Market Information and Rating Agency Catering

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Abstract

We examine how the potential for public market scrutiny and the availability of market information affects the credit ratings process. Market information can serve as a disciplining device that limits conflicts of interest arising from the issuer-pay model. Consistent with this view, for a sample of unlisted and listed Indian firms, we find that unlisted firms have higher (i.e., more favorable) ratings than listed firms. The ratings of the former are also less dispersed and are less sensitive to financial condition as reflected in audited financial statements. Consistent with lax rating agency monitoring of unlisted firms, downgrades of listed firms in an industry predict subsequent downgrades of unlisted firms. We do not find a similar pattern for upgrades. Ratings and rating transitions of listed firms are also incrementally more informative about subsequent defaults. Collectively, these findings suggest that lack of market information increases conflicts of interest from the issuer-pay compensation model. The Basel Accords allow banks to condition capital allocation on borrowers' credit ratings. Our study cautions against this practice for unlisted firms.

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

JEL Classifications: K00, G24, M40

1 Introduction

Over the past two decades credit rating agencies have periodically come under significant scrutiny for providing low quality ratings. Critics of the rating agencies point to the "regulatory license" that the agencies grant due to the proliferation of regulations that incorporate credit ratings (Partnoy, 1999, 2006) and the possible conflicts of interest in the issuer-pay compensation model (Jiang et al., 2012, Xia and Strobl, 2012, Cornaggia and Cornaggia, 2013, Xia, 2014, Bonsall et al., 2015, Baghai and Becker, forthcoming) as potential causes for ratings failures.[1] While regulators have undone some of the regulatory reliance placed on ratings in recent years (for instance, the Dodd-Frank Act reduces the reliance placed on credit ratings), credit ratings still play a major role in credit allocation within debt markets. For instance, the Basel Accords (Basel I, II and III) strengthened the use of credit ratings in allowing banks to condition regulatory capital adequacy on borrowers' credit ratings. This rule encourages all firms that borrow from banks – in countries that have adopted the Basel capital adequacy norms – to obtain credit ratings. This is predominantly the case in India where over 5,000 public and private firms have credit ratings.

While there are a number of important differences between public and private firms, we are primarily interested in unlisted firms' lack of market information. We collectively refer to the secondary market prices for equity, debt, analyst coverage and media scrutiny as market information. While public Indian firms have some or all elements of market information, unlisted firms (hereafter, we refer to public and private firms as "listed" and "unlisted" firms, respectively), predominantly lack these institutional features. We examine how these differences in information availability affect the properties of credit ratings of listed and unlisted firms.

Credit rating agencies consider their reputations to be their most valuable asset (Cantor and Packer, 1995, Covitz and Harrison, 2003). However, credit rating agencies routinely face a potential trade-off between acquiescing to borrowers and maintaining respectable

[1] Some have also argued that lower quality ratings are due to weaker reputational concerns arising from increased competition (Becker and Milbourn, 2011).

reputations. While borrowers may benefit from ratings inflation (i.e., catering), credit rating agencies may selectively cater in instances when reputational penalties are limited (Piccolo and Shapiro, 2017). The dearth of market information – and consequently market scrutiny – is one instance where the aforementioned trade-off can favor catering to unlisted firms.

Due to the small size of the public debt market in India,[2] the main consumers of credit ratings in India are banks and their regulator, the Reserve Bank of India (RBI). Banks may benefit from ratings inflation, and hence may prefer or go along with it. For instance, because banks can condition capital allocation on firms' stated credit quality, inflated credit ratings will allow banks to allocate less capital towards the loans they underwrite. Indian banks, in particular, might find this situation favorable, since many banks in India are capital constrained.[3] 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 *quality* of credit ratings. In the case of listed firms, market information will allow the RBI – among others – to better evaluate the quality of these firms' assigned ratings. This check on ratings inflation is more difficult for unlisted firms. In other words, market information could serve as a disciplining device for rating agencies, and the absence of market information could allow the agencies to more freely cater to unlisted borrowers relative to listed borrowers. 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 the audited financial statements.

[2]According to the Reserve Bank of India, non-financial public limited firms in India raised about 27.14 billion Indian rupees through public bond issues in 2015-16 (Reserve Bank of India, 2016).

[3]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, 2015).

The availability of market information can also impact credit rating agencies' monitoring functions. Prior research supports this notion as Bonsall et al. (2015) suggest that credit rating agencies reduce their ongoing monitoring for firms with certain opaque assets. Therefore, we expect downgrades of unlisted firms only under extreme circumstances. Similarly, if downgrades are due to common industry shocks then we expect downgrades of listed firms in an industry to predict subsequent downgrades of unlisted firms. Lastly, the reluctance of rating agencies to downgrade unlisted firms would also imply that their ratings and rating transitions will be less predictive of subsequent defaults, which is arguably rating agencies' most important function (Cantor and Packer, 1995).

We conduct our analyses with Indian firms because of data availability. While coverage of Indian borrowers by rating agencies was relatively sparse in the 1990s, coverage of both listed and unlisted Indian firms increased thereafter. For instance, as of 2015, roughly 5,000 firms were rated, with the largest growth in coverage occurring for unlisted firms. Furthermore, Indian regulations require all firms registered with the Registrar of Companies as a public limited company to file financial statements with the Registrar.[4] However, we note that each state in India has its own Registrar, and each Registrar is responsible for the firms domiciled within its respective state. In addition, market participants can only review firms' information filed with a Registrar if they are willing to travel to a respective Registrar's location and pay the prescribed fee.

While data availability for a large sample of listed and unlisted firms makes India a worthwhile setting to examine our hypotheses, we believe our results can be generalized to other settings such as other emerging markets and the U.S. First, two of the three rating agencies in our sample are affiliates of Standard & Poor's (S&P) and Moody's Investors Service (Moody's). Hence, they employ rating technologies that are similar to their U.S. parents. Second, several countries adopted Basel II within the past decade. Given this, the potential exists for banks in these countries to benefit from inflated credti ratings on private

[4]In India, firms can be incorporated either as a private limited company or a public limited company. Private limited companies are limited to having less than 50 shareholders and have less stringent reporting requirements. Our data source, Prowess, provides data for all listed and unlisted public limited companies.

bank debt, as well as other debt offerings (i.e., asset-backed securities, etc.). Third, 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, while recent regulations have begun to reduce the reliance placed on firms' credit ratings (i.e., Dodd-Frank), overall regulatory 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. This is particularly troublesome given that listed firms' ratings may already be inflated.[5]

We obtain our data from Prowess, a database maintained by the Center for Monitoring the Indian Economy (CMIE). We begin our analysis by comparing the ratings of listed and unlisted firms. We find that unlisted firms have higher (i.e., more favorable) credit ratings throughout our sample period. Specifically, unlisted firms are assigned credit ratings that are roughly 0.60 notches higher than those of comparable listed firms, on average. A one notch rating difference equates to the difference between consecutive letter ratings (i.e., A and A+ on S&P's rating scale).

Our tests are subject to two important identification concerns. First, a firm's listed status is likely to impact multiple aspects of its behavior and performance, and listed firms may be different from unlisted firms along unobserved dimensions. We rely on testing multiple predictions and a number of robustness tests to overcome potential biases due to time-varying unobserved differences. For instance, our inference remains unchanged when we include firm and credit rating agency fixed effects, as well as when we conduct a matched-sample analysis. Second, the sample of firms with credit ratings may be self-selected. In other words, firms that obtain unfavorable ratings may choose not to disclose their ratings. To alleviate this concern, we repeat our tests after imputing pseudo ratings for all firms that experience increases in bank debt greater than ten percent in a given year but that do not have ratings outstanding. Our inferences remain unchanged when we re-estimate our primary tests after

[5]To the best of our knowledge, the only other study to examine private firm credit ratings is Badertscher et al. (2015).

assigning pseudo ratings to both listed and unlisted firms that we expect borrowed from banks but chose not to disclose their credit ratings.

When we compare the sensitivity of ratings of listed and unlisted firms to financial ratios, we find that the ratings of unlisted firms are less sensitive to audited financial ratios relative to those of listed firms. For example, while an approximate 14 basis point increase in *Leverage* results in a one notch decrease in listed firms' credit ratings, a similar increase only translates to a 0.28 notch decrease in unlisted firms' credit ratings, on average. Furthermore, we find that a 25 (14) basis point decrease in *Cash* (*Debt-to-Earnings*) decreases listed firms' credit ratings by one notch, on average. However, unlisted firms' *Cash* (*Debt-to-Earnings*) is not statistically related to their ratings. These results suggest that rating agencies put less emphasis on quantitative factors such as *Leverage*, *Debt-to-Earnings*, and *Cash* when rating unlisted firms relative to listed firms.

On average, the unlisted firms in our sample have both higher *Leverage* and higher *Debt-to-Earnings* ratios as compared to listed firms. These features, combined with the lower sensitivity of their ratings to leverage, helps explain unlisted firms' higher ratings. In other words, if unlisted firms' ratings were as sensitive to leverage as those of listed firms', then the "higher" leverage of unlisted firms would result in them having lower ratings than they are assigned. Collectively, our results suggest that not only do rating agencies assign higher (i.e., more favorable) ratings for unlisted firms but that they also selectively alter their rating methodology by reducing the emphasis placed on quantitative factors in their analysis.

Consistent with lax credit rating agency monitoring, we find that unlisted firms have fewer rating changes over the course of a fiscal year when compared to listed firms. The fewer rating changes are due to unlisted firms having fewer rating downgrades than listed firms. We also investigate the predictability of ratings changes within the same industry. We find that downgrades of listed firms predict subsequent downgrades of unlisted firms in the same industry. However, we do not find a similar pattern for upgrades. This asymmetry indicates that while rating agencies are slow in downgrading unlisted firms, they do not exhibit a similar pattern when it comes to upgrading unlisted firms. When we examine the ability for ratings and ratings changes to predict subsequent default, we find that listed firms' ratings and rating changes have greater sensitivity to subsequent defaults. Alternatively stated, listed firms' ratings convey more information about subsequent defaults. Collectively, these results suggest that rating agencies engage in lax monitoring of unlisted borrowers.

