings for unlisted firms may be more "bunched" together relative to those of listed firms, especially if the financial conditions of listed and unlisted firms have similar levels of dispersion. In Figure 3, we plot the distributions of listed and unlisted firms' ratings to examine each subgroup's ratings distribution. This figure shows two strikingly different distributions. For instance, while the ratings of listed firms are more widely dispersed throughout the ratings scale (bars), the ratings of unlisted firms (dotted line) are distributed with a single peak near the investment-grade/speculative-grade threshold.

From the figure it is clear that the distribution of the ratings of both listed and unlisted firms exhibit a discontinuity at the investment-grade/speculative-grade threshold. We follow an empirical methodology similar to Bennett et al. (2017) to examine if the size of the discontinuity at the threshold is statistically different across listed and unlisted firms. To do so, we perform a bootstrapping exercise in which we draw two samples of 100 observations each from our sample of unlisted and listed firms. In these samples we count the number of observations that lie just to the right and left of the threshold. We use the same bin width equal to 1 notch for both the unlisted and listed firm subsamples. We repeat this procedure 1,000 times and compare the difference in the number of observations to the right and left of the speculative-grade/investment-grade threshold for unlisted and listed firms. Consistent with the evidence presented in Figure 3, we find that the discontinuity is larger for unlisted firms relative to listed firms. On average, the number of unlisted firms with ratings just above (i.e., to the right of) the investment-grade threshold is 7.2 more than the number of unlisted firms with ratings just below (i.e., to the left) the threshold (untabulated). In comparison, the same difference is only 5.8 for listed firms. The difference between these two numbers is statistically significant (t-statistic = 6.92), suggesting that the discontinuity at the investment-grade threshold is greater for unlisted firms versus listed firms.

Credit Rating Agency Monitoring and Listed Status

Frequency of Ratings Changes

Our main hypothesis predicts that unlisted firms will have fewer downgrades than listed firms. The lower sensitivity of unlisted firms' ratings to changes in *Leverage* that we document in section implies that their ratings may remain at a particular level longer than the ratings of listed firms. In order to test this prediction, we use a model similar to equation (1) and regress the frequency of rating changes, downgrades, and upgrades on changes in firm financial condition. Our dependent variables in these regressions are either the natural logarithm of one plus the number of rating changes, the natural logarithm of one plus the number of downgrades, or the natural logarithm of one plus the number of upgrades during the year. Our independent variables are the changes in credit risk determinants, as previously defined, from fiscal year t-1 to t.

We present our results in Table 6. Since we use changes in firm credit risk characteristics as explanatory variables, we exclude firm fixed effects and employ industry-year and auditor fixed effects instead. When $Ln(1 + \sum Ratings\,Changes_{i,t})$ is our dependent variable (column (1)), we find that the coefficient on *Unlisted* is negative but not statistically related to the number of ratings changes. Again, we find no statistical relation between *Unlisted* and $Ln(1 + \sum Upgrades_{i,t})$ in column (2). However, we do find a negative and statistically significant relation between *Unlisted* and the number of downgrades over a fiscal year in column (3). In other words, while unlisted firms have fewer downgrades over the course of a fiscal year, the number of upgrades for listed and unlisted firms are statistically similar. These results suggest that when rating agencies assign bank loan ratings to informationally opaque firms, ratings changes (specifically downgrades), occur less frequently for unlisted firms relative to listed firms. These results offer evidence that rating agencies are more lax in their monitoring standards for private borrowers.

Ability of Ratings to Predict Default

One of the most important functions of credit ratings is to predict future defaults (Cantor and Packer, 1995). While Indian firms can enter bankruptcy through specialized bankruptcy-like creditor recovery systems, such as Corporate Debt Restructuring, it is difficult to identify if and when the firm defaults on its debt in such situations. Therefore, we focus explicitly on instances when one or more securities of the firm are rated "D" by the rating agencies.[23] To the extent the rating agencies are lax in their monitoring of unlisted firms, rating changes for such firms will be less correlated with subsequent default.

To test this conjecture, we re-estimate an augmented version of equation (1) with *Default* as the dependent variable. *Default* takes a value one if an issue is assigned a "D" rating in a particular month, and zero otherwise. We confine the sample to issues for which we have rating information for at least one year. That is, we focus on issues with maturity greater than one year. We also drop issues after they receive a "D" rating for the first time. We conduct this analysis at the issue-month level because in our sample firms selectively default on a security but remain current on others. In such a situation, defining default at the firm level becomes problematic. We relate *Default* to the issue's credit rating in the previous month. We include firm and year fixed effects in this specification.

We present our results in Panel A of Table 7. For columns (1) and (2), we find that the coefficients on *Rating* (the rating in the month before default) are negative and statistically significant at the 0.01 level. This indicates that (as expected) the likelihood of default in a given month is higher for firms with lower (i.e., less favorable) ratings in the previous month. In column (3), we find that this difference is statistically significant at the 0.01 level. This difference indicates that while prior month ratings serve as an indicator for default for both listed and unlisted firms, defaults of listed firms are more sensitive to their prior period rating. In columns (4) - (6) we conduct our analysis in a multivariate setting. We find that the coefficients on *Rating* are negative and statistically significant at the 0.01 level in columns (4) and (5). More importantly, we find that the difference in coefficients is statistically significant at the 0.01 level (column (6)). Eco-

[23]See Gopalan et al. (2016a) for more information on the various bankruptcy systems present in India.

nomically, these results suggest that a one standard deviation decrease in listed firms' ratings increases the likelihood of default in the next month by approximately 1.1 percent versus only a 0.3 percent increase for unlisted firms.

In Panel B of Table 7, we use the change in rating from month *m -11* to month *m -1* ("*m*" refers to the current month) as our main explanatory variable. Our explanatory variable captures the differential change in ratings captured in our summary statistics in Table 3. As with Table 6, because we employ a changes specification we exclude firm fixed effects from this analysis. However, to ensure that we account for unobserved heterogeneity we employ both industry and year fixed effects. As expected, we find a negative and statistically significant relation between the change in ratings and subsequent default in columns (1), (2), (4), and (5). More importantly, we find that the difference between the association for unlisted firms and listed firms is statistically significant at the 0.01 level in both columns (3) and (6); thus the changes in listed firms' credit ratings are more informative about future defaults relative to the changes in unlisted firms' credit ratings. Collectively these findings suggest that credit rating agencies engage in lax monitoring for unlisted firms relative to listed firms, and is consistent with the notion that banks prefer more favorable loan ratings for unlisted firms relative to listed firms. This is particularly relevant since such ratings potentially allow banks to reserve less capital for unlisted firms' loans longer than would otherwise be possible.

