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The price of honesty: Indian firms' response to stringent disclosure regulations

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Abstract

Using a regulation implemented by SEBI in November 2016 as an exogeneous shock, I test whether firms with bad quality of information disclosures attempt to conceal firm-specific information when faced with a business environment marked with heightened disclosure quality requirement mandated by law for the CRAs. Specifically, the study empirically attempts to analyze whether regulation is sufficient to create a separating equilibrium, in terms of the quality of disclosures to CRAs by firms. I find a statistically significant decrease in number of security issuances and number of CRAs bad type firms engage with, as well as an increase in the number of security downgrades that they suffer in the post-regulation environment. However, the decrease in number of issues is weakened if the firm is listed, has high proportion of independent directors in its board or gets its statements audited by a Big 4 auditor, all of which signal that the firm is of a good type. These findings indicate that bad type firms strategically chose to reduce their issuances and initiate new firm-CRA relationships after the regulation to conceal their firm type, but they weren't successful in escaping from the suffering for long.

1 Introduction

Credit rating agencies serve as vital information providers in credit markets, and the quality of their ratings holds significant importance for the proper functioning of the financial system (White, 2010; Bannier and Hirsch, 2010). These ratings find application in various contexts, including investment mandates, loan contracts (covenants), and financial regulation. By systematically rating every issued security, involving in-depth analyses of both the security and the issuing firm, credit rating agencies (CRAs) function as passive monitors of firms. This role empowers them to mitigate information asymmetry existing between firms and the capital markets (Hu et al., 2019).

However, concerns about the effectiveness of the rating system are intertwined with the business model of rating agencies. Their primary revenue stream is derived from the companies whose securities they evaluate. Compounding this issue, in the initial growth phases of a credit rating agency's life cycle, there is an inherent inclination to attract more business, potentially leading to the issuance of favourable ratings for the securities of the very firms they assess. This scenario exacerbates information asymmetry, contradicting the fundamental fiduciary duty of a credit rating agency. Though the first channel, often described as the 'issuer-pays' model related conflict of interest, has been extensively studied in finance literature (Cornaggia and Cornaggia, 2013; Xia, 2014), no substantial work has been done on the role of small-fast growing CRAs in compounding information asymmetries.

In this paper, I attempt to fill this gap in literature by studying firms' tendency to conceal their 'firm type' and exacerbate information asymmetry, when faced with a regulatory requirement that intends to improve the quality of disclosures by CRAs. Specifically, I study if a regulatory mandate is a strong enough facilitator for 'bad type' firms to disclose more good quality information which they attempt to hide by getting their securities rated from small fast-growing CRAs. I define firm type not on the basis of quality of firms themselves, but on the basis of quality of their information disclosures that they make specifically through their engagement with CRAs. In that sense, a 'bad type' firm is a firm that has poor quality of disclosures and hence high information asymmetry, even though it may have a strong current financial position or future growth prospects. Figure 1 provides a diagrammatic representation of the interactions at play between firms and CRAs, and the critical role of information in this setting. Like the figure depicts, it is more probable that firms which get their issues rated from large, mature CRAs would have low information asymmetry and are therefore more likely to be good type firms. In contrast, firms which get most of their securities rated from small, fast-growing CRAs should have high information asymmetry and are hence likely to be bad type firms. This difference is likely to exist because of difference in priority of objectives for these 2 sets of CRAs- while the former would prioritise reputational concerns, the latter would treat firm growth as their primary goal.

In this study, I exploit a regulation that was introduced by SEBI in Nov 2016, which standardized the format in which ratings action are to be communicated in a press release by all CRAs, including critical sections like rating rationale and key drivers for every rating action that CRAs take on every security. The success of such a regulatory change in creating a separating equilibrium (on the basis of firm type) depends on the cost of other alternatives that bad type firms have, which can help them in concealing their type. In the spirit of Spence (1973) if the cost imposed by the regulation is high relative to the benefits for the bad type firms but not for the good type firms, it should lead to a separating equilibrium immediately. Intuitively, a bad type firm can choose to issue less securities or initiate ratings relationships with other CRAs which would give it a favourable rating in the post-regulation environment, both strategic choices which can help it to conceal its firm type. However, since CRAs have to mandatorily abide by the regulation, if the cost of revealing their type is lesser than their financing requirement, they would continue to issue securities but most probably get a lower rating in the post-regulation period.

First, I find that in the post-regulation period (proxy for mandated high-quality disclosure requirement period), bad type firms decrease their number of issues substantially more than good type firms, even though the number of new instrument issues decreases for both type of firms. Although the unequivocal decrease in number of decreases is likely explained by rise in compliance costs for all firms, the fact that it is significantly more for bad type firms suggests they wanted to conceal their type by avoiding stricter due diligence by CRAs mandated by the requirements of the regulation. Next, I find that the bad type firms also suffered relatively higher rating downgrades on their issued securities as compared to good type firms in the post-regulation period, suggesting that the stringent due diligence mandated by the requirement of the regulation helped in reducing information asymmetry to some extent. Finally, I find weak evidence for rating-shopping behaviour among bad type firms in the post-regulation period. Specifically, I find modest evidence of bad type firms attempting to initiate more ratings relationships with CRAs in the post-regulation period, compared to good-type firms.