We conduct several robustness tests to further alleviate the aforementioned identification concerns with our analysis. Unlike the U.S. audit market, India's audit industry is highly fragmented. While we include auditor fixed effects throughout our analyses, we also re-estimate our primary analysis by confining the sample to auditors that serve both listed and unlisted firms. This further ensures that differences across auditors, and thus differences in firms' financial statement quality, do not bias our primary findings. Next, we examine whether the financial characteristics of unlisted firms are inherently less informative about future financial performance relative to listed firms. When we examine the sensitivity of future firm sales (and profits) to current financial characteristics, we find no significant difference 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.

Currently, scant evidence exists that examines the relationship between ratings inflation and firms' listed status. Our study provides unique evidence that unlisted firms may benefit from ratings inflation relative to listed firms. This is significant as the majority of firms in most geographies are privately held (Doidge et al., 2017). In addition, a related study by Badertscher et al. (2015) 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; thus the lack of market information and its disciplining role appears to dominate the effect of limited capital market access in influencing the rating properties of unlisted firms.

While prior studies have examined the potential for ratings inflation in both the corporate bond and asset-backed securities markets, our paper is the first to examine the potential for ratings inflation in the private debt market. This is significant as prior research suggests that a negative relation exists between firms' credit quality and firms' ability to issue public debt (Kisgen, 2006, Rauh and Sufi, 2010); thus firms may opt or be forced to obtain private debt financing before they can obtain public debt financing. This may be particularly true for private firms relative to public firms if the former are typically smaller and less financially sound.

Prior research that studies the ability of the market to produce incremental information about a firm's credit quality examines the stock and bond market reactions to rating changes (Hand et al., 1992, Jorion et al., 2005). Isolating the impact of information content around rating changes from these studies is cumbersome because the market is likely to react both to the information revealed by the rating change and to the effect of the rating change on future firm performance (Kisgen, 2006, Kisgen and Strahan, 2010). However, by comparing the ratings of listed and unlisted firms, we isolate the role of market information availability in the ratings process.

While prior research presents some evidence that suggests that credit rating agencies do not apply their rating standards uniformly across asset classes (Cornaggia et al., 2016), there is no evidence to suggest that rating agencies employ different rating methodologies for listed versus unlisted corporate debt issuers.[6] Our study extends prior research by providing new evidence that rating agencies alter their rating methodologies *within* asset classes.

Prior research also suggests that while external market participants discipline rating agencies around bond offerings, the threat of discipline declines post-issuance as external market participants' attention declines. This results in lax ongoing rating agency monitoring, particularly for both qualitative and/or opaque firm characteristics (Bonsall et al., 2015, Kraft, 2015). Our study extends prior research by highlighting that rating agencies cater to certain borrowers via differential *quantitative* analysis of non-opaque quantitative characteristics.

.Our study is the first to suggest that external market participants (i.e., banks) influence

[6] Conversations with rating agency personnel both in India and the U.S. indicate that in their view they employ the same methodology across both geographies and firms.

credit rating agencies' catering/monitoring incentives, resulting in inflated credit ratings for unlisted firms. Given this, our results suggest 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.[7] Our results also suggest that banks should exercise caution in linking the interest rates on their loans to the credit ratings of unlisted borrowers. However, it is important to note that even if one were to eliminate the quality difference in ratings between listed and unlisted firms, the conflicts inherent in the issuer-pay model illustrated by prior studies with regard to listed firms caution against over reliance on ratings for bank capital allocation.

2 Background on the Indian Credit Rating Market and Hypothesis Development

2.1 Background on the Indian Credit Rating Market

After gaining independence from Britain in 1947, India entered a period marked by centralized planning. During this time, certain industries, particularly those in manufacturing, were subject to a number of regulations that limited economic growth. For instance, until the early 1980s, the Indian economy grew at a rate of roughly three percent per annum (Panagariya, 2008). However, liberalization in the mid-1980s and a welcoming of both trade and capital flows predominantly in 1991 allowed India's economy to expand at a roughly six percent rate per annum thereafter. This resulted partly from the Indian government's decision to reduce state control, thus limiting government intervention, as well as a reduction in the number of regulations that were created prior to liberalization. Collectively, these

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

actions allowed the private sector to play a greater role in India's economy, which benefitted from various market-oriented mechanisms (Bhagwati, 1993, Panagariya, 2008).

While the impact of India's liberalization was dramatic for the country's equity market, the impact of liberalization on India's public debt markets were much less extraordinary. For instance, while several banking reforms were initiated in 1992 in an effort to liberalize the sector and increase banking competition, little had been done to circumvent key problems with public debt markets (Khatakhate, 2002, Mohan, 2009). A primary concern in India's debt markets relates to the lack of expediency in resolving litigation. For instance, India's insolvency laws are particularly weak, with the average claim taking roughly 10 years to complete (Goswami, 2003, Batra, 2003). This problem is magnified by the fact that India has traditionally had a small number of judges per capita, and that lawyers are typically paid by appearance and thus have an incentive to extend the duration of litigation. Given this, it is unsurprising that India's aggregate bank credit has grown substantially over time, while the market for corporate debt remains almost nonexistent.[8]

The credit rating industry in India started 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.

[8] For a more thorough historical perspective on India's economy and its capital markets, see Armour and Lele (2009).

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.

2.2 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, both Bolton et al. (2012) and Bar-Isaac and Shapiro (2013) argue that rating agencies may allow their reputations to wane in periods of significant economic growth, only to rebuild them during and after an economic downturn. In addition, Kraft (2015), Baghai and Becker (forthcoming), Griffin and Tang (2012), Griffin et al. (2013), and Cornaggia et al. (2016) provide evidence of inflated ratings in different contexts, while Bonsall et al. (2015) and Bruno et al. (2016) provide evidence of variability in rating agency monitoring based on their incentives. These studies suggest that rating agencies can strategically alter their rating methodologies in certain instances for listed firms, as well as the importance placed on their reputations. In our setting, the presence of market information for listed firms may serve as a mechanism to discipline rating agencies' actions, and thus limit their ability to adjust their rating methodologies relative to unlisted firms.

The primary consumers of credit ratings in India are banks. While banks may care about the quality of unlisted firms' credit ratings, several incentives exist which may cause banks to prefer inflated credit ratings. First, as ratings increase (i.e., move towards AAA), banks can hold less equity relative to assets. Second, banks can improve their short-term accounting-based performance by provisioning less against expected loan losses, since provisioning itself may be a function of credit ratings. Thus, banks have a regulatory incentive to encourage less stringent rating methodologies by rating agencies for unlisted borrowers.

Credit rating agencies may also have fewer reputational concerns when assigning credit ratings to unlisted firms. This is due to the fact that unlisted firms' information environments are generally more opaque than those of listed firms. This opacity reduces external parties' ability to evaluate any differences in their assessments of unlisted firms' creditworthiness versus those of the credit rating agencies. Such is the case for India's primary bank regulator, the RBI, as market information will allow the RBI to better evaluate the quality of listed firms' assigned credit ratings relative to unlisted firms. Collectively, we refer to these arguments as the *Disciplining hypothesis*.

Credit rating agencies may be influenced by banks' incentives for certain borrowers to obtain more favorable credit ratings, coupled with lower threats of detection of ratings inflation by external market participants. Thus, our first prediction under the *Disciplining hypothesis* is that ceteris paribus, credit ratings for unlisted firms will be higher (i.e., more favorable) than they are for listed firms. Lower reputational costs may also result in credit rating agencies failing to respond to changes in credit risk determinants for unlisted firms relative to listed firms. Thus, our second predication under the *Disciplining hypothesis* is that the credit ratings of unlisted firms will be less sensitive to their financial condition as reflected in the audited financial statements relative to listed firms.

Prior research suggests that lower fees, ongoing costs, and reduced reputational concerns cause credit rating agencies to engage in lax borrower monitoring for certain opaque asset classes (Bonsall et al., 2015). If limited market information increases rating agencies' incentives to cater to borrowers then this lax monitoring may be asymmetric. In other words, while rating agencies may be lax in downgrading unlisted firms, they may be prompt in upgrading them. On the other hand, the securities market and other intermediaries may limit the laxity of rating agencies in their monitoring of listed firms. Therefore, we predict that credit rating agencies will downgrade unlisted firms less often relative to listed firms. If the rating transitions are due to common industry shocks, then the rating changes of listed firms (especially with respect to downgrades) will predict subsequent rating changes of unlisted firms within a given industry. In addition, to the extent the ratings of listed firms impound more information, they are likely to be more informative about future defaults. In contrast, rating agencies' lax monitoring of unlisted firms' will make their ratings less informative about future defaults. Thus, we predict that defaults of listed firms will be more sensitive to prior ratings and prior rating changes relative to defaults of unlisted firms.

A large literature in finance and accounting highlights that the secondary stock and bond markets produce incremental information about a firm's financial condition and that managers and other market participants learn from this information (Bond et al., 2012, Chen et al., 2007). This informational role could ultimately reduce the rating agencies' overall uncertainty about the credit quality of listed firms relative to that of unlisted firms, which should result in more favorable credit ratings for the former (Ganguin and Bilardello, 2005).[9] Prior research suggests that the rating agencies' reputations are their most valuable asset, and that inaccurate ratings will be of little value to market participants (Cantor and Packer, 1995, Covitz and Harrison, 2003). Thus, credit rating agencies may not cater to unlisted firms relative to listed firms by any meaningful degree, especially 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. Lastly, unlisted firms' default risk could be greater than that for listed firms, given the former's limited access to capital (Badertscher et al., 2015). Any of these arguments, if true, would bias us from finding support for the *Disciplining* hypothesis.