Robustness Tests

We believe our primary tests do not identify the causal effect of a firm's listed status on its credit ratings. A firm's listed status is likely to impact multiple aspects of its behavior and performance. Furthermore, listed firms may be different from unlisted firms along unobserved dimensions. These differences are likely to affect the estimates we document. To isolate the causal effect of a firm's listed status on credit ratings, we need an exogenous shock to listing status, which we lack. We attempt to overcome this challenge using a number of alternatives, described below.

Ability Predictability of Future Firm Performance

If audited financial statements of unlisted firms are innately less informative about future financial performance, this could explain why their ratings are less sensitive to financial ratios. To alleviate this concern, we evaluate the ability of financial ratios to predict future firm performance. Specifically, we test the extent to which financial statement characteristics in year t are able to predict firm *Sales* in fiscal years $t+2$ and $t+3$. Columns (3) and (6) of Table 8 show that there are nearly no systematic differences across unlisted and listed firms in the ability of financial statement characteristics to predict future sales.[24] Perhaps more importantly, we find virtually no differences in the sensitivity of future sales to leverage-related indicators. Collectively, these results suggest that audited financial characteristics of unlisted firms are no less informative about future firm performance relative to those of listed firms.

Other Issues

Saunders and Steffen (2011) use the distance between the location of U.K. firms' headquarters and London as an instrumental variable (IV) for whether firms choose to list their shares on the London Stock Exchange. Unfortunately, in India both the main stock exchange and the rating agencies' headquarters are located in Mumbai. While the distance of a firm's headquarters from Mumbai can affect the firm's decision to list its shares, it is also likely to affect the ability of the rating agency to learn about the firm and periodically monitor it. Therefore, the distance between a firm's headquarters and the rating agencies can independently affect the firms' credit ratings. Given this, we do not believe that this distance will satisfy the exclusion restriction; hence we do not implement an IV estimation.

In addition, Baghai and Becker (2018) supplement Indian credit ratings data with data on revenue that rating agencies earn from non-rating business. They find that Indian rating agencies provide more favorable ratings to firms that purchase more non-rating services from those rating agencies. To alleviate the concern that non-rating fees could bias our results, we amend our firm-year dataset to include non-rating revenue and find that only three percent of our observations have non-rating revenue. Our inferences remain unchanged after we control for non-rating

[24]For robustness, we also perform this test on firm sales in fiscal year t+1 and our inferences remain unchanged (untabulated).

revenue in our primary analysis (untabulated).[25]

V. CONCLUSION

In this study, we provide large sample evidence that assesses the quality of bank loan ratings. Because commercial banks (the ultimate customers of bank loan ratings) may be conflicted in their desire for accurate ratings, rating agencies may acquiesce to lenders' demands when they face lower reputational costs and assign poorer quality ratings. This incentive may heighten the already perverse incentives in the issuer paid rating model to cater to issuers' demands.

Our evidence shows that bank loan ratings are poor summary measures of borrower distress in instances where borrowers have high information asymmetry (i.e., those bank borrowers that are unlisted). While unlisted firms have more favorable ratings on average, these firms' bank loan ratings are less sensitive to financial ratios than those of listed firms. Thus, our evidence suggests that rating agencies recalibrate their methodologies when rating bank loans of unlisted borrowers to incorporate less "hard information". We also find that bank loan ratings for unlisted borrowers are downgraded less frequently, while no such asymmetry occurs for upgrades. Moreover, we find that listed firm bank loan ratings incorporate more default-relevant information into credit rating assignments, since listed firm bank loan ratings and ratings changes are more sensitive to future default when compared to those bank loan ratings of unlisted borrowers.

Overall, our study is the first to our knowledge to provide large sample evidence that assesses the quality of ratings assigned to private debt. While prior work examines ratings' associations with bond prices or yields, we examine whether bank loan ratings serve as suitable summary indicators of borrower distress. Our evidence suggests that regulators, commercial banks, and other investors should pause before relying explicitly on bank loan ratings as summary measures of bank distress.

[25]We thank Ramin Baghai and Bo Becker for sharing their data on non-rating revenue for Indian credit rating agencies.

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Appendix A: Variable Definitions

1. **Rating:** The numeric credit rating for any firm-month-year where AAA = 20 and D = 1. If more than one credit rating agency rates the firm, then the rating is the average rating for all agencies that rate the firm.

2. **RatingsGap**: The difference between a firm's actual and expected rating. A firm's expected rating is calculated by using coefficients from estimating equation (1) with month-year observations from firms that either remain listed or unlisted throughout our sample period.

3. **PredictedRating**: The predicted rating for firms that do not have a rating but that experience a greater than 10% growth in bank debt outstanding in a given year. We predict ratings using the methodology that we describe in Section 4.1.1.

4. **Log(SumRatingChanges):** The natural logarithm of one plus the aggregate number of individual security ratings changes for a firm in a fiscal year.

5. **Log(SumDowngrades):** The natural logarithm of one plus the aggregate number of downgrades of individual securities of a firm in a fiscal year.

6. **Log(SumUpgrades):** The natural logarithm of one plus the aggregate number of upgrades of individual securities of a firm in a fiscal year.

7. **Downgrades>0, Upgrades>0:** Indicator variables equal to one if at least one security is downgraded or upgraded for a particular firm in a given month.

8. **Default:** A dummy variable equal to 1 if the debt issue is assigned a "D" rating during the month, and zero otherwise.

9. **Sales** ($\frac{Sales}{Assets}$)**:** Firm sales divided by total assets.

10. **Unlisted**: A dummy variable that identifies firms that do not not have publicly traded equity.

11. **Ln(Listed Firm Downgrades), Ln(Listed Firm Upgrades):** The natural log of one plus the number of listed firm downgrades or upgrades for each industry in one of three horizons: one month (m-1 to m), one quarter (m-3 to m), or six months (m-6 to m). Ratings changes are calculated at the security level and then aggregated to the industry level.

12. **Leverage** ($\frac{Borrowings}{Assets}$)**:** Total borrowings divided by total assets.

13. **Debt-to-Earnings** ($\frac{Borrowings}{PBITDA}$)**:** Total borrowings divided by profits before depreciation, interest, taxes, and amortization.

14. **Cash** ($\frac{Cash}{Assets}$)**:** Cash and bank balances divided by total assets.

15. **Interest Coverage** ($\frac{PBITDA}{Int.Expense}$)**:** Profits before depreciation, interest, taxes, and amortization divided by interest expense.

16. **Profitability** ($\frac{PBITDA}{Sales}$)**:** Profits before depreciation, interest, taxes, and amortization divided by total sales.