However, it would be unreasonable to imply that every firm that I categorize as bad type according to my criteria (never get their issues rated from any of the top 3 CRA in the pre-regulation sample period) should have bad quality of information disclosures, as it may just be the case that they have an established relationship with one of the bottom 4 CRAs. And given the stickiness in firm-CRA relationships, they get all their securities rated from a bottom 4 CRA, without any intention of concealing information. To test this argument empirically, I determine the heterogenous effect of the regulation on bad type firms conditional on other common proxies of degree of information asymmetry like listing status (Tran et al., 2019), board autonomy (Armstrong et al., 2014), auditor choice (Hrazdil et al., 2021) and accruals status (Park et al., 2018). Not surprisingly, I find that firms which should be characterized as good type on the basis of these additional proxies suffer to a lesser extent in their ability to issue new securities in the post-regulation period, compared to firms that are categorized as bad type even in these proxies.

Finally, I attempt to empirically test whether the bad type firms were successful in their endeavours of attempting to conceal their firm type in the post-regulation period. I find that the bad type firms were able to get similar ratings in the post-regulation period as in the pre-regulation period, even though they got their securities rated from the same or slightly more reputed CRAs in the post-regulation period as compared to the pre-regulation period. This points to a lag effect in information flow after the regulation, possibly due to infrequent nature of rating revisions and the strategic choices by firms uncovered previously to conceal their type. As evidence of their successful attempt of concealing their firm type, I find that they were able to increase their leverage more in the post-regulation period, compared to the good-type firms. This is because, as Figure 1 shows, a rating has 3 elements- security risk, firm risk and information asymmetry risk. Since in the post-regulation period, firms are able to get similar ratings by similar or slightly more reputed CRAs, they were successful in sending a false signal of reduction in their information asymmetry risk. This could have led to better access to credit markets for these firms in the post-regulation period as compared to the good type firms. However, these effects plateaued or reversed to some extent in 2020, the last year in the post-regulation period, which indicates that the bad type firms weren't able to conceal their firm type for long.

These findings point to the importance of managing conflicts of objectives of CRAs, especially when they are small and in their growth stage of the corporate life cycle. Anecdotal evidence suggests that calendar year 2016 was a year marred with sharp rating revisions by some CRAs for some firms, which pointed to lack of proper due-diligence and unjustified favourable ratings being awarded to these firms in the previous year. For instance, according to a LiveMint article dated 18 Sep 2015 [1], ". . . *JP Morgan AMC was forced to restrict redemptions from two investment plans following CARE Ratings' decision to suspend the rating of Amtek Auto Ltd. Another credit assessor, Brickwork Ratings, lowered the company's rating by 12 notches in one shot. In the past one year, there have been other instances where ratings have been cut sharply by three notches or more in one revision. In July, CARE Ratings downgraded Jaiprakash Associates Ltd by six notches from a rating of BB to D-, a rating that reflects a default in the debt security. Non-convertible debentures of Bhushan Steel Ltd also saw their rating drop by six notches following a revision by CARE Ratings in December 2014. Punj Lloyd Ltd faced a similar drop in ratings in July. Monnet Ispat and Energy Ltd, Bhushan Power and Steel Ltd, 20 Microns Ltd and Shree Renuka Sugars Ltd are other companies that have seen rating downgrades of more than three notches each in the past year.*" Similarly, in October 2018, while covering the IL&FS crisis, The Wire reported [2], "*India Rating & Research Pvt Ltd, had downgraded a group company's (ITNL) long-term borrowings to a sub-investment grade in July, but continued to accord good risk grades to ITNL's short-term paper. Most importantly, India Rating affirmed its excellent long-term credit rating for IL&FS, the parent company, even though ITNL had already defaulted on its repayment/redemption obligations under a Commercial Paper tranche even as IL&FS had simply looked on.*" These instances prove that faulty ratings were not a rare instance in corporate credit markets in India in the pre-regulation

[1] https://www.livemint.com/Companies/nKiB6RuSI5fXpvPVqxBr6H/Have-rating-agencies-been-caught-napping.html

[2] https://thewire.in/business/ilfs-moodys-fitch-care-icra-rating-companies

period. Additionally, Figure 2 shows the number of downgrades by CRAs over a 6-year period around the implementation of the regulation. Although the figure clearly shows an increase in the number of downgrades by all CRAs in the post-regulation period, this effect is starker for the smaller CRAs, who recorded a noteworthy jump in the number of their downgrades every year after the regulation was implemented.

The rest of the paper is organized as follows. Section 2 first discusses the regulation and then discusses the literature and testable hypotheses. Section 3 describes the data sources and variable construction. Thereafter, Section 4 discusses the empirical strategy deployed in this paper. In Section 5, I present the key results of the paper. Section 6 tests the robustness of the key results discussed in this paper. Finally, Section 7 concludes.