[9] Consistent with this notion, Odders-White and Ready (2006) find that firms with greater adverse selection have lower (i.e., more conservative) ratings.

3 Data and Sample Selection

3.1 Data

We obtain the data to conduct our empirical tests from Prowess, a database maintained by the CMIE, which has been used by a number of prior studies on Indian companies, including Bertrand et al. (2002), Gormley et al. (2012), Gopalan et al. (2007), and Baghai and Becker (forthcoming). Prowess provides annual financial statement information and other characteristics, such as firms' industry classifications, auditor identification, as well as firms' 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 the 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 highest market share in India.[10]

Indian firms often have credit ratings for different types of debt instruments such as structured products, term loans, term deposits, and corporate debt. For our analysis, we focus on the ratings of long-term loans and debt products for which the rating scale closely matches that of the long-term debt scale in the United States.

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

[10]For more background information on CARE, please visit: www.careratings.com/about-us

assigned to the firm's debt 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. 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]

From the overall sample of Prowess firm-year observations from 1991 to 2015, we exclude all financial firms (NIC codes: 641 - 663), firms owned wholly or partially by the government or a 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.

Banks may sometimes require firms to provide credit enhancements on their borrowings. Given their opaque nature, unlisted firms may be required to provide such enhancements more often than listed firms. Debt securities with such credit enhancements are typically referred to as "structured obligations" by the rating agencies.[12] To the extent rating agencies take into account such credit enhancements, unlisted firms' loans may be assigned more favorable credit ratings relative to listed firms. To alleviate the concern that this could bias our findings, we exclude all ratings of structured obligations from our analyses. Furthermore, while the presence of credit enhancements may explain the higher ratings of unlisted firms, they are less likely to explain some of our subsequent results such as the predictability of downgrades within an industry and the differential sensitivity of defaults to prior downgrades. Finally, the role of credit enhancements in helping lenders recover money is questionable in India due to its weak contract enforcement regime (Gopalan et al., 2016a).[13]

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

[12] Consistent with the rating agencies taking into account such credit enhancements, CRISIL states that "CRISIL's rating on structured obligations reflects CRISIL's opinion on the degree of credit protection provided by the credit enhancement structure. The assessment takes into consideration arrangements for payment on the instrument by an entity other than the issuer to fulfill the financial obligations on the instrument. It also takes into account other means of enhancing the credit quality of the rated obligation" (CRISIL Ratings, 2010).

[13] 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 credit ratings.

3.2 Summary Statistics

Table 1 provides summary statistics of the key variables we use in our analysis. We have a total of 14,139 (155,416) firm-year (firm-month-year) observations in our sample. We model credit 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 2% and 98% levels.[14]

From Table 1, the mean value of *Rating* is 12.41, 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.[15] Indian firms in our sample have leverage comparable to that of U.S. firms. For instance, the average *Leverage* in our sample is 0.36, while the average leverage among U.S. firms featured in Compustat is 0.30. The mean *Interest Coverage* for our sample is 9.53, slightly higher 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 0.17. Furthermore, Indian firms in our sample have higher *PP&E* as compared to U.S. firms. The mean *PP&E* for our sample is 0.53, 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 half of the firms 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.[16]

[14] We also estimate our empirical tests after winsorizing at the 1% levels; our inferences remain unchanged.

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

[16] 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. Please refer to Table 1 of the Internet

Table 2 reports the mean differences for the variables that we use in our analysis for listed and unlisted firms. We find that on average listed firms have credit ratings that are 1.54 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 to BBB+ (BBB) on S&P's rating scale, both of which are investment-grade. Interestingly, once we control for the known determinants of credit ratings, listed firms actually have lower ratings than unlisted firms. In our sample, unlisted (listed) firms are upgraded 3,736 times (1,881 times), which is roughly 54 percent (39 percent) of all unlisted (listed) firm rating changes. Conversely, there are 3,219 (2,890) unlisted (listed) firm downgrades, or roughly 46 percent (61 percent) of all unlisted (listed) firm 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 unlisted firms relative to listed firms. We find that unlisted firms have higher leverage as compared to listed firms (mean *Leverage* of 0.38 as compared to 0.34, 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 credit ratings.

Column (3) of Table 3 displays summary statistics for our sample of individual securities that eventually default (i.e., receive a "D" credit rating). One year prior to default, these issues have an average rating of 8.77, which is between BB and BB-. As these firms get into financial distress and head towards default, their ratings progressively decline. One month prior to default, they have an average rating of 7.93, 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

Appendix for this analysis.

from 8.06 to 7.70 (column (4)), a 0.36 notch decline, those of listed firms' decline from 9.93 to 8.30 (column (5)), a 1.63 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 credit 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.

4 Research Design and Empirical Results

4.1 Ratings and Listed Status

4.1.1 Ratings Levels

As mentioned in section 2, the *Disciplining hypothesis* predicts that unlisted firms will be assigned more favorable credit ratings relative to listed firms. 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*)[17] , $\frac{Cash}{Assets}$ (*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' credit ratings with their most recent fiscal year-end financial information. We control for within industry-year fixed effects, in addition to auditor fixed effects.[18] 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 the *Disciplining hypothesis*, we find that the coefficient on *Unlisted* is positive and statistically significant at the 0.01 level. Specifically we find that unlisted firms' credit ratings are on average 0.609 notches higher than those of comparable listed firms.[19] These results are consistent with rating agencies providing more favorable ratings when market discipline is weak or nonexistent. Focusing on the coefficients

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

[18]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.

[19]These magnitudes are in-line with recent research which examines ratings inflation. For instance, Baghai and Becker (forthcoming) 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.

on the control variables, we find that firms with lower leverage, firms with lower debt-to-earnings, firms with more cash, and firms with higher interest coverage ratios have more favorable credit ratings. This is consistent with lower leverage, measured in different ways, being correlated with higher credit ratings. Furthermore, ceteris paribus, 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 credit ratings.

In column (2) we consolidate our observations at the firm-fiscal year level and repeat our analyses. Our dependent variable is the average rating for the fiscal year-end month.[20] We find that the coefficient on *Unlisted* continues to be positive and statistically significant at the 0.01 level. The size of the coefficient is also comparable to that in Column (1). In addition, the coefficients on the control variables in column (2) are similar to those in column (1). Collectively, these findings support the *Disciplining hypothesis* in that unlisted firms are assigned more favorable credit ratings than listed firms.

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 control for time invariant differences between listed and unlisted firms via the inclusion of firm fixed effects. In addition, the propensity for multiple large rating agencies to provide a rating for a given firm in India is much smaller than it is in the United States. In other words, Indian firms can choose their rating agency. If unlisted firms systematically choose a different rating agency as compared to listed firms, then this could bias our results. To alleviate this concern, we employ rating agency fixed effects in our analyses.

In columns (3) and (4) of Panel A of Table 4 we present our results after including firm fixed effects and rating agency fixed effects. We find that the coefficient on *Unlisted* continues to be positive and statistically significant at the 0.10 level in both columns. Collectively, these findings add further support for the notion that market information serves a disciplining

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

mechanism for credit rating agencies, resulting in more favorable credit ratings for unlisted firms relative to listed firms.

Our results in columns (3) and (4) with firm fixed effects show that ceteris paribus, firms that transition from being unlisted to listed experience a decrease in their ratings.[21] In Panel B of Table 4 we illustrate this in a more intuitive manner by comparing the average difference between actual and expected ratings (the *RatingsGap*) for the subset of firms that change their listing status during our sample period. We provide the average value of their *RatingsGap* during the times when they are both unlisted and listed. According to the results in Panel A, we expect the *RatingsGap* to be higher when the firms are unlisted as compared to when they are listed.

We calculate expected ratings using two alternate methods. We first estimate equation (1) on a subsample of firms that remain listed throughout our sample period and obtain the loadings (betas). We combine these loadings and the characteristics of firms that transition to calculate the expected rating. We provide the *RatingsGap* based on this methodology in column (1). We find that the average *RatingsGap* is 0.461 when the the firms are unlisted. This coefficient is statistically significant at the 0.01 level. Thus, the actual ratings of these unlisted firms is 0.461 notches higher than what it would have been if they were rated using the model that best fits the ratings of listed firms. The positive and statistically significant coefficient of 0.173 in column (1) indicates that the ratings of the (transitioning) firms is higher than expected even during the period they are listed. We further find that the difference in *RatingsGap* of 0.289 is positive and statistically significant below the 0.01 level, indicating that the *RatingsGap* is higher when these firms are unlisted as compared to when they are listed. In column (2), we repeat our procedure by using the loadings estimated from a subsample of firms that remain unlisted throughout our sample. Our findings are similar to those reported in column (1).[22] Collectively, these findings suggest that credit rating

[21] Note that in a model with firm fixed effects, the coefficients are only identified using within firm variation. Alternatively, firms that transition in the other direction experience a ratings increase.

[22] Note that the magnitude of our effects estimated in Panel B will not match those in Panel A for two reasons. First, we only include firm fixed effects in Panel A. Second, while in Panel A we estimate one average loading for both listed and unlisted firms, in Panel B we use alternate loadings estimated with only listed and only unlisted firms to measure the *RatingsGap*.

agencies alter their rating methodologies once firms alter their listing status in a manner consistent with the *Disciplining 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.[23] 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 Appendix B, we compare the characteristics of the unlisted firms and their matched listed firms after grouping variables into matching and control variables. We identify 1,805 unlisted and listed firms in our matched sample. When we compare our control variables after matching on *Debt-to-Earnings* and *Profitability*, we find that listed firms are larger, have lower leverage, and greater interest coverage. Our matches have roughly equal asset tangibility and cash balances. In columns (6) and (7) of Appendix B, we compare the median values and distribution, respectively, of our matching and control variables and report the p-values of the comparisons. We find that listed and unlisted firms in our sample are indistinguishable along *Debt-to-Earnings* and *Profitability*. In column (8), we present the scaled difference. This is similar to a t-statistic and helps estimate the goodness of the match. Imbens and Rubin (1997) suggest that linear controls are adequate if the absolute value of the scaled difference is less than 0.25. We find that the absolute value of the scaled difference is less than 0.25 for all variables other than *Size* and *Group Membership*. The large difference in size is one of the reasons we do not include *Size* as one of the matching

[23]We prefer to match on ratios with income statement variables because they do not rely on size as a scaling variable.

co-variates. Its inclusion significantly reduces the size of treated and control samples. To account for the size difference, we percentile-rank observations by *Size* and include 99 *Size* percentile-rank fixed effects (one category is excluded to be the base case). Furthermore, we include indicator variables for whether the firm is part of a larger conglomerate throughout our analyses (*Group Membership*). Since this variable takes a value of 0 or 1, it is equivalent to including *Group Membership* fixed effects.