17. **PP&E** ($\frac{PP\&E}{Assets}$)**:** Gross fixed assets divided by total assets.

18. **Size** ($Log(Assets)$)**:** The natural logarithm of total assets.

19. **CRA Coverage**: The number of credit rating agencies that assign a rating to a debt security in any given firm-month-year.

20. **Group Membership**: An indicator variable equal to one if the firm is part of a family owned business group (conglomerate), and zero otherwise.

Figure 1: Distribution of Credit Ratings for Defaulted Firms

Figure 1(a) - Listed Firms

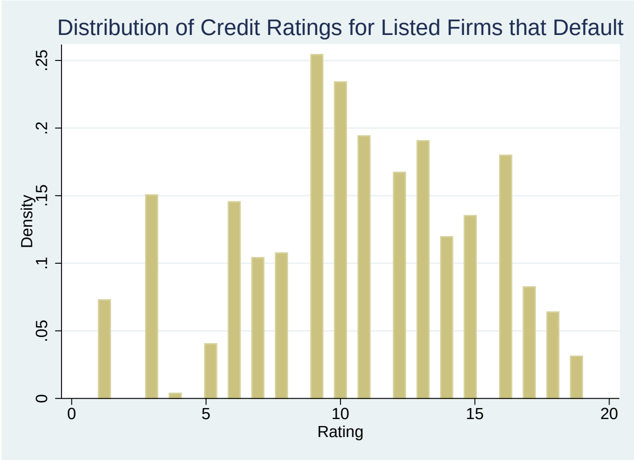

Figure 1(b) - Unlisted Firms

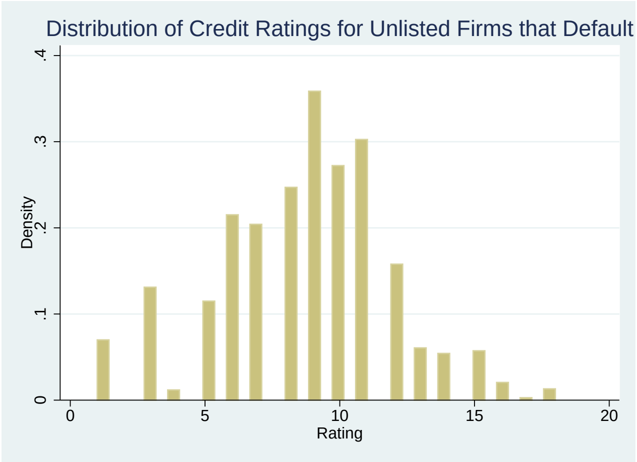

Figure 1 shows the distribution of credit ratings for firms that default partitioned on listed status. Panel A shows the sub-sample of issue-month-year observations for listed firms. Panel B shows the sub-sample of issue-month-year observations for unlisted firms. Rating is an ordinal number from 1 to 20, with 20 representing the highest credit quality debt (i.e., AAA).

Figure 2: Ratio of Firm-Years with Bank Debt and Ratings

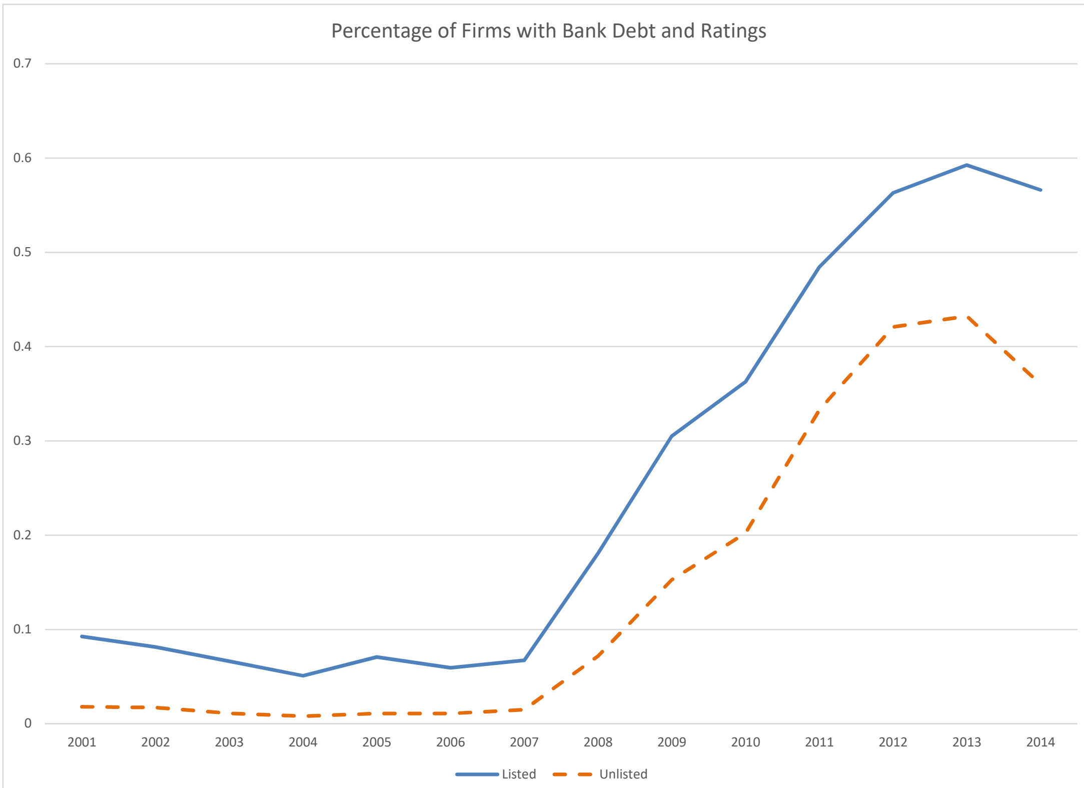

Figure 2 plots the percentage of listed and unlisted firm-years over time that have more than a 10% increase in bank debt and have at least one rating outstanding. The orange dotted line represents the data for unlisted firms while the solid blue line represents the data for listed firms.