2 Background and Hypotheses

Most existing work in understanding the role of credit rating agencies in the development of financial system has focussed on the conflicts of interests arising because of their 'issuer-pays' model. This stream of literature argues that because the primary source of revenue for CRAs is their ratings business, an activity for which they are paid by the issuers themselves, they would have incentives to provide favourable ratings to those firms which significantly contribute to their revenues. Indirect support for the conflict-of-interest argument is evident in the influence of competition between CRAs on ratings, as documented by Becker and Milbourn (2011). Additionally, there is evidence indicating that ratings paid for by investors tend to be more precise, as demonstrated by Jiang et al. (2012). Models addressing this agency problem have been proposed by Bar-Isaac and Shapiro (2013), Bolton et al. (2012), and Sangiorgi and Spatt (2017).

Another stream of literature studying conflicts of interests argues that since rating revenues are fixed in many countries due to the deficiencies in the issuer-pays model, it is through non-rating and subsidiary services, which have more flexibility in renumeration for services offered, that these conflicts of interests manifest in firm-CRA relationships. For instance, He et al. (2012) and Efing and Hau (2015) find that substantial issuers, and issuers extensively engaged in providing securitization business to rating agencies, tend to receive more preferential ratings. In a similar vein, Baghai and Becker (2018) exploit a 2010 SEBI regulation that mandated disclosure of revenue split by firms for all CRAs for both ratings and non-ratings businesses, and show that Indian firms which provide more non-ratings business to CRA's are likely to get preferential ratings which aren't justified by their fundamentals. Both these arguments, though differing in the channel of conflicts of interest are about the same issue- the issuer-pays model. In contrast, this study is the first paper which looks at another channel through which inefficient credit ratings may be awarded by some CRAs to some firms- the growth motive of small CRAs.

2.1 Regulation

In 1999, SEBI introduced the inaugural set of regulations pertaining to rating agencies through the "SEBI (Credit Rating Agencies) Regulations, 1999." These regulations established the comprehensive framework governing the formation, functioning, and oversight of rating agencies. In November 2016, following incidents of sharp rating downgrades mentioned above, SEBI recognized a lapse in thorough due diligence by the CRAs. To improve disclosure standards by CRAs, SEBI significantly tightened the rating action standards for CRAs in November 2016 through the "Circular SEBI/HO/MIRSD/MIRSD4/CIR/P/2016/119" [3]. The guidelines cover various areas

[3] https://www.sebi.gov.in/sebi_data/attachdocs/1477999985100.pdf

such as rating criteria formulation and public disclosure of the same, accountability of rating analysts, functioning and evaluation of rating committees, disclosure of ratings in case of non-acceptance by issuer, policy for non-cooperation by issuer and strengthening the relevance of internal audit of CRAs. Of special importance to this paper is Section 2.D of the Annexure A of the circular that lays down a standardized format in which CRAs had to publish press releases notifying their rating actions for a firm's security.

"*2. Rating criteria, rating process and their disclosure*

...

2.D. Standardization of press release for rating actions

2.D. III. Each CRA shall assign a rating outlook and disclose the same in the Press Release.

2.D. IV. Press Release related to review of rating shall also carry the rating transition/ history of all instruments of that issuer, rated by the CRA in the past 3 years, irrespective of whether the instrument is currently outstanding or not.

2.D. V. The rating history, Press Releases and Rating Reports, including those ratings which have been withdrawn, shall be available on the CRA's website."

Furthermore, Annexure A2 details the components that are mandatory for such a press release. Among others, the most important segments of the press release that CRAs had to discuss extensively in the press release include- Rating Action, Detailed Rationale, Key Drivers (list and description) and analytical approach undertaken to arrive at the rating. A snapshot of the key components of this annexure is shown in Figure A1 in the Appendix.

These new guidelines had to be implemented by all CRAs in 2 months, i.e., by

January 2017. Since these enhanced reporting (of rating action) standards (referred to as 'the regulation' hereon) are expected to induce a higher compliance cost on the bottom 4 CRAs as compared to the top 3 CRAs due to reasons mentioned earlier, firms which get their ratings issued from bottom 4 CRAs should be more affected by this regulation. This is because they would have to face more stringent due diligence by the CRAs and hence if they are of the bad type, reveal the undisclosed information to the CRAs. However, firms may choose to get some securities rated by one of top 3 CRAs and other securities rated by one of bottom 4 CRAs. In such a case, the ratings given by the top 3 CRA would be considered as the true rating for the firm by lenders, and therefore the ratings given by bottom 4 CRA for similar securities is bound to be of a similar range. Therefore, I categorize a firm as belonging to the treatment group, which I call bottom4_ratings group, if it gets all its issued securities rated from one/multiple bottom 4 CRAs in the pre-regulation period. If it gets at least 1 security rated from a top 3 CRA in the pre-regulation period, it becomes part of the control group.