In Panel C of Table 4 we re-estimate equation (1) within the treated and control matched sample. Consistent with our prior findings, unlisted firms continue to have higher 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.[24]

In contrast to the United States, firms in India can choose to not disclose their ratings. Figure 2 shows why this issue may be problematic for our setting. Specifically, it shows the ratio of firms that have more than a 10% increase in bank debt and have at least one rating outstanding. 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.[25]

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

[24]In untabulated analyses, we re-estimate our matched sample analysis by including both firm and year fixed effects. We also re-estimate our primary analysis from Panel A of Table 4 by replacing *Size* with *Size* percentile-rank fixed effects. Our inferences remain unchanged to these alternate specifications. Please see Table 2 of the Internet Appendix for these analyses.

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

effects. While the coefficient on *Unlisted* is smaller than those reported in Panel A of Table 4, they are statistically significant below the 0.10 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. These results provide further support that rating agencies provide inflated ratings to unlisted firms relative to listed firms, consistent with the *Disciplining hypothesis.*

It is possible for our primary findings to be biased by a correlated omitted variable. To evaluate the gravity of this issue, we calculate the magnitude of the correlated omitted variable required to overturn our findings (Frank, 2000, Larcker and Rusticus, 2010). We find that a correlated omitted variable would need an impact score that is at least 1.07 times (untabulated) larger than that of any of our controls (most notably *Profitability*) to overturn our results. Given our model's adjusted R-squared of 0.687 in column (1) of Table 4 Panel A, it seems unlikely that such a variable exists.

4.1.2 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 columns (1) - (3) of Table 5 at the firm-month-year level. We present the sensitivities of unlisted firms in column (1), of listed firms in column (2), and the difference between the coefficients in column (3). Consistent with the *Disciplining hypothesis*, we find that the credit 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 14 basis point increase in *Leverage* decreases listed firms' credit ratings by one notch (.14 × 7.360=1), the same increase in *Leverage* for unlisted firms only decreases their ratings by 0.28 notches (.14 × 1.980=0.28). In contrast, while a 14.3 basis point increase in listed firms' *Debt-to-Earnings* increases their credit ratings by one notch, changes in *Debt-to-Earnings* are not statistically related to unlisted firms' ratings. Likewise, while a 25 basis point increase in *Cash* decreases listed firms' credit ratings by one notch, unlisted firms' credit ratings are not significantly related to *Cash*.

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 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. We present these findings in columns (4) - (6) of Table 5. We find that our results are consistent with those reported at the firm-month-year level in columns (1) - (3). 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.

The lower sensitivity of unlisted firms' ratings to firm financial condition may also imply that the ratings of unlisted firms may be "bunched" together as compared 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 tow 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. (forthcoming) 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 5.6 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 4.2 for listed firms. The difference between these two numbers is statistically significant (t-statistic = 6.99), suggesting that the discontinuity at the investment-grade threshold is greater for unlisted firms as compared to for listed firms.

4.2 Credit Rating Agency Monitoring and Listed Status

4.2.1 Frequency of Ratings Changes

The *Disciplining hypothesis* predicts that unlisted firms will have fewer downgrades than listed firms. The lower sensitivity of unlisted firms' ratings to changes in *Leverage* (as well as a lack of sensitivity to *Debt-to-Earnings* and *Cash*) that we document in section 4.1.2 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 and year fixed effects instead. When *Log(SumRatingChanges)* is our dependent variable (column (1)), we find that the coefficient on *Unlisted* is negative and statistically significant at the 0.01 level. We find a similar result when *Log(SumDowngrades)* is our dependent variable (column (2)). However, we find no statistically significant result for upgrades *(Log(SumUpgrades))* 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 face less scrutiny from the market in assigning ratings, ratings changes, specifically downgrades, occur less frequently for unlisted firms relative to listed firms. These results offer evidence consistent with lax monitoring.

4.2.2 Predictability of Ratings Changes

Because unlisted firms' credit rating changes occur less frequently than those for listed firms, rating agencies may be slower to incorporate common shocks that may affect both listed and unlisted firms. A consequence of delayed incorporation of industry-level news is that credit rating changes for listed firms should predict subsequent changes in the ratings of unlisted firms within an industry. We test this prediction using a model similar to equation (1). Our sample for these tests is confined to unlisted firms. The dependent variables in these tests are either *Downgrades>0* or *Upgrades>0,* which are defined as indicator variables equal to one if at least one security was downgraded or upgraded, respectively, for a particular unlisted firm over the course of a given month. The main independent variables are either the natural log of one plus the number of listed firm downgrades (*Ln(Listed Firm Downgrades)*) or the natural log of one plus the number of listed firms' upgrades (*Ln(Listed Firm Upgrades)*) in the same industry over three alternate time windows: one month (months m-1 to m), three months (months m-3 to m) and six months (months m-6 to m). We include the change in financial characteristics that were employed in Table 6 as control variables, along with industry-year fixed effects.

We present our results in Table 7. We suppress the coefficients on the control variables for brevity. From columns (1), (3), and (5) we find that the coefficients on *Ln(Listed Firm Downgrades)* are positive and statistically significant at the 0.05, 0.10, and 0.05 levels, respectively. This indicates that downgrades of listed firms in an industry predict subsequent downgrades of unlisted firms in the same industry. Interestingly, the coefficients on *Ln(Listed Firm Upgrades)* in columns (2), (4), and (6) are statistically insignificant. Thus, upgrades of listed firms do not predict subsequent upgrades of unlisted firms. Collectively, the asymmetry between upgrades and downgrades indicates that when upgrading unlisted firms' credit ratings, rating agencies do not show the same laxity that they show for downgrades. These results are consistent with lax monitoring via the *Disciplining hypothesis.*

4.2.3 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.[26] To the extent the rating agencies are lax in their monitoring of unlisted firms, rating changes

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

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 get 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 while being 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 8. 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 a lower rating the previous month. We also find that in absolute terms, the coefficient on *Rating* for listed firms is roughly 100% larger than the coefficient for unlisted firms. 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 0.05 level (column (6)). Economically, these results suggest that a one standard deviation decrease in listed firms' ratings increases the likelihood of default in the next month by approximately 1.8 percent. In contrast, a one standard deviation decrease in unlisted firms' credit ratings only increases the likelihood of default by 0.9 percent.

In Panel B of Table 8, 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 0.10 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, consistent with the *Disciplining hypothesis.*

Note that the lax monitoring of rating agencies as a firm approaches default can prove costly because it prevents the lenders from obtaining prior warnings of impending defaults. This will not only result in banks under-provisioning for possible losses on the loans but may also preclude them from intervening early enough to restructure the loan.

4.3 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.

4.3.1 Auditor Coverage

Differences across auditors could impact the quality of firms' financial statements, which could bias our primary findings The audit industry in India is highly fragmented. For instance, Panel A of Table 9 shows that there are over 16,000 audit firms in the Prowess Auditors dataset. The average number of clients per firm is 3.8, much smaller than the large, diverse client bases of the Big 4 auditing firms in the United States. Given this, auditor fixed effects may prove inadequate to control for audit quality if there are systematic differences across auditors in terms of their propensity to audit listed versus unlisted firms. Therefore, we focus on auditors that audit reasonably equal proportions of listed and unlisted firms (i.e., those whose client base comprises of 40 to 60 percent of unlisted firms). In Panel B of Table 9, we find that we have over 900 audit firms that satisfy this criteria and that they audit 7.2% of the firms in our sample.

We re-estimate equation (1) within the subsample of firms audited by the restricted set of auditors and present the results in Panel C of Table 9. As shown in columns (1) and (2), our results are stronger in this augmented analysis, despite the significantly reduced sample size. Collectively, these results reinforce the robustness of our main findings to controlling for the quality of firms' audited financial statements.

4.3.2 Predictability of future firm performance

If audited financial statements of unlisted firms are 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 10 show that there are no systematic differences across unlisted and listed firms in the ability of financial statement characteristics to predict future sales.[27] Perhaps more importantly,

[27]For robustness, we also perform this test on firm sales in fiscal year t+1 and our inferences remain unchanged. We also employ future firm profitability as our measure of future firm performance and our

we do not find any difference 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.

4.3.3 Unlisted Firms' Propensity for Greater Information Sharing

Given their limited access to financial markets, unlisted firms are likely to depend on credit ratings to a greater extent to gain access to external capital. Credit rating agencies state that uncertainty during the rating process should result in more conservative (i.e., less favorable) ratings (Ganguin and Bilardello, 2005). In addition, prior literature suggests that credit rating agencies are more likely to disagree over their credit risk assessments of firms that either exhibit greater overall uncertainty or that fail to provide transparent disclosures (see Morgan (2002), Livingston et al. (2007) and Bonsall et al. (forthcoming)), resulting in a greater propensity for and magnitude of "split ratings" (i.e., disagreement) between major rating agencies. In the context of our study, our primary findings could manifest if unlisted firms provide more information to the rating agencies compared to listed firms in an effort to reduce uncertainty during the rating process. If true, unlisted firms should experience less rating agency disagreement relative to listed firms. In untabulated analyses, we do not find evidence of less disagreement among rating agencies for unlisted firms relative to listed firms. Thus, our primary findings do not appear to be due to greater information sharing by unlisted firms during the rating process (see Table 4 of the Internet Appendix).