Figure 3: Distribution of Issue-Level Credit Ratings for Listed and Unlisted Firms

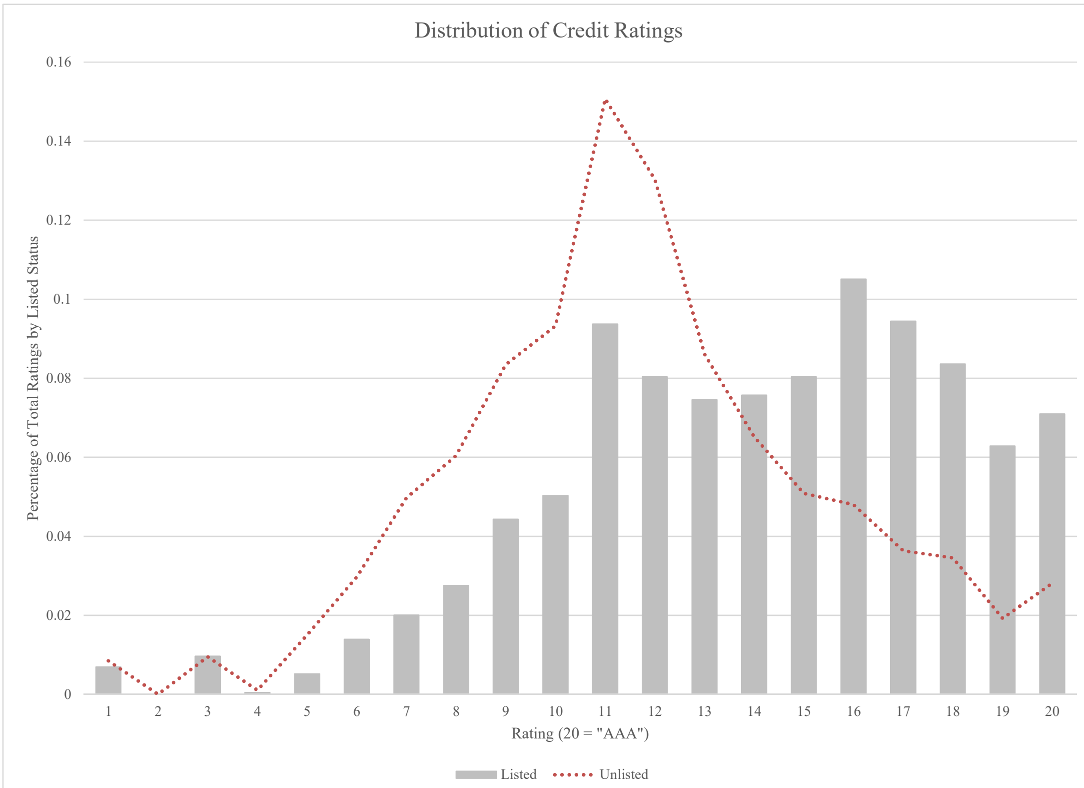

Figure 3 shows the distribution of issue-level credit ratings in our sample. The grey bars show the percentage of total listed firm issue-level ratings observations at each notch. The red dotted line show the percentage of total unlisted firm issue-level ratings observations at each notch. Rating is an ordinal number from 1 to 20, with 20 representing the highest credit quality debt (i.e., AAA).

Figure 4: Number of Rated Firm-Years by Year

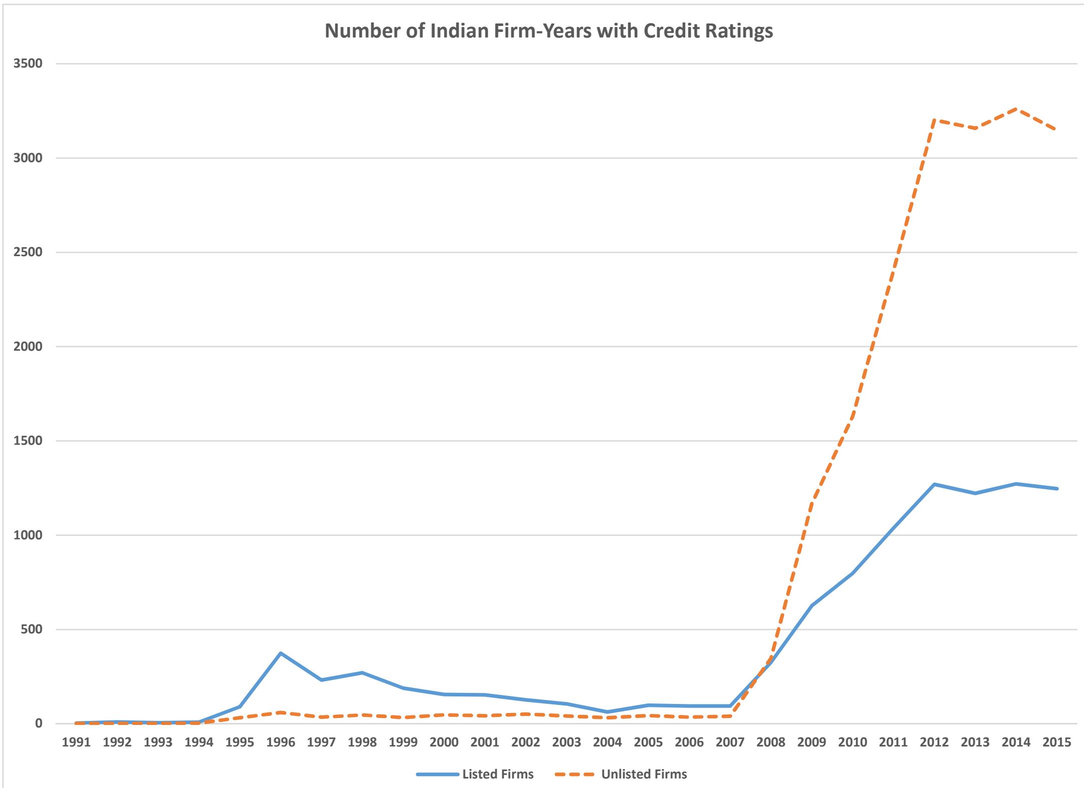

Figure 4 plots the number of listed and unlisted firm-years over time that have at least one rating outstanding. The orange dotted line represents the data for unlisted firms while the solid blue line represents the data for listed firms.