2.2 Hypotheses

2.2.1 Primary hypothesis

The regulation mandated stringent due diligence of firm financials by CRAs in order for them to publish the rating reports in the prescribed standardized report (via press release). Since this was a detailed and extensive document, the granularity of information about a firm's financials that CRAs would require to rate its security would increase manifold. This additional cost of compliance should be more for the smaller, fast-growing CRAs as compared to the more reputed, larger CRAs. Exploring relation between firm size and tax compliance costs, Almunia and Lopez-Rodriguez (2018) explore the effect of tax compliance costs on small businesses and find these to be disproportionately high for small firms as compared to large firms. Consequently, firms would have to decide between continuing to issue securities but provide high quality disclosures to the CRAs or reduce the number of security issues to avoid disclosing information to CRAs. If the firm is of good type, one should expect they would do the former but on the other hand, if they are bad type firms, they would be forced to do the latter. Since firms belonging to the bottom4_ratings group are expected to be primarily of bad type, one should expect their number of security issuance to reduce in the post-regulation period. This argument leads to me hypothesize that:

Hypothesis 1: Bottom 4 CRA firms decrease their issue of new securities more than top 3 CRA firms when information disclosure norms become stricter to avoid frequent stringent due diligence by CRAs and hence conceal their firm type.

2.2.2 Secondary hypotheses

Since implementation of the regulation should have resulted in creating an evolved informational environment with increased disclosures and hence relatively lesser information asymmetry, we should expect the 'bad type' firms to suffer more because of this regulation than the 'good type' firms. With more stringent due-diligence by CRAs post this regulation, the 'bad type' firms should experience more firm-specific information coming out in the public domain. This would result in a decrease in information asymmetry for the treatment group, which would have earlier been much more than that in the control group. This is because the non-bottom4_rating firms would already have better disclosure standards and hence lower information asymmetry even in pre-regulation period. As an obvious consequence to this argument, one may expect an increase in treatment firms' number of securities downgraded relative to that of the control firms. For instance, Hu et al. (2019) find that the number of rating downgrades by CRAs increase in a low information asymmetry environment spurred by the entry of a new entrant in the CRA industry in China. This leads me to hypothesize the following:

Hypothesis 2: Bottom 4 CRA firms suffer more rating downgrades than top 3 CRA firms when information disclosure regulations become stricter.

In an informationally inefficient environment, bad quality firms are able to pose as good quality firms by withholding information that may reveal their type. These bad quality firms, which must have inherently had higher information asymmetry than the good quality firms in the pre-regulation period, are likely to suffer because of the separating equilibrium the identified regulation intends to create with more information disclosures. Consequently, in response to heightened regulatory scrutiny and the imposition of information disclosure requirements, it is anticipated that such bad quality firms may strategically increase their interactions with credit rating agencies. This tactical approach aims to perpetuate a pooling equilibrium by engaging in a form of 'rating shopping'. Such type of firm response has been widely documented in literature, for instance, Skreta and Veldkamp (2009) provide a theoretical model of rating shopping in case of high instrument complexity and increasing CRA competition. More broadly, multiple recent studies empirically show the existence of rating shopping in multiple countries and markets (Bakalyar and Galil, 2014; He et al., 2016; Chang et al., 2021). By selectively seeking ratings from agencies that have demonstrated a propensity to assign favourable evaluations, these firms endeavour to avoid being adversely affected by the separating equilibrium envisaged by the regulatory framework. In effect, their concerted efforts to secure positive ratings serve as a defensive mechanism to mitigate the potential repercussions of the regulation-induced information revelation dynamics, allowing them to maintain a semblance of financial viability in the market. This stream of argument leads me to formulate the following hypothesis:

Hypothesis 3: Bottom 4 CRA firms engage in more rating shopping (or have more number of relationships with different CRAs) than top 3 CRA firms when information disclosure regulations become stricter.

3 Data description

I collect data spanning the period 2015-2020 for my primary analysis. First, I obtain data for credit ratings on all securities issued by Indian non-financial firms in the above period from the Centre for Monitoring Indian Economy (CMIE) Prowess database (September 2023 vintage). Therefore, the sample of firms used in this study are only those firms that have issued at least one credit security in the sample period. Prowess database is a source of high-quality corporate data that has been used in several recent studies (Baghai and Becker, 2018; Vig, 2013). Credit ratings are accessible for CRISIL, ICRA, CARE, Brickwork, ACUITE, IND-RA, and IVR, and are documented for each company on a debt security basis. Although distinct identifiers for individual debt instruments are not present in the database, they are categorized into instrument types, including debentures, long-term loans, and term loans. For the primary analysis, I include all instruments that a firm has issued in this period. In robustness check, I filter the observations to only include those corresponding to non-structured instruments that are assigned medium- or long-term credit ratings by the agencies, and only the ten most common instrument categories.