4.3.4 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

inferences remain unchanged to this alternate specification (untabulated). Please refer to Table 3 of the Internet Appendix for this analysis.

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 (forthcoming) 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 revenue in our primary analysis (untabulated).[28]

Lastly, Figure 4 shows that ratings activity for listed and unlisted firms increased dramatically in 2008, when bank capital regulations increased their reliance on external credit rating agencies for risk-based capital purposes. To ensure that our primary results are not confined to the post-2008 period, we segment our sample into observations before and after 2008. We find that our results (untabulated) remain in both the pre- and post-2008 time periods (see Table 6 of the Internet Appendix).

5 Conclusion

In this study, we use a unique dataset of listed and unlisted Indian firms to examine the relation between listing status and credit ratings. If market information primarily helps to inform credit rating agencies, then they will face lower uncertainty about the credit quality of listed borrowers. On the other hand, the availability of market information could serve as a disciplining device for rating agencies, in the absence of which they are more likely to cater to unlisted borrowers.

[28] We thank Ramin Baghai and Bo Becker for sharing their data on non-rating revenue for Indian credit rating agencies. Please refer to Table 5 of the Internet Appendix for this analysis.

Our evidence is consistent with market information serving a disciplining role. After controlling for common determinants of credit ratings, unlisted firms have systematically higher ratings than listed firms. These results persist even after we match unlisted and listed firms on observable characteristics. Moreover, we find that unlisted firms' credit ratings exhibit less sensitivity to financial ratios than those of listed firms. We take this decreased sensitivity as evidence that rating agencies re-calibrate their methodologies for unlisted firms relative to listed firms.

We also examine whether credit rating agencies alter their ongoing monitoring efforts for unlisted firms relative to listed firms. We find that rating agencies monitor both unlisted firms and listed firms inconsistently. Specifically, for any given firm-fiscal year, after controlling for known credit risk determinants, unlisted firms' credit ratings change less often as compared to those of listed firms. Further, downgrades of listed firms in an industry predict subsequent downgrades of unlisted firms within that same industry. Consistent with rating agencies impounding more default-relevant information into credit rating assignments for listed firms, their credit ratings and their respective rating changes are more informative about future defaults as compared to those of unlisted firms.

Overall, our study contributes to the growing academic literature on credit ratings by being the first to evaluate the role of market information in the credit rating process. While prior work examines the information content of ratings by examining their association with bond prices or yields, we examine whether the availability of market information impacts the credit rating process. We also extend our understanding of how credit rating agencies cater to debt issuers and document how listed status, one of the most important choices that a firm can make, affects the quality of credit ratings.

Our study provides the first evidence to suggest that rating agencies alter their rating methodologies *within* asset classes. In addition, our findings highlight that external market participants negatively influence the rating agencies' catering incentives. This is unique as prior research provides evidence that suggests that external parties discipline rating agencies in certain circumstances. Given our results, we urge caution in using credit ratings as a suitable signal of unlisted firms' creditworthiness as it may decrease the overall stability of financial institutions.

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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 the text (see 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.

Appendix B: Mahalanobis Matching Median Comparison

$$T = \frac{\overline{X_1} - \overline{X_0}}{\sqrt{S_1^2 + S_0^2}}$$

Variable	N		Values		p-values		
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Unlisted	Listed	Unlisted	Listed	Medians	Distribution	Scaled Difference
Matching Variables							
Debt-to-Earnings	1,805	1,805	2.774	2.767	0.973	0.990	0.009
Profitability	1,805	1,805	0.110	0.111	0.920	1.000	0.005
Control Variables							
Leverage	1,805	1,805	0.374	0.347	0.003	0.000	0.086
Cash	1,805	1,805	0.011	0.011	0.764	0.690	-0.012
Interest Coverage	1,805	1,805	2.22	2.31	0.369	0.350	-0.031
PP&E	1,805	1,805	0.489	0.489	0.973	0.100	-0.037
Size	1,805	1,805	7.415	8.314	0.000	0.000	-0.425
CRA Coverage	1,805	1,805	1.000	1.000	0.006	0.960	-0.068
Group Membership	1,805	1,805	0.000	0.000	0.000	0.000	-0.298

This table presents a comparison of the treated (unlisted) and matched control (listed) firm-year observations. The matched control firms are from the same industry-year as the treated firms and are closest in terms of *Debt-to-Earnings* and *Profitability*. We employ the *Mahalanobis* distance to identify the closest match. Column (8) reports the scaled difference statistic proposed by Abadie and Imbens (2016). All variables are winsorized at the 2nd and 98th percentiles. All variables are defined in Appendix A.

Figure 1: Distribution of Credit Ratings for Defaulted Firms

Figure 1(a) - Listed Firms

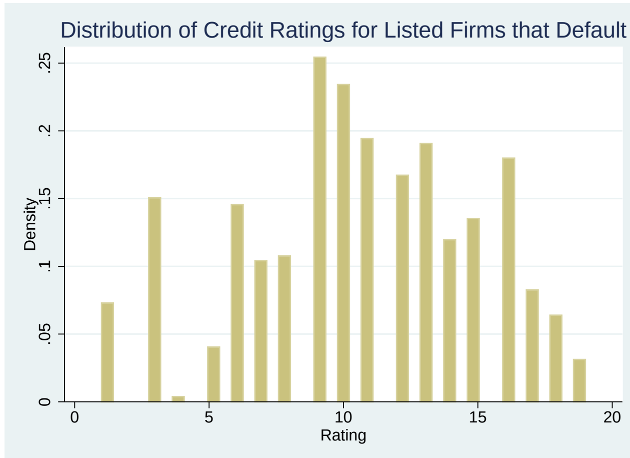

Figure 1(b) - Unlisted Firms

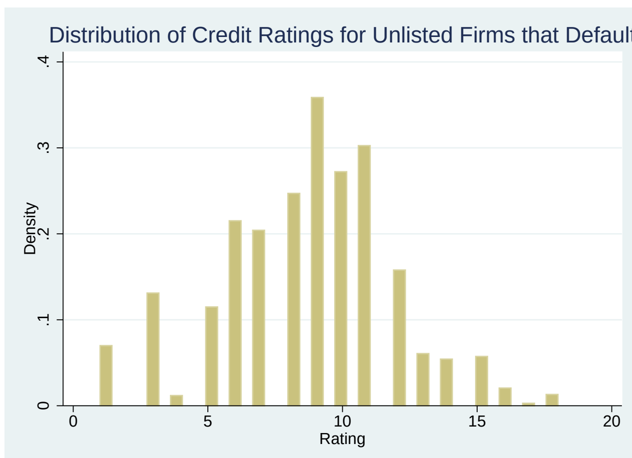

Figure 1 shows the distribution of credit ratings for firms that default partitioned on listed status. Panel A shows the sub-sample of issue-month-year observations for listed firms. Panel B shows the sub-sample of issue-month-year observations for unlisted firms. Rating is an ordinal number from 1 to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

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

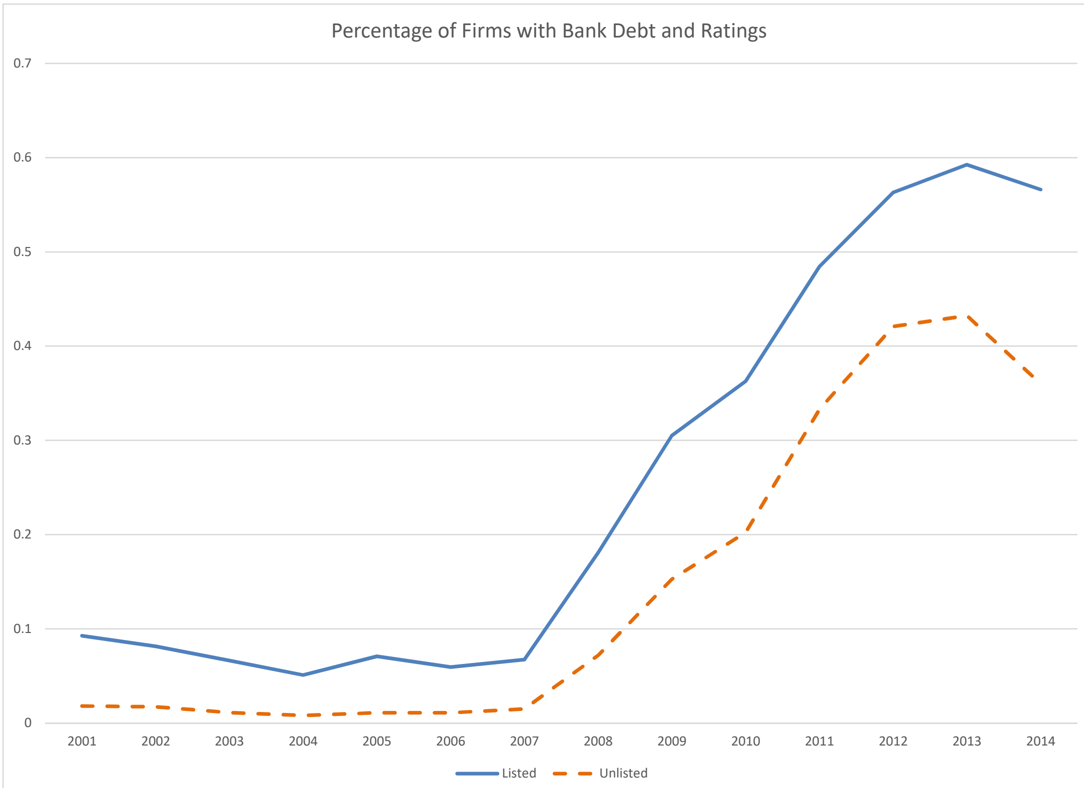

Figure 2 plots the percentage of listed and unlisted firm-years over time that have more than a 10% increase in bank debt and have at least one rating outstanding. The orange dotted line represents the data for unlisted firms while the solid blue line represents the data for listed firms.