Table 1: Descriptive Statistics

	N	Mean	SD	P25	P50	P75
Panel A: Entire Sample						
Ratings	21,576	11.61	3.64	10.00	12.00	14.00
Leverage	21,576	0.38	0.19	0.24	0.37	0.51
Debt-to-Earnings	21,576	3.84	3.71	1.69	3.03	4.71
Cash	21,576	0.03	0.05	0.002	0.013	0.04
Interest Coverage	21,576	7.27	21.41	1.36	2.19	4.32
Profitability	21,576	0.18	0.19	0.08	0.12	0.19
PP&E	21,576	0.51	0.30	0.28	0.49	0.71
Size	21,576	7.78	1.50	6.64	7.65	8.75
CRA Coverage	21,576	1.03	0.17	1.00	1.00	1.00
Group Membership	21,576	0.30	0.46	0.00	0.00	1.00
Panel A: Listed Firm-Years						
Ratings	7,851	12.59	3.80	11.00	13.00	15.00
Leverage	7,851	0.33	0.17	0.21	0.34	0.46
Debt-to-Earnings	7,851	3.30	2.95	1.45	2.73	4.28
Cash	7,851	0.027	0.04	0.002	0.011	0.03
Interest Coverage	7,851	9.15	25.44	1.47	2.50	5.16
Profitability	7,851	0.17	0.16	0.09	0.13	0.20
PP&E	7,851	0.54	0.30	0.32	0.53	0.74
Size	7,851	8.44	1.54	7.30	8.37	9.43
CRA Coverage	7,851	1.04	0.18	1.00	1.00	1.00
Group Membership	7,851	0.48	0.50	0.00	0.00	1.00
Panel C: Unlisted Firm-Years						
Ratings	13,725	11.04	3.43	9.00	11.00	13.00
Leverage	13,725	0.40	0.19	0.26	0.40	0.53
Debt-to-Earnings	13,725	4.15	4.04	1.83	3.22	4.99
Cash	13,725	0.032	0.05	0.003	0.014	0.04
Interest Coverage	13,725	6.20	18.64	1.32	2.05	3.90
Profitability	13,725	0.18	0.21	0.07	0.11	0.19
PP&E	13,725	0.49	0.30	0.26	0.47	0.70
Size	13,725	7.40	1.34	6.38	7.29	8.27
CRA Coverage	13,725	1.02	0.15	1.00	1.00	1.00
Group Membership	13,725	0.20	0.40	0.00	0.00	0.00

Table 1 presents descriptive statistics for the variables used in our analysis for the 1999 - 2017 sample period. Panel A presents descriptive statistics for the full sample of listed and unlisted firms in the PROWESS dataset used in our estimation sample. Panel B presents descriptive statistics for the set of firm-year observations for listed firms, while Panel C presents descriptive statistics for the set of firm-year observations for unlisted firms. All variables are defined in Appendix A.

Table 2: Univariate Differences in Observable Characteristics Across Listed Status

	Mean: Listed Firm-Years	Mean: Unlisted Firm-Years	Difference	t-stat
Ratings	12.592	11.045	1.547	30.65***
Upgrade	0.140	0.170	-0.03	-7.96***
Downgrade	0.160	0.140	0.02	6.20***
Leverage	0.333	0.400	-0.067	-25.14***
Debt-to-Earnings	3.304	4.153	-0.849	-16.29***
Cash	0.026	0.031	-0.005	-7.72***
Interest Coverage	9.150	6.201	2.949	9.76***
Profitability	0.172	0.177	-0.005	-1.87*
PP&E	0.541	0.495	0.047	10.92***
Size	8.439	7.398	1.041	51.84***
CRA Coverage	1.035	1.024	0.011	4.75***
Group Membership	0.478	0.196	0.282	45.55***

Table 2 presents a univariate comparison of the variables used in our analyses across listed and unlisted firms. Statistical significance at the 10%, 5%, and 1% levels is denoted by *, **, and ***, respectively. All variables are defined in Appendix A.

Table 3: Trend in Credit Ratings for Loans That Default

	Obs	All	Unlisted Firms	Listed Firms
(1)	(2)	(3)	(4)	(5)
-12	1,220	8.43	8.17	9.21
-11	1,220	8.34	8.09	9.12
-10	1,220	8.27	8.02	9.00
-9	1,220	8.19	7.97	8.85
-8	1,220	8.14	7.92	8.80
-7	1,220	8.07	7.87	8.68
-6	1,220	8.00	7.82	8.55
-5	1,220	7.91	7.75	8.39
-4	1,220	7.88	7.73	8.32
-3	1,220	7.80	7.69	8.16
-2	1,220	7.77	7.67	8.07
-1	1,220	7.73	7.65	7.99

Table 3 presents descriptive statistics of credit ratings for the 12 months prior to default (i.e., being assigned a "D" credit rating).

Table 4: The Relation Between Listed Status and Ratings

Panel A: Average Monthly, Average Annual, and Security Level Ratings Observations

Explanatory Variables	$Rating_{i,m,y}$	$Rating_{i,m,y}$	$Rating_{i,y}$	$Rating_{i,y}$	$Rating_{i,s,m,y}$	$Rating_{i,s,m,y}$
	(1)	(2)	(3)	(4)	(5)	(6)
Unlisted	0.418***	0.494***	0.325***	0.476***	0.430***	0.483***
	(3.99)	(4.39)	(3.18)	(3.78)	(4.08)	(4.06)
Leverage	-3.781***	-3.294***	-3.594***	-3.271***	-3.864***	-3.385***
	(-12.76)	(-8.47)	(-12.98)	(-7.93)	(-12.29)	(-8.34)
Cash	2.489***	2.313***	2.490***	2.332***	2.490***	2.078***
	(3.92)	(3.97)	(3.30)	(3.81)	(3.72)	(3.31)
Debt-to-Earnings	-0.202***	-0.171***	-0.177***	-0.142***	-0.221***	-0.183***
	(-13.29)	(-10.02)	(-16.60)	(-9.35)	(-12.93)	(-9.34)
Interest Coverage	0.165***	0.134***	0.160***	0.129***	0.179***	0.149***
	(13.10)	(10.31)	(13.82)	(9.98)	(13.19)	(10.23)
Profitability	1.341***	1.081***	1.320***	1.039***	1.203***	0.934***
	(5.75)	(4.31)	(6.31)	(4.11)	(4.76)	(3.76)
PP&E	0.440**	0.056	0.270	-0.047	0.351	-0.042
	(2.12)	(0.28)	(1.31)	(-0.23)	(1.58)	(-0.20)
Ln(Assets)	1.050***	0.839***	1.081***	0.880***	1.083***	0.852***
	(34.25)	(20.11)	(35.99)	(20.11)	(30.67)	(17.60)
Business Group Membership(0/1)	0.992***	0.883***	1.012***	0.902***	1.004***	0.929***
	(10.28)	(8.45)	(10.87)	(8.00)	(9.42)	(8.16)
CRA Coverage	0.050	0.132	-0.114	-0.036	-0.001	0.062
	(0.34)	(0.94)	(-0.79)	(-0.23)	(-0.01)	(0.47)
N	227,908	227,635	21,491	20,490	270,406	270,374
adj. R-sq	0.459	0.668	0.453	0.608	0.468	0.676
Fixed Effects	Industry-Yr	Industry-Yr, Auditor	Industry-Yr	Industry-Yr, Auditor	Industry-Yr	Industry-Yr, Auditor
Std Errors Clustered At	Firm,Yr	Firm,Yr	Firm,Yr	Firm,Yr	Firm,Yr	Firm,Yr

Table 4 Panel A presents regression estimates for the effect of listed status on ratings levels. Columns (1) and (2) present results when the dependent variable is the average rating outstanding at the firm-month-year level. Columns (3) and (4) present results when the dependent variable is the average rating outstanding at the end of firms' fiscal years. Columns (5) and (6) presents results at the security-firm-month-level. Standard Errors are clustered by firm and year, and t-statistics are reported in parentheses. *, **, and *** represent significance at 10%, 5%, and 1% level, respectively. All variables are defined in Appendix A.