Rating symbols employed to assess entities can be categorized into eight distinct grades based on the level of risk linked to either the instrument or issuer. Good ratings aim to signify a reduced likelihood of default. The rating scale is denoted by the following alphanumeric sequence: AAA (indicating the highest creditworthiness), AA, A, BBB, BB, B, C, and D (indicating default).To create the variable *avg. risk score*, I assign numeric values to these grades with AAA taking the value 1 and D taking the value 8, and then calculate the mean risk grade of all securities issued by a firm in a year. Similarly, to create the variable *avg. CRA score*, I assign a numerical rating to all CRAs depending on their revenues, asset base and number of securities rated. CRISIL, which ranks the highest in all these metrics is assigned the value 1, and IVR, which ranks the lowest is assigned the value 7 (CARE, ICRA, IND-RA, BRICKWORK and ACUITE being assigned the score 2-6 respectively). Figure 3 shows the difference in sizes of all CRAs in the samples on 3 metrics mentioned above- revenues, asset base and number of securities rated in the sample period. The variables *no. of IR* (Initial Ratings) and *no. of downgrades* are calculated in a similar manner, by calculating the total number of initial ratings (Prowess marker which corresponds to both, new issues and CRA switching by firms for old issues) and total number of downgrades for issued securities, for a firm in a financial year. Finally, to create the variable *no. of unique CRAs*, I retain only those observations that correspond to the rating status 'initial rating', 'upgraded' or 'downgraded', and calculate the number of unique CRAs remaining at a firm-year level in this filtered dataset. This essentially captures the number of CRAs the firm has a ratings relationship within that year.

I supplement this dataset with information on firm financials which is also extracted from Prowess for the relevant time period. The variable logD is calculated as the logarithm of debt outstanding for a given firm for a financial year. Finally, I employ the product-market-based industry classification system created by CMIE to allocate firms to specific industries, encompassing a total of 152 industries within the sample.

The final sample consists of 50,919 firm-year observations corresponding to 12,356 firms, with total number of security issues by all firms in the sample period amounting to 34,815.

3.1 Summary statistics

The definitions of the variables used in this study and their calculation methodology are given in Table 1 and the corresponding summary statistics are presented in Table 2. All the firm specific independent variables, and firm debt among the list of dependent variables, have been winsorized at the 1^{st} and 99^{th} percentiles. Average size of firms in the sample is INR 11.34 billion based on total assets and INR 7.17 billion based on average total sales in a year, while the median firm has much smaller INR 1.94 billion total assets and INR 1.76 billion average total sales in a year. This indicates that the distribution of the population of firms that have issued credit instruments in the sample period is right skewed in favour of large firms. The average (median) firm has a leverage ratio of 0.42 (0.37), indicating the critical role of debt in their capital structure mix. Additionally, these firms have more intangible assets than fixed assets in their asset base as can be seen from the average (median) tangibility of only 0.3 (0.25). Finally, most of these firms are profitable, and retain close to a quarter of their profits as retained earnings, as can be seen from the median value of ebit (retained_profits) of INR 111.5 million and INR 22.1 million respectively. However, when it comes to cash flow profitability, the median firm has net cash flow of only 0.2 million, which indicates a significant proportion of firms in the sample have negative net cash flows. Nevertheless, looking at both the size and profitability characteristics, one can see a significant variation exists across the sample exists, as evident by the standard deviations and corresponding values at the 25^{th} and the 90^{th} percentiles.

The sample firms are reliant on the Indian credit markets. The average firm issues

0.68 new credit instruments in a given financial year. Furthermore, the average firm has firm-CRA relationship with only one CRA, implying the strength of firm-CRA relationships in the sample with firms rarely engaging with more than 1 CRA. And more often than not, this CRA tends to be one of the top 3 CRAs, given that the average CRA score of the average firm is 2.45. This is expected given the magnitude of difference in sizes and reputation of the top 3 CRAs versus the others. The number of downgrades suggest that rating downgrades are not a frequent event, with only 0.42 downgrades for an average firm in a year. Additionally, the average risk score of a firm is 4.27 translates to moderate riskiness level (BBB rating) of the average firm, all of which are stylized artefacts of firms in India. Nevertheless, significant heterogeneity exists in these firm outcomes, as is evident from the large standard deviations of these variables.

3.2 Comparison and analysis of univariate trends

A comparison of the univariate trends in dependent variables for the bottom4_rating and non-bottom4_rating firms before and after the identified regulation is presented in Table A1 of the Appendix. For the key dependent variable, the univariate comparison of average number of security issues in the pre-and post-regulation period indicates a sharp decline (36%) in frequency of security issuances by bottom4_rating firms after the implementation of the regulation. Similarly, when we compare the average number of downgrades across both the firm grows, one can clearly observe a significant increase of around 100% for the bottom4_rating firms in the post-regulation period. Nonetheless, the univariate comparisons fail to consider various factors that may exert an impact on the cross-sectional results.