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

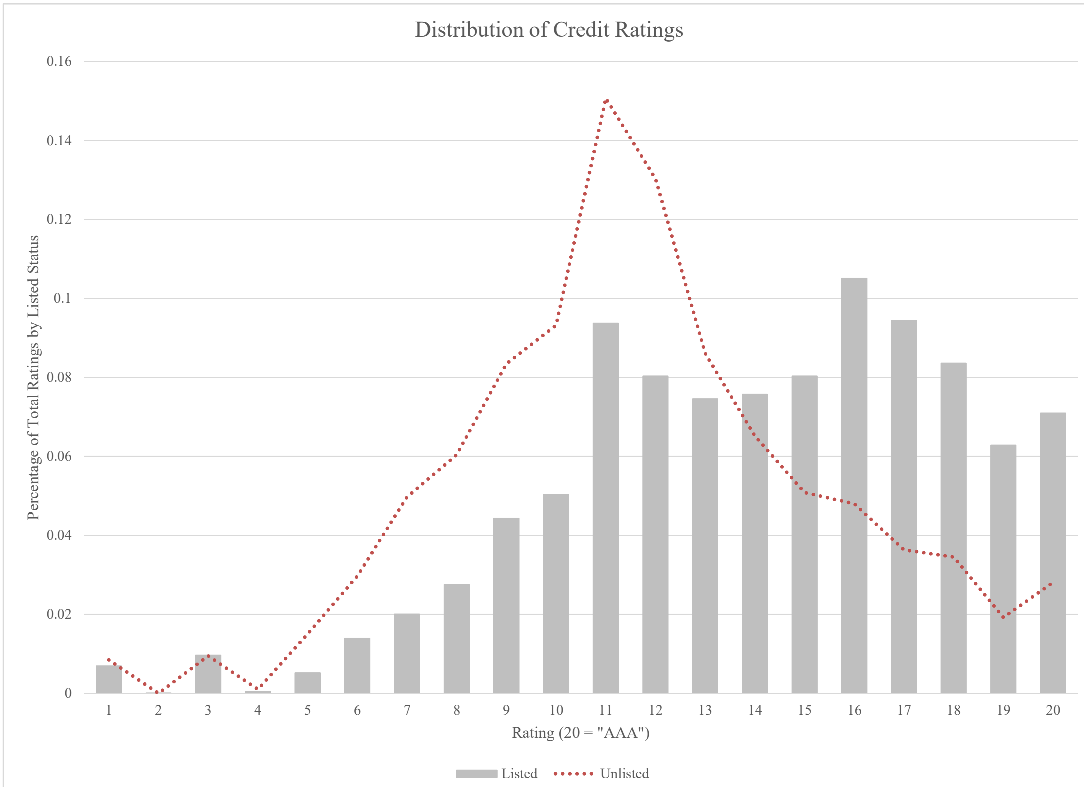

Figure 3 shows the distribution of issue-level credit ratings in our sample. The grey bars show the percentage of total listed firm issue-level ratings observations at each notch. The red dotted line show the percentage of total unlisted firm issue-level ratings observations at each notch. Rating is 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

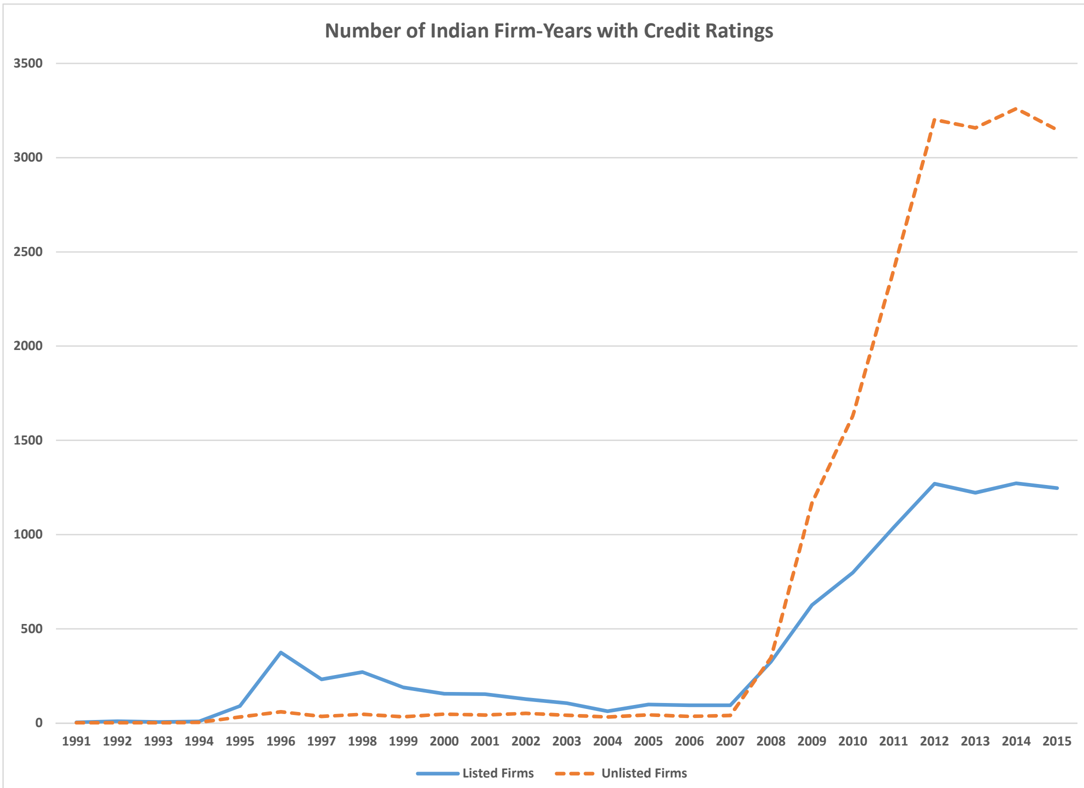

Figure 4 plots the number of listed and unlisted firm-years over time that have at least one rating outstanding. The orange dotted line represents the data for unlisted firms while the solid blue line represents the data for listed firms.

Table 1: Descriptive Statistics

Panel A: Total Sample

Variable	n	Mean	StD	Min	P25	Median	P75	Max
Ratings	14,139	12.41	4.40	1.00	10.00	12.50	16.00	20.00
Leverage	14,139	0.36	0.19	0.00	0.22	0.35	0.49	0.77
Debt-to-Earnings	14,139	3.49	4.42	-7.19	1.33	2.69	4.38	23.04
Cash	14,139	0.02	0.04	0.00	0.00	0.01	0.03	0.18
Interest Coverage	14,139	9.53	27.45	-2.03	1.34	2.35	5.02	168.38
Profitability	14,139	0.17	0.15	-0.04	0.08	0.13	0.20	0.78
PP&E	14,139	0.53	0.29	0.02	0.31	0.50	0.72	1.21
Size	14,139	8.08	1.52	5.38	6.94	7.95	9.07	11.77
CRA Coverage	14,139	1.04	0.20	1.00	1.00	1.00	1.00	3.00
Group Membership	14,139	0.46	0.50	0.00	0.00	0.00	1.00	1.00

Panel B: Listed Firm Sample

Variable	n	Mean	StD	Min	P25	Median	P75	Max
Ratings	8,174	13.06	4.62	1.00	11.00	14.00	16.75	20.00
Leverage	8,174	0.34	0.18	0.00	0.21	0.34	0.46	0.77
Debt-to-Earnings	8,174	3.30	4.06	-7.19	1.32	2.57	4.13	23.04
Cash	8,174	0.02	0.04	0.00	0.00	0.01	0.03	0.18
Interest Coverage	8,174	10.70	29.97	-2.03	1.41	2.51	5.33	168.38
Profitability	8,174	0.17	0.13	-0.04	0.09	0.14	0.21	0.78
PP&E	8,174	0.54	0.28	0.02	0.33	0.52	0.73	1.21
Size	8,174	8.46	1.53	5.38	7.34	8.42	9.47	11.77
CRA Coverage	8,174	1.05	0.22	1.00	1.00	1.00	1.00	3.00
Group Membership	8,174	0.57	0.50	0.00	0.00	1.00	1.00	1.00

Panel C: Unlisted Firm Sample

Variable	n	Mean	StD	Min	P25	Median	P75	Max
Ratings	5,965	11.52	3.90	1.00	10.00	12.00	14.00	20.00
Leverage	5,965	0.38	0.20	0.00	0.23	0.38	0.53	0.77
Debt-to-Earnings	5,965	3.74	4.87	-7.19	1.34	2.88	4.75	23.04
Cash	5,965	0.02	0.04	0.00	0.00	0.01	0.03	0.18
Interest Coverage	5,965	7.93	23.46	-2.03	1.26	2.13	4.58	168.38
Profitability	5,965	0.16	0.16	-0.04	0.06	0.12	0.18	0.78
PP&E	5,965	0.51	0.30	0.02	0.28	0.48	0.71	1.21
Size	5,965	7.55	1.34	5.38	6.55	7.44	8.40	11.77
CRA Coverage	5,965	1.02	0.15	1.00	1.00	1.00	1.00	3.00
Group Membership	5,965	0.32	0.46	0.00	0.00	0.00	1.00	1.00

Table 1 presents descriptive statistics for the variables used in our analysis for the 1991 - 2015 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 Analysis: Difference in Observable Characteristics Across Listed Status