Table 4 (Continued)

Panel B: Univariate Analysis for Firms that Switch Listed Status

Actual Ratings Based On:	Expected Ratings Based On:	
	Listed Firm Loadings	Unlisted Firm Loadings
	$Ratings\ Gap_{i,m,y}$	$Ratings\ Gap_{i,m,y}$
	(1)	(2)
Unlisted Firm-Month-Years	0.504***	0.00
	(14.87)	(0.00)
Listed Firm-Month-Years	0.00	-0.322**
	(0.00)	(-7.03)
Difference	0.504***	0.322***
	(9.54)	(5.79)

Table 4 Panel B presents summary information that compares actual versus predicted ratings for firms that transition from unlisted to listed status (or vice versa). All observations are at the firm-month-year level. Standard Errors are clustered by firm and year, and t-statistics are reported in parentheses. *, **, and *** represent significance at 10%, 5%, and 1% level, respectively. All variables are defined in Appendix A.

Table 4 (Continued)

Panel C: Matched Sample Analysis

Explanatory Variables	$Rating_{i,y}$	$Rating_{i,y}$	$Rating_{i,y}$
	(1)	(2)	(3)
Unlisted	0.421***	0.597***	0.599***
	(2.97)	(2.80)	(2.94)
Leverage	-3.960***	-3.873***	-3.938***
	(-7.79)	(-5.40)	(-5.69)
Cash	1.980*	0.751	0.198
	(1.74)	(0.73)	(0.20)
Debt-to-Earnings	-0.221***	-0.166***	-0.165***
	(-8.50)	(-8.23)	(-8.62)
Interest Coverage	0.174***	0.142***	0.150***
	(6.17)	(4.22)	(4.86)
Profitability	1.766***	1.172***	1.162***
	(3.70)	(2.41)	(2.34)
PP&E	0.024	-0.507	-0.548
	(0.08)	(-1.44)	(-1.60)
Ln(Assets)	1.074***	0.902***	
	(28.52)	(11.21)	
Business Group Membership(0/1)	0.717***	0.729***	0.771***
	(6.69)	(3.86)	(4.07)
CRA Coverage	-0.179	0.114	0.081
	(-0.55)	(0.28)	(0.19)
N	5,716	4,979	4,979
adj. R-sq	0.467	0.611	0.614
Fixed Effects	Industry-Yr	Industry-Yr, Auditor	Industry-Yr, Auditor, Size Pctile
Std Errors Clustered At	Firm,Yr	Firm,Yr	Firm,Yr

Table 4 Panel C presents regression estimates for the effect of listed status on ratings levels at the firm-year level using a matched sample of firm-year observations. Standard Errors are clustered by firm and year, and t-statistics are reported in parentheses. *, **, and *** represent significance at 10%, 5%, and 1% level, respectively. All variables are defined in Appendix A.

Table 4 (Continued)

Panel D: Pseudo Ratings Analysis

Explanatory Variables	$Rating_{i,y}$	$Rating_{i,y}$
	(1)	(2)
Unlisted	0.171***	0.089*
	(3.18)	(1.90)
Leverage	-5.939***	-5.990***
	(-35.02)	(-34.18)
Cash	2.024***	1.800**
	(3.26)	(2.22)
Debt-to-Earnings	-0.052***	-0.036***
	(-6.51)	(-7.18)
Interest Coverage	0.020***	0.011***
	(5.09)	(3.89)
Profitability	0.021***	0.004
	(5.66)	(0.90)
PP&E	0.872***	0.510***
	(19.14)	(5.77)
Ln(Assets)	1.028***	0.978***
	(108.26)	(31.65)
Business Group Membership(0/1)	0.944***	
	(32.64)	
N	72,736	67,619
adj. R-sq	0.725	0.840
Fixed Effects	Industry-Yr	Firm, Year
Std Errors Clustered At	Firm,Yr	Firm,Yr

Table 4 Panel D presents regression estimates for the effect of listed status on ratings levels at the firm-year level after incorporating predicted ratings to account for the possibility of ratings non-disclosure. Standard Errors are clustered by firm and year, and t-statistics are reported in parentheses. *, **, and *** represent significance at 10%, 5%, and 1% level, respectively. All variables are defined in Appendix A.

Table 5: Sensitivity Between Firm Financials and Ratings

Panel A: Monthly Ratings Observations

Explanatory Variables	$Rating_{i,m,y}$	$Rating_{i,m,y}$	$Difference$
	$Unlisted$	$Listed$	
	(1)	(2)	(1) - (2): (3)
Leverage	-1.240***	-2.927***	1.687***
	(-4.47)	(-5.76)	(3.21)
Cash	0.952**	2.333***	-1.381**
	(2.52)	(3.96)	(-1.96)
Debt-to-Earnings	-0.051***	-0.222***	0.171***
	(-5.87)	(-7.30)	(5.78)
Interest Coverage	0.002***	-0.000	0.002
	(2.44)	(-0.05)	(1.50)
Profitability	0.114	-1.172***	1.28***
	(0.47)	(-3.06)	(3.16)
PP&E	-0.250	-1.212***	0.962***
	(-1.26)	(-3.96)	(2.65)
Ln(Assets)	0.554***	0.919***	-0.365***
	(6.83)	(6.37)	(-2.43)
N	141,555	85,733	227,288
adj. R-sq	0.911	0.872	0.899
Fixed Effects	Firm, Yr, Auditor	Firm, Yr, Auditor	Firm, Yr, Auditor
Std Errors Clustered At	Firm,Yr	Firm,Yr	Firm,Yr

Table 5 Panel A presents regression estimates that examine the sensitivity between firm financial characteristics and ratings levels, by listed status. Observations are at the firm-month-year level. Standard Errors are clustered by firm and year, and t-statistics are reported in parentheses. *, **, and *** represent significance at 10%, 5%, and 1% level, respectively. All variables are defined in Appendix A.