The parallel trends plot for my main dependent variable, number of issues, for a 6-year window around the regulation implementation, grouped by the treatment and the control group, is shown in Figure 4. Figure 4a includes all credit security issuances by the firms while Figure 4b includes only long-term (and medium term) security issuances by the same firms. The figure distinctly offers initial evidence of the fact that the regulation might have exerted a notable influence on the issuance activity of the companies. This figure shows that a key reason for the decline in issuance activity is the decline in long-term loans issuance. Long-term security ratings are considered a better proxy for the level of information asymmetry between the firm and the rating agency, as rating a long-term security involves a much more thorough due diligence of firm financials as compared to rating a short-term security. The fact that most of the effect seems to be coming from long-term security issuances points to the possibility of bad type firms expending efforts in concealing their type after the regulation.

To capture the trends in other dependent variables studied in this paper for a 6-year time window around the regulation implementation, grouped by bottom4_rating and non-bottom4_rating firms, I present a parallel trends plot of their raw means in Fig. A2 in the Appendix. The figure provides some indicative evidence of the fact that the regulation may have had a significant impact on the firms. The trend of number of security downgrades and leverage shows a marginal increase in the wedge between the bottom4_rating and non-bottom4_rating firms. In contrast, the trend of average CRA score shows a significant decrease in the wedge between bottom4_rating and non-bottom4_rating firms. The wedge between both these type of firms for the variable average_risk_score appears to be constant across the sample period and hence unaffected by the regulation. Although the number of unique CRA relationships for the bottom4_ firms compared to non-bottom4_rating firms shows a slow convergence in this parallel trend plot, it is important to note that these are only suggestive plots as they do not account for other factors that may have affected the firm outcome in question. Therefore, merely looking at the parallel trends plot here does not give sufficient evidence to reject hypothesis 3 at this stage.

4 Empirical Strategy

4.1 Difference-in-differences analysis

I investigate the effects of heightened mandated credit disclosures by Credit Rating Agencies (CRAs) on firm-level outcomes using a Difference-in-Differences (DiD) analysis. This comparison is made between 'bottom4_rating' firms and 'non-bottom4_rating' firms, which exhibit substantial differences in their interactions with CRAs and the extent (as well as quality) of their information disclosures. The quasi-natural experimental design, which incorporates an exogenous shock in the form of an information disclosure requirement, enables me to discern the potential impact at the firm level.

My analysis compares the outcomes of firms that do not get even a single security that they issued between FY2015-17 rated from a top 3 CRA, namely CRISIL, CARE and ICRA (and therefore supposedly have lower quality of information disclosures), and firms that get at least one security rated from any of these top 3 CRAs. Intuitively, larger CRAs should be able to address information asymmetry concerns better because of greater reputational concerns (more reputation at stake in case of poor ratings quality) and lesser conflict of objectives- firm growth and more reliable ratings. As opposed to this, smaller CRAs have lesser reputational concerns, but more importantly, need to grow at a fast rate even if at the cost of poorer due diligence and hence poor-quality credit ratings. Therefore, among these 2 groups of CRAs, if a firm always opts to get their securities rated from smaller CRAs, it is highly likely that the quality of their information disclosures through CRAs is of poor quality.

I compare the firm outcomes of the two groups, both within firms before and after the implementation of the identified regulation, and across firms between bottom4_rating firms (no rated security from top 3 CRAs between FY 2015-17) and non-bottom4_rating firms. 'bottom4_rating' firms act as the treatment group and 'non-bottom4_rating' firms act as the control group. A very closely related DiD specification has been termed a 'difference-in-differences estimator' by Lemmon and Roberts (2010) (see also Fracassi et al. (2016)). Past research within the finance literature has utilized a comparable approach to gauge the effects of regulatory modifications (Christensen et al., 2016; Gopalan et al., 2016; Murfin and Njoroge, 2015). The DiD estimation equation is given below:

$$Y_{ijt} = a_0 + a_1(Post \times Treat) + a_2X + Fixed\ effects + \epsilon_{ijt} \tag{1}$$

where i, j, t index for firm, industry and time respectively. The outcome variable Y_{ijt} is one of the discussed outcome variables corresponding to the 3 hypotheses (number of issues, number of downgrades and number of unique CRA relationships) in subsequent regressions. X is a vector of the list of firm control variables, which are: log(total assets), log(sales), leverage, tangibility, NWC, EBIT, RE, NCF and the other outcome variables that do not serve as the outcome variable in that specific regression. Post is a dummy variable that takes the value 1 for the period FY 2015-2017 and 0 for the period FY 2018-2020. Treat is a dummy variable that takes the value 1 for bottom4_rating firms and 0 for non-bottom4_rating firms.

In all output tables, I show results for 3 regression specifications corresponding to 3 different fixed-effects structures, with increasing degree of saturation. Fixed-effects structure varies as: Column 1- Firm fixed effects, Column 2- Firm, year fixed effects, Column 3- Firm, industry interacted with year fixed effects. To address potential endogeneity concerns, all explanatory variables are lagged by one year. The inclusion of firm fixed-effects accounts for time-invariant, unobserved firm-specific heterogeneities, which also encompasses the industry fixed effects. The year-specific fixed effect captures all unobserved common macro-level shocks. In all estimations, standard errors are clustered at the firm level (as suggested by Petersen (2009)).