	Mean: Listed	Mean: Unlisted	Difference	t-stat
Rating	13.06	11.52	1.54	20.94***
Downgrade	0.17	0.14	0.03	9.19***
Upgrade	0.11	0.16	-0.05	-13.95***
Leverage	0.34	0.38	-0.04	-13.30***
Debt-to-Earnings	3.30	3.74	-0.44	-5.80***
Cash	0.02	0.02	-0.00	-3.40***
Interest Coverage	10.70	7.93	2.77	5.93***
Profitability	0.17	0.16	0.01	4.11***
PP&E	0.54	0.51	0.03	6.90***
Size	8.46	7.55	0.91	30.84***
CRA Coverage	1.05	1.02	0.03	7.78***
Group Membership	0.57	0.32	0.25	30.28***

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

Months Before Default	Observations	Avg - All Firms	Avg - Unlisted Firms	Avg - Listed Firms
(1)	(2)	(3)	(4)	(5)
-12	1,167	8.77	8.06	9.93
-11	1,167	8.69	8.02	9.79
-10	1,167	8.62	7.98	9.66
-9	1,167	8.54	7.96	9.50
-8	1,167	8.49	7.92	9.42
-7	1,167	8.40	7.88	9.25
-6	1,167	8.34	7.86	9.13
-5	1,167	8.26	7.81	9.00
-4	1,167	8.19	7.78	8.87
-3	1,167	8.11	7.74	8.71
-2	1,167	7.99	7.71	8.45
-1	1,167	7.93	7.70	8.30

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: Credit Ratings and Listed Status

Panel A: Baseline Analyses

Explanatory Variables	$Rating_{i,m,y}$	$Rating_{i,y}$	$Rating_{i,m,y}$	$Rating_{i,y}$
	(1)	(2)	(3)	(4)
Unlisted	0.609***	0.574***	0.395*	0.403*
	(3.50)	(2.98)	(1.89)	(1.92)
Leverage	-7.848***	-7.732***	-5.608***	-5.698***
	(-14.70)	(-14.45)	(-7.24)	(-7.94)
Debt-to-Earnings	-0.098***	-0.112***	-0.048***	-0.061***
	(-5.04)	(-5.01)	(-3.72)	(-4.33)
Cash	4.106***	4.731***	3.034***	3.377***
	(3.87)	(3.78)	(3.89)	(4.87)
Interest Coverage	0.007***	0.008***	0.001	0.001
	(4.64)	(4.95)	(0.61)	(0.72)
Profitability	3.377***	3.647***	1.659***	1.877***
	(6.59)	(6.51)	(3.53)	(3.35)
PP&E	-0.104	-0.032	-0.816**	-0.782*
	(-0.42)	(-0.12)	(-2.25)	(-2.00)
Size	1.045***	1.004***	0.784***	0.637***
	(18.00)	(16.37)	(5.14)	(3.91)
CRA Coverage	0.518**	0.503**		
	(2.61)	(2.43)		
Group Membership	0.474***	0.489***		
	(2.94)	(2.97)		
N	146,458	12,694	149,475	12,781
R-sq	0.693	0.683	0.870	0.870
adj. R-sq	0.687	0.624	0.867	0.830
Fixed Effects	Industry-Yr, Auditor	Industry-Yr, Auditor	Firm, Rating Agency, Yr	Firm, Rating Agency, Yr
Std Errors Clustered At	Firm,Yr	Firm, Yr	Firm,Yr	Firm,Yr

Panel B: Univariate Analysis for Firms That Switch Listed Status

Actual Ratings Based on:	Expected Ratings Based On:	
	Listed firm loadings	Unlisted firm loadings
	$RatingsGap_{i,m,y}$	$RatingsGap_{i,m,y}$
	(1)	(2)
Unlisted Firm-Month-Years	0.461***	0.145**
	(8.73)	(2.65)
Listed Firm-Month-Years	0.173***	-0.028
	(3.31)	(-0.510)
Difference	0.289***	0.173**
	(3.70)	(2.12)

Panel C: Matched Sample Analysis

Explanatory Variables	$Rating_{i,y}$	
	(1)	(2)
Unlisted	0.453**	0.583**
	(2.40)	(2.53)
Leverage	-6.790***	-6.906***
	(-7.89)	(-12.18)
Debt-to-Earnings	-0.090**	-0.070**
	(-2.71)	(-2.50)
Cash	3.620**	3.348*
	(2.59)	(1.76)
Interest Coverage	0.015***	0.012***
	(8.59)	(4.72)
Profitability	-0.713**	-0.927*
	(-2.74)	(-1.96)
PP&E	-0.740**	-0.956*
	(-2.79)	(-2.04)
CRA Coverage	0.300	0.556
	(0.66)	(1.36)
Group Membership	0.778***	0.918***
	(4.93)	(3.10)
N	3,610	2,883
R-sq	0.536	0.752
adj. R-sq	0.493	0.651
Fixed Effects	Industry-Yr, Size Percentile	Industry-Yr, Auditor, Size Percentile
Std Errors Clustered At	Firm,Yr	Firm, Yr

Panel D: Predicted Rating Analysis

Explanatory Variables	$PredictedRating_{i,y}$	$PredictedRating_{i,y}$
	(1)	(2)
Unlisted	0.102*	0.097*
	(1.71)	(2.04)
Leverage	-10.704***	-10.587***
	(-94.05)	(-74.92)
Debt-to-Earnings	-0.008***	-0.006***
	(-6.82)	(-4.80)
Cash	-2.626***	-2.349**
	(-3.52)	(-2.73)
Interest Coverage	0.003***	0.001**
	(4.45)	(2.51)
Profitability	0.282***	0.208***
	(9.30)	(6.22)
PP&E	0.486***	0.280***
	(13.77)	(4.00)
Size	1.067***	1.007***
	(93.60)	(36.03)
Group Membership	0.880***	
	(30.86)	
N	77,927	72,624
R-sq	0.831	0.884
adj. R-sq	0.828	0.859
Fixed Effects	Industry- Yr	Firm, Yr
Std Errors Clustered At	Firm,Yr	Firm,Yr

Table 4 examines the relationship between firms' listed status and their assigned credit ratings. Panel A presents results for our baseline analyses and the analyses that include firm, rating agency, and year fixed effects. Panel B presents summary information on *RatingsGap*, for firms that transition listing status during our sample period. Panel C presents results for our matched sample analyses. Panel D presents results for our analyses after taking into consideration the non-disclosure of poor ratings. 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.

Table 5: Sensitivity to Financial Condition

Explanatory Variables	$Rating_{i,m,y}$ Unlisted	Listed	Difference	$Rating_{i,y}$ Unlisted	Listed	Difference
	(1)	(2)	(1)-(2): (3)	(4)	(5)	(4) - (5): (6)
Leverage	-1.980***	-7.360***	5.380***	-2.457***	-7.346***	4.889***
	(-4.83)	(-8.62)	(5.99)	(-5.10)	(-10.48)	(5.09)
Debt-to-Earnings	-0.000	-0.070***	0.069***	-0.012	-0.089***	0.077***
	(-0.03)	(-3.84)	(3.45***)	(-1.24)	(-5.37)	(3.19)
Cash	1.012	4.074***	-3.062*	-0.161	4.721***	-4.882***
	(1.00)	(3.65)	(-1.67)	(-0.21)	(3.95)	(-3.04)
Interest Coverage	0.000	-0.001	0.001	0.000	-0.001	0.001
	(0.10)	(-0.60)	(0.57)	(0.12)	(-0.44)	(0.39)
Profitability	0.998***	1.285*	-0.287	1.488***	1.380*	0.108
	(3.46)	(1.89)	(-0.38)	(3.18)	(1.85)	(0.10)
PP&E	-0.840**	-0.708	-0.132	-1.254***	-0.673	-0.581
	(-2.21)	(-1.38)	(-0.22)	(-3.03)	(-1.27)	(-0.84)
Size	0.492***	0.944***	-0.452*	0.333**	0.649***	-0.316
	(3.98)	(4.67)	(-1.94)	(2.27)	(3.23)	(-1.13)
CRA Coverage	0.261*	0.491**	-0.230	0.288	0.563**	-0.275
	(2.00)	(2.15)	(-0.89)	(1.59)	(2.48)	(-0.80)
N	55,851	90,422	146,273	4,523	7,742	12,265
R-sq	0.946	0.850	0.882	0.943	0.851	0.881
adj. R-sq	0.943	0.845	0.879	0.888	0.791	0.840
Fixed Effects	Firm,Yr,Auditor	Firm,Yr,Auditor	Firm,Yr,Auditor	Firm,Yr,Auditor	Firm,Yr,Auditor	Firm,Yr,Auditor
Std Errors Clustered At	Firm,Yr	Firm,Yr	Firm,Yr	Firm,Yr	Firm,Yr	Firm,Yr

Table 5 examines the sensitivity of credit ratings to firm financial condition. In columns (1) - (3) observations are reported at the firm-month-year level. In columns (4) - (6) observations are reported at the firm-year level. 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.