Table 5 (Continued)

Panel B: Yearly Ratings Observations

Explanatory Variables	$Rating_{i,y}$	$Rating_{i,y}$	$Difference$
	$Unlisted$	$Listed$	
	(1)	(2)	(1) - (2): (3)
Leverage	-1.028***	-2.681***	1.653***
	(-3.78)	(-4.80)	(2.70)
Cash	1.251***	2.181***	-0.930
	(3.11)	(4.01)	(-1.37)
Debt-to-Earnings	-0.030***	-0.187***	0.157***
	(-3.78)	(-5.68)	(4.52)
Interest Coverage	0.002**	-0.000	0.002*
	(2.25)	(-0.30)	(1.66)
Profitability	0.234	-1.371***	1.605***
	(0.86)	(-3.01)	(2.94)
PP&E	-0.196	-1.029***	0.7833**
	(-1.02)	(-3.03)	(2.03)
Ln(Assets)	0.554***	1.232***	-0.680***
	(4.66)	(7.28)	(-3.42)
N	11,893	7,523	19,416
adj. R-sq	0.861	0.846	0.879
Fixed Effects	Firm, Yr, Auditor	Firm, Yr, Auditor	Firm, Yr, Auditor
Std Errors Clustered At	Firm,Yr	Firm,Yr	Firm,Yr

Table 5 Panel B presents regression estimates that examine the sensitivity between firm financial characteristics and ratings levels, by listed status. Observations are at the firm-year level. Standard Errors are clustered by firm and year, and t-statistics are reported in parentheses. *, **, and *** represent significance at 10%, 5%, and 1% level, respectively. All variables are defined in Appendix A.

Table 5 (Continued)

Panel C: Security Level Ratings Observations

Explanatory Variables	$Rating_{i,y}$	$Rating_{i,y}$	$Difference$
	$Unlisted$	$Listed$	
	(1)	(2)	(1) - (2): (3)
Leverage	-1.237***	-2.702***	1.475***
	(-4.31)	(-5.33)	(2.68)
Cash	1.115***	2.238***	-1.13
	(3.00)	(3.96)	(-1.60)
Debt-to-Earnings	-0.055***	-0.214***	0.159***
	(-6.26)	(-7.14)	(5.41)
Interest Coverage	0.002***	0.000	0.001
	(2.57)	(0.34)	(1.10)
Profitability	0.065	-1.215***	1.28***
	(0.30)	(-3.25)	(3.06)
PP&E	-0.306	-1.077***	0.771**
	(-1.38)	(-3.63)	(2.13)
Ln(Assets)	0.561***	0.939***	-0.378***
	(6.86)	(6.78)	(-2.58)
N	166,850	103,486	270,336
adj. R-sq	0.904	0.875	0.896
Fixed Effects	Firm, Yr, Auditor	Firm, Yr, Auditor	Firm, Yr, Auditor
Std Errors Clustered At	Firm,Yr	Firm,Yr	Firm,Yr

Table 5 Panel C presents regression estimates that examine the sensitivity between firm financial characteristics and ratings levels, by listed status. Observations are at the security-firm-month-year level. Standard Errors are clustered by firm and year, and t-statistics are reported in parentheses. *, **, and *** represent significance at 10%, 5%, and 1% level, respectively. All variables are defined in Appendix A.

Table 5 (Continued)

Panel D: Ratings Changes and Asymmetry in Changes to Debt to Earnings

Explanatory Variables	$\triangle Rating_{i,t}$		$Difference$
	$Unlisted$	$Listed$	
	(1)	(2)	(1) - (2): (3)
$\triangle Debt-to-Earnings_{it} * \triangle Debt-to-Earnings_{it} < 0$	0.013	0.062***	-0.049**
	(1.39)	(3.49)	(-2.24)
$\triangle Debt-to-Earnings_{it} * \triangle Debt-to-Earnings_{it} > 0$	-0.005	-0.042***	0.037**
	(-0.85)	(-2.92)	(2.11)
$Other\ Controls\ Included$	Yes	Yes	
N	179,147		
adj. R-sq	0.359		
Fixed Effects	Security, Yr		
Std Errors Clustered At	Firm,Yr		

Table 5 Panel D presents regression estimates that examine the differential sensitivity between improvements and deteriorations in firm financial condition and changes in ratings levels, by listed status. Observations are at the security-firm-year level. Standard Errors are clustered by firm and year, and t-statistics are reported in parentheses. *, **, and *** represent significance at 10%, 5%, and 1% level, respectively. All variables are defined in Appendix A.

Table 6: The Relation Between Listed Status and The Number of Ratings Changes

Explanatory Variables	$Ln(1+\sum Ratings\ Changes_{i,t})$	$Ln(1+\sum Upgrades_{i,t})$	$Ln(1+\sum Downgrades_{i,t})$
	(1)	(2)	(3)
Unlisted	-0.009	0.007	-0.016***
	(-1.01)	(0.97)	(-2.93)
$\triangle Leverage_{i,t}$	-0.182***	-0.185***	-0.000
	(-3.09)	(-2.98)	(-0.00)
$\triangle Cash_{i,t}$	0.115	0.144	-0.038
	(1.17)	(1.80)	(-1.52)
$\triangle Debt-to-Earnings_{i,t}$	0.000***	0.000**	0.000**
	(2.34)	(2.60)	(2.22)
$\triangle Interest\ Coverage_{i,t}$	0.000	0.000	-0.000
	(0.36)	(1.39)	(-0.95)
$\triangle Profitability_{i,t}$	0.000	0.000	0.000***
	(0.93)	(0.47)	(4.20)
$\triangle PP\&E_{i,t}$	-0.029	-0.018	-0.012
	(-0.80)	(-0.65)	(-0.50)
$\triangle Ln(Assets)_{i,t}$	0.035**	0.081***	-0.049**
	(2.30)	(5.70)	(-2.25)
N	11,442	11,442	11,442
adj. R-sq	0.049	0.063	0.095
Fixed Effects	Industry-Yr, Auditor	Industry-Yr, Auditor	Industry-Yr, Auditor
Std Errors Clustered At	Firm,Yr	Firm,Yr	Firm,Yr

Table 6 presents regression estimates that examine the relation between listed status and the frequency of ratings changes in a fiscal year. Observations are at the firm-year level. Standard Errors are clustered by firm and year, and t-statistics are reported in parentheses. *, **, and *** represent significance at 10%, 5%, and 1% level, respectively. All variables are defined in Appendix A.