Additionally, interactive fixed effects are incorporated to accommodate the influence of potential unobserved variables contributing to firm-level outcomes. The incorporation of interactive fixed effects should mitigate omitted variable bias in the estimations by addressing time-variant unobserved effects across different levels of aggregation (Gormley and Matsa, 2014). In alternative estimations, I control for Industry × Year fixed effects, which captures unobserved industry-specific outcomes that fluctuate depending on time.

4.2 Parallel trends test and differential post-regulation year-wise effect

The DiD estimation is carried out for a six-year event window (t-3 to t+2 years) around the implementation of the identified regulation. I also disaggregate the average effect estimated over the event window for the year of implementation (bottom4_rating × Post (t = 0)) and for each of the two years following the year in which the regulation was implemented. To capture this differential impact of the treatment on the affected group across years, the following model specification is used where all the years in the sample period (except 2015) have 1 dummy each, indicating if the observation belongs to that year:

$$
\begin{aligned}
Y_{ijt} = a_0 + a_1(Y_{16} \times Treat) + a_2(Y_{17} \times Treat) + a_3(Y_{18} \times Treat) + \\
a_4(Y_{19} \times Treat) + a_5(Y_{20} \times Treat) + Fixed\ effects + a_6 X + (\beta_i + \gamma_j * \delta_t) + \epsilon_{ijt}
\end{aligned}
\tag{2}
$$

where i , j , t indexes for firm, industry and time respectively. The outcome variable Y_{ijt} is one of the 3 discussed outcome variables corresponding to the 3 hypotheses in subsequent regressions. X is a vector of the list of firm control variables. Y16-Y20 are year dummies for FY's 2016 - 2020 respectively, and Treat is a dummy variable that takes the value 1 for bottom4_rating firms and 0 for non-bottom4_rating firms.

Additionally, since the regression model specified above has treatment dummy interacted with year dummies for 2 years in the pre-regulation period (2016 and 2017) with 2015 acting as the base year, a statistical test for the validation of parallel trends assumption would be to check for the significance of the interaction terms for 2016 and 2017. If the interaction terms for these 2 years are insignificant, it would indicate that the wedge between the outcome variable for the treatment and control group is not statistically different from each other in these 3 years belonging to the pre-regulation period. This is a more robust test of the parallel trends assumption than visual inspection of the trend in the raw means, as it controls for a number of firm controls and fixed effects that are likely related to the trend in the outcome variable.

5 Results

5.1 Impact on number of security issuances

To begin with, I test the primary hypothesis, which stated that the bad type firms should reduce their number of security issuances in the post-regulation period. The results from the estimation of Eq. 1 on the impact of the regulation on number of new security issuance across bottom4_rating firms or the treatment group and non-bottom4_rating firms or control group are presented in columns (1)-(3) of Table 3. I take log(1 + no. of issues) as the dependent variable, given that number of issues have a right-skewed distribution with many firm-year observations clustered around 0 (as firms do not issue a security in all years). This type of transformation has been widely used in corporate finance literature recently (Hirshleifer et al., 2012; Fang et al., 2017). The specification reported in column 1 employs only firm fixed effects; specification 2 employs firm × year fixed effects; finally, specification 3 includes firm and industry × year fixed effects.

The results in Table 3 indicate that relative to the control group of non-bottom4_rating firms, bottom4_rating firms decided to issue significantly lesser number of securities in the period following the implementation of the regulation. The coefficients are significant at the 1% level. In terms of economic magnitude, as indicated by the coefficient of bottom4_rating × post, the decrease in number of security issuances is around 22 to 23 percent higher (as indicated in columns (1)-(3)) for the bottom4_rating firms, when compared to that for the non-bottom4_rating firms in the post-regulation period. This can be inferred from the coefficient of bottom4_rating × post, which is -0.255 in the most saturated model (column 3). Since the outcome is log-transformed, to interpret the percentage change in number of issues, the coefficient needs to be transformed as (1- exp(-0.255))*100. Figure 5 shows the coefficient plot (only for the coefficients corresponding to financial years) for estimation of equation 2, with the same dependent variable and control variables as described above. This plot disaggregates the average effect estimated for the post-regulation period across the 3 periods FY 2018-2020, and also additionally formally test for parallel trends in the dependent variable after controlling for the relevant covariates.

The estimation results in the coefficient plot indicate a significant negative impact on the number of security issuances of the bottom4_rating firms in the year of regulation implementation and in the following years compared to that of non-bottom4_rating firms. For instance, the number of security issuances of the treatment firms is lower by 16%, 22% and 31% percent in the immediate three years following the implementation of the regulation. Additionally, the coefficient plot shows that the coefficients for FY16 and FY17 are insignificant. Since FY15 forms the base year in this regression specification, this implies the coefficients of these 3 years aren't statistically different from each other, thus confirming parallel trends of number of issues for treatment and control group in the pre-regulation period. These findings strongly support my primary hypothesis- Hypothesis 1.