Table 6: Frequency of Credit Rating Changes

Explanatory Variables	$Log(SumRatingChanges)_{i,t+1}$ (1)	$Log(SumDowngrades)_{i,t+1}$ (2)	$Log(SumUpgrades)_{i,t+1}$ (3)
Unlisted	-0.033***	-0.035***	0.002
	(-5.38)	(-5.17)	(0.32)
△Leverage	0.116*	0.360***	-0.248***
	(1.86)	(8.24)	(-4.94)
△Debt-to-Earnings	-0.001*	-0.000	-0.000**
	(-1.80)	(-0.67)	(-2.72)
△Cash	-0.026	-0.239***	0.210***
	(-0.21)	(-2.98)	(2.99)
△Interest Coverage	-0.004	-0.008***	0.003
	(-1.05)	(-3.43)	(1.14)
△Profitability	-0.089***	-0.033	-0.056***
	(-3.46)	(-1.23)	(-7.05)
△PP&E	0.040	0.059**	-0.016
	(0.90)	(2.74)	(-0.37)
△Size	-0.097*	-0.209***	0.113***
	(-1.97)	(-4.76)	(7.27)
CRA Coverage	-0.035***	-0.025	-0.011
	(-3.45)	(-1.36)	(-0.94)
Group Membership	-0.017*	-0.014**	-0.003
	(-1.88)	(-2.64)	(-0.34)
N	18,221	18,221	18,221
R-sq	0.076	0.131	0.087
adj. R-sq	0.044	0.101	0.055
Fixed Effects	Industry-Yr	Industry-Yr	Industry-Yr
Std Errors Clustered At	Firm,Yr	Firm,Yr	Firm,Yr

Table 6 examines the relation between firms' rating changes over a given fiscal year and listed status. Dependent variables are calculated by aggregating ratings changes from the end of fiscal year t to the end of fiscal year t+1. Independent variables are calculated as the change in credit risk determinants from the end of fiscal year t-1 to the end of fiscal year t. 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.

Table 7: Predictability of Credit Rating Changes for Firms in the Same Industry

Explanatory Variables	Downgrades > 0 (1)	Upgrades > 0 (2)	Downgrades > 0 (3)	Upgrades > 0 (4)	Downgrades > 0 (5)	Upgrades > 0 (6)
	m-1 to m		m-3 to m		m-6 to m	
Ln(Listed Firm Downgrades)	0.003**		0.002*		0.003**	
	(2.24)		(1.85)		(2.31)	
Ln(Listed Firm Upgrades)		0.001		0.001		0.001
		(0.56)		(0.67)		(0.61)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
N	52,567	52,567	52,587	52,587	52,605	52,605
R-sq	0.012	0.011	0.012	0.011	0.012	0.011
adj. R-sq	0.003	0.002	0.003	0.002	0.003	0.002
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 examines the predictability of rating changes for both listed and unlisted firms in the same industry. 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.

Table 8: Ability of Ratings to Predict Future Default

Panel A: Levels Analysis

Explanatory	$Default_{i,m,y}$			$Default_{i,m,y}$		
Variables	Unlisted	Listed	Difference	Unlisted	Listed	Difference
	(1)	(2)	(1)-(2): (3)	(4)	(5)	(4) - (5): (6)
Rating	-0.002***	-0.004***	0.002***	-0.002***	-0.004***	0.002**
	(-4.60)	(-5.29)	(3.30)	(-3.83)	(-5.18)	(3.47)
Leverage				0.005	0.005	0.000
				(1.57)	(1.51)	(0.01)
Debt-to-Earnings				-0.000	-0.000	0.000
				(-0.49)	(-0.15)	(0.20)
Cash				-0.009*	-0.038***	0.029***
				(-1.78)	(-6.24)	(3.21)
Interest Coverage				0.000***	0.000***	0.000*
				(3.27)	(4.23)	(1.87)
Profitability				-0.013**	-0.010*	-0.002
				(-2.47)	(-2.03)	(-0.30)
PP&E				0.007***	0.001	0.006
				(3.34)	(0.24)	(1.66)
Size				0.001	0.005***	-0.004**
				(1.00)	(4.26)	(-2.21)
CRA Coverage				-0.001	0.001	-0.002
				(-0.93)	(1.01)	(-1.31)
N	117,449	148,504	265,953	117,449	148,504	265,953
R-sq	0.089	0.054	0.066	0.090	0.055	0.067
adj. R-sq	0.069	0.043	0.051	0.069	0.043	0.052
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

Panel B: Changes Analysis

Explanatory Variables	$Default_{i,m,y}$ Unlisted (1)	$Default_{i,m,y}$ Listed (2)	$Default_{i,m,y}$ Difference (1)-(2): (3)	$Default_{i,m,y}$ Unlisted (4)	$Default_{i,m,y}$ Listed (5)	$Default_{i,m,y}$ Difference (4) - (5): (6)
Ratings Change: m -11 to m-1	-0.003***	-0.004***	0.001*	-0.002***	-0.004***	0.002*
	(-5.15)	(-4.14)	(1.73)	(-4.91)	(-4.03)	(1.69)
△Leverage				0.008*	0.012**	-0.004
				(2.06)	(2.23)	(-0.70)
△Debt-to-Earnings				-0.000	0.000	-0.000
				(-1.26)	(0.80)	(-1.12)
△Cash				-0.011	-0.032***	0.021
				(-1.68)	(-4.47)	(1.97)
△Interest Coverage				0.00*	0.00	0.00
				(1.98)	(0.37)	(0.68)
△Profitability				-0.011***	-0.010*	-0.001
				(-4.52)	(-1.94)	(-0.19)
△PP&E				0.005*	-0.002	0.007*
				(1.93)	(-0.72)	(1.69)
△Size				0.000	-0.003**	0.003*
				(0.08)	(-2.15)	(1.88)
CRA Coverage				-0.002*	-0.000	-0.001
				(-1.95)	(-0.32)	(-1.30)
N	68,278	106,794	175,072	68,070	106,772	174,842
R-sq	0.004	0.010	0.008	0.005	0.010	0.009
adj. R-sq	0.003	0.009	0.007	0.003	0.009	0.008
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 8 examines the relationship between defaults and prior ratings and rating changes. Panel A presents results that relate defaults to the level of ratings, while Panel B presents results that relate defaults to changes in ratings. 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.

Table 9: Robustness: Auditor Coverage

Panel A: Indian Audit Industry Summary Statistics, n = 16,141

	Minimum	P25	P50	P75	Max	Average
Number of Firms Audited	1	1	2	3	1,247	3.8
Number of Unlisted Firms Audited	0	1	1	2	1,002	3.1
Number of Industries Covered	1	1	1	3	62	2.3
Number of States Active	1	1	1	1	26	1.4

Panel B: Indian Audit Industry Summary Statistics, n = 997

Audit Firms with Unlisted Firm Coverage Between 40 - 60 Percent

	Minimum	P25	P50	P75	Max	Average
Number of Firms Audited	1	2	2	4	255	3.8
Number of Unlisted Firms Audited	1	1	1	2	141	2.0
Number of Industries Covered	1	2	2	3	45	2.8
Number of States Active	1	1	1	2	21	1.6

Panel C: Auditor Coverage

Explanatory Variables	$Rating_{i,m,y}$	$Rating_{i,y}$
	(1)	(2)
Unlisted	1.847***	1.581**
	(3.88)	(2.31)
Leverage	-10.657***	-11.059***
	(-6.78)	(-4.26)
Debt-to-Earnings	-0.094***	-0.134**
	(-3.34)	(-2.46)
Cash	7.024**	8.341**
	(2.34)	(2.26)
Interest Coverage	0.007	0.005
	(1.35)	(0.73)
Profitability	7.542***	8.899**
	(3.55)	(2.67)
PP&E	-0.332	-0.649
	(-0.33)	(-0.44)
Size	1.375***	1.313***
	(5.92)	(4.44)
CRA Coverage	-1.575	-0.500
	(-1.67)	(-0.46)
Group Membership	0.054	-0.374
	(0.08)	(-0.44)
N	10,545	756
R-sq	0.862	0.853
adj. R-sq	0.854	0.756
Fixed Effects	Industry-Yr, Auditor	Industry-Yr, Auditor
Std Errors Clustered At	Firm,Yr	Firm,Yr

Table 9 examines the relation between listed status and firms' assigned credit ratings after controlling for auditor coverage. Panel A presents the number of audit firms present in the Auditors dataset in Prowess. Panel B presents statistics for audit firms that cover a roughly equal number of unlisted and listed firms (between 40 - 60 percent unlisted firms). Panel C presents the results of our multivariate regression estimation. 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.

Table 10: Robustness: Sensitivity to Future Sales

Explanatory Variables	$Sales_{i,t+2}$ Unlisted	Listed	Difference	$Sales_{i,t+3}$ Unlisted	Listed	Difference
	(1)	(2)	(1)-(2): (3)	(4)	(5)	(4) - (5): (6)
Leverage	-0.090***	-0.149***	0.059	-0.065	-0.003	-0.062
	(-2.86)	(-4.75)	(1.39)	(-1.29)	(-0.08)	(-0.95)
Debt-to-Earnings	0.001***	0.001***	0.000	0.001**	0.000	0.001
	(4.61)	(3.91)	(0.49)	(2.15)	(0.48)	(0.66)
Cash	0.244	0.662*	-0.418	0.181	0.471	-0.290
	(1.25)	(1.84)	(-1.11)	(0.35)	(1.14)	(-0.51)
Interest Coverage	-0.040**	0.000	-0.040	-0.070**	-0.020	-0.050
	(-2.25)	(0.02)	(-1.45)	(-2.46)	(-0.97)	(-1.22)
Profitability	-0.075***	-0.137***	0.062*	-0.054	-0.111***	0.108
	(-2.97)	(-3.59)	(1.99)	(-1.61)	(-2.89)	(0.10)
PP&E	0.035	0.162***	-0.127**	0.010	0.169***	-0.582
	(1.09)	(4.78)	(-2.59)	(0.18)	(4.03)	(-0.84)
Size	-0.107***	-0.127***	0.020	-0.137***	-0.130***	-0.007
	(-8.69)	(-9.00)	(1.22)	(-5.91)	(-7.15)	(-0.29)
N	57,144	47,787	104,931	48,053	43,746	91,799
R-sq	0.819	0.708	0.790	0.753	0.590	0.721
adj. R-sq	0.784	0.681	0.759	0.703	0.551	0.680
Fixed Effects	Firm,Yr	Firm,Yr	Firm,Yr	Firm,Yr,Auditor	Firm,Yr,Auditor	Firm,Yr,Auditor
Std Errors Clustered At	Firm,Yr	Firm,Yr	Firm,Yr	Firm,Yr	Firm,Yr	Firm,Yr

Table 10 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.