Table 7: Sensitivity Between Ratings and Future Default

Panel A: Ratings Levels

Explanatory Variables	$Default\,(0,1)_{i,m}$	$Default\,(0,1)_{i,m}$	$Difference$	$Default\,(0,1)_{i,m}$	$Default\,(0,1)_{i,m}$	$Difference$
	$Unlisted$	$Listed$		$Unlisted$	$Listed$	
	(1)	(2)	(1) - (2): (3)	(4)	(5)	(4) - (5): (6)
$Rating$	-0.001***	-0.004***	0.003***	-0.001***	-0.003***	0.002***
	(-6.07)	(-6.60)	(3.54)	(-5.24)	(-6.46)	(3.53)
$Leverage$				-0.001	-0.014***	0.013***
				(-0.58)	(-4.15)	(4.39)
$Cash$				-0.009***	-0.019***	0.010
				(-5.63)	(-2.56)	(1.43)
$Debt-to-Earnings$				0.001***	0.001***	0.000***
				(3.83)	(3.93)	(-2.32)
$Interest\ Coverage$				0.000	0.000	0.000
				(1.44)	(1.01)	(0.82)
$Profitability$				-0.000	0.004	-0.004
				(-0.27)	(1.44)	(-1.60)
$PP\&E$				0.001	0.007***	-0.006*
				(0.82)	(3.01)	(-1.73)
$Ln(Assets)$				0.001	0.003**	-0.002**
				(0.68)	(2.61)	(-1.96)
N	155,830	93,042	248,872	155,830	93,042	248,872
adj. R-sq	0.048	0.036	0.042	0.048	0.038	0.043
Fixed Effects	Firm, Yr	Firm, Yr	Firm, Yr	Firm, Yr	Firm, Yr	Firm, Yr
Std Errors Clustered At	Firm,Yr	Firm,Yr	Firm,Yr	Firm,Yr	Firm,Yr	Firm,Yr

Table 7 Panel A presents regression estimates that examine the sensitivity between firm financial characteristics and future default, by listed status. Observations are at the security-firm-month-year level. Standard Errors are clustered by firm and year, and t-statistics are reported in parentheses. *, **, and *** represent significance at 10%, 5%, and 1% level, respectively. All variables are defined in Appendix A.

Table 7 (Continued)

Panel B: Ratings Changes

Explanatory Variables	$Default\,(0,1)_{i,m,y}$	$Default\,(0,1)_{i,m,y}$	$Difference$	$Default\,(0,1)_{i,m,y}$	$Default\,(0,1)_{i,m,y}$	$Difference$
	$Unlisted$	$Listed$		$Unlisted$	$Listed$	
	(1)	(2)	(1) - (2): (3)	(4)	(5)	(4) - (5): (6)
$Rating\ Change:\ m-11\,to\,m-1$	-0.002***	-0.004***	0.002***	-0.002***	-0.004***	0.002***
	(-3.96)	(-7.74)	(3.39)	(-3.73)	(-7.12)	(3.08)
$\triangle Leverage$				0.002	-0.008	0.010**
				(0.75)	(-1.49)	(2.15)
$\triangle Cash$				-0.004*	-0.013	0.009
				(-2.04)	(-1.64)	(1.27)
$\triangle Debt-to-Earnings$				0.000***	0.001*	-0.001
				(3.84)	(1.97)	(-1.21)
$\triangle Interest\ Coverage$				0.000	-0.000	0.000
				(0.12)	(-0.12)	(0.16)
$\triangle Profitability$				-0.002	-0.001	-0.001
				(-0.88)	(-0.36)	(-0.07)
$\triangle PP\&E$				0.000	0.004	-0.003
				(0.02)	(1.18)	(-0.72)
$\triangle Ln(Assets)$				-0.001	0.001	-0.002
				(-1.17)	(0.82)	(-1.23)
N	109,847	69,109	178,956	109,847	69,109	178,956
adj. R-sq	0.001	0.007	0.004	0.002	0.008	0.004
Fixed Effects	Industry, Yr	Industry, Yr	Industry, Yr	Industry, Yr	Industry, Yr	Industry, Yr
Std Errors Clustered At	Firm,Yr	Firm,Yr	Firm,Yr	Firm,Yr	Firm,Yr	Firm,Yr

Table 7 Panel B presents regression estimates that examine the sensitivity between changes in firm financial characteristics and future default, by listed status. Observations are at the security-firm-month-year level. Standard Errors are clustered by firm and year, and t-statistics are reported in parentheses. *, **, and *** represent significance at 10%, 5%, and 1% level, respectively. All variables are defined in Appendix A.

Table 8: Robustness: Sensitivity to Future Sales

Explanatory Variables	$Sales_{i,t+2}$			$Sales_{i,t+3}$		
	Unlisted	Listed	Difference	Unlisted	Listed	Difference
	(1)	(2)	(1)-(2): (3)	(4)	(5)	(4) - (5): (6)
Leverage	0.322***	0.265***	0.057	0.282***	0.248***	0.034
	(7.04)	(3.91)	(0.76)	(5.82)	(3.57)	(0.41)
Debt-to-Earnings	-0.028***	-0.032***	0.003	-0.023***	-0.026***	0.003
	(-16.78)	(-13.76)	(1.27)	(-10.88)	(-9.30)	(1.15)
Cash	1.276***	0.874***	0.402	1.624***	0.968***	0.656*
	(4.74)	(3.10)	(1.27)	(3.93)	(2.84)	(1.98)
Interest Coverage	-0.000**	-0.000	-0.000	-0.000**	-0.000	0.000
	(-2.60)	(-1.21)	(-0.97)	(-2.63)	(-1.60)	(-0.81)
Profitability	-0.025***	-0.028***	0.003	-0.029***	-0.030***	0.001
	(-8.76)	(-9.23)	(1.18)	(-8.32)	(-8.98)	(0.56)
PP&E	-0.407***	-0.057	-0.350	-0.370***	-0.046	-0.324
	(-14.69)	(-1.36)	(-6.98)	(-11.92)	(-1.04)	(-5.87)
Size	-0.100***	-0.074***	-0.026***	-0.099***	-0.077***	-0.022**
	(-15.21)	(-10.46)	(-2.84)	(-15.02)	(-10.63)	(2.30)
N	73311	41714	115025	59755	37755	97510
adj. R-sq	0.326	0.272	0.324	0.328	0.278	0.325
Fixed Effects	Industry-Year	Industry-Year	Industry-Year	Industry-Year	Industry-Year	Industry-Year
Std Errors Clustered At	Firm,Yr	Firm,Yr	Firm,Yr	Firm,Yr	Firm,Yr	Firm,Yr

Table 8 examines the sensitivity of firms' future sales-to-total assets ratio to firms' financial financial statement information. In columns (1) - (3) we examine the relation between financial statement information in fiscal year *t* and *Sales* in fiscal year *t*+2. In columns (4) - (6) we examine the relation between financial statement information in fiscal year *t* and *Sales* in fiscal year *t*+3. Continuous variables are winsorized at the 2nd and 98th percentiles. Statistical significance at the 10%, 5%, and 1% levels is denoted by *, **, and ***, respectively. All variables are defined in Appendix A.