5.2 Impact on number of downgrades

Now, I move to empirically test the two secondary hypotheses, which speculate about the effect of the regulation on the number of downgrades and number of unique CRA relationships of the bottom4_ratings group firms. The results on the impact on number of security downgrades based on the estimation of Eq. 1 are presented in Table 4. I take log(1+no. of downgrades) as the dependent variable, given that number of downgrades have a right-skewed distribution with many firm-year observations clustered around 0 (as firms do not suffer rating downgrades in all years).

The results in Table 4 indicate that relative to the control group of non-bottom4_rating firms, bottom4_rating firms suffered a significantly greater number of rating downgrades on their issued securities in the period following the implementation of the regulation. The coefficients are significant at the 1% level. In terms of economic magnitude, as indicated by the coefficient of bottom4_rating × post, the increase in number of rating downgrades is around 6.5% to 7% higher (as indicated in columns (1)-(3)) for the bottom4_rating firms, when compared to that for the non-bottom4_rating firms in the post-regulation period.

Figure 6 shows the coefficient plot (only for the coefficients corresponding to financial years) for estimation of equation 2, with the same dependent variable and control variables as described above. The estimation results in the coefficient plot indicate a significant positive impact on the number of rating downgrades of the bottom4_rating firms in the year of implementation of the regulation and in the following years compared to that of non-bottom4_rating firms. For instance, the number of rating downgrades of the treatment firms is higher by 8% and 10% in the immediate two years following the year in which the regulation was implemented. The coefficient for FY18, though positive, is statistically insignificant. This may be the case because rating downgrades would possibly have a lag effect, because of the low frequency with which rating revisions are carried out for a firm in a year. Additionally, the coefficient plot shows that the coefficients for FY16 and FY17 are insignificant. Since FY15 forms the base year in this regression specification, this implies the coefficients of these 3 pre-regulation years aren't statistically different from each other, thus confirming parallel trends of number of rating downgrades for treatment and control group in the pre-regulation period. These findings strongly support Hypothesis 2.

5.3 Impact on number of unique CRAs

Finally, the results on the impact on number of unique CRA relationships based on the estimation of Eq. 1 are presented in Table 5. I take log(1+no. of unique CRA relationships) as the dependent variable, given that number of downgrades have a right-skewed distribution with some firm-year observations clustered around 0. The results in Table 5 indicate that relative to the control group of non-bottom4_rating firms, bottom4_rating firms engaged with a significantly greater number of CRAs in the period following the implementation of the regulation. The coefficients are significant at the 1% level. In terms of economic magnitude, as indicated by the coefficient of bottom4_rating $\times$ post, the impact on number of unique CRA relationships is around 3 percent higher (as indicated in columns (1)-(3)) for the bottom4_rating firms, when compared to that for the non-bottom4_rating firms. This is economically not a very significant widening of the wedge between the treatment and control group, as it implies that compared to the non-bottom4_rating firms, most of the bottom4_rating firms either engaged with the same number of CRAs in both the periods or at most, engaged with only around 1 additional CRA in the post-regulation period. Nevertheless, the DiD coefficient is statistically significant, providing some evidence, albeit weak, in support of the hypothesis that bad quality firms engage in rating shopping in the post-regulation period.

Figure 7 shows the coefficient plot (only for the coefficients corresponding to financial years) for estimation of equation 2, with the same dependent variable and control variables as described above. The estimation results in the coefficient plot indicate a significant positive impact on the number of unique CRA relationships of the bottom4_rating firms in the year the regulation was implemented and in the follwoing years compared to that of non-bottom4_rating firms. For instance, the number of unique CRA relationships of the treatment firms is higher by 3%-4% in the three years immediately following the year in which the regulation was implemented. However, the coefficient plot shows that the coefficient for FY17 is positive and statistically significant, even though only marginally (at the 5% significance level). This may be the case because, as discussed in section 2.1, the regulation was issued in November 2016 and had to be implemented by January 2017. Therefore, the regulation would have been in effect in the last two months of FY 2017. Even prior to the implementation of the regulation, it is possible that some CRAs might have anticipated the regulation and, consequently, strengthened their due diligence processes. This anticipation may have prompted certain bottom4_rating firms to engage in rating shopping behaviour slightly before the official post-regulation period. Nevertheless, because the coefficient of FY 2017 is found to be statistically insignificant at a 1% significance level, it underscores the challenges associated with drawing robust conclusions from the observed data. Finally, the coefficient plot shows that the coefficients for FY16 and FY17 are insignificant at a 1% significance level. Since FY15 forms the base year in this regression specification, this implies the coefficients of these 3 pre-regulation years aren't statistically different from each other, thus confirming parallel trends of number of unique CRA relationships for treatment and control group in the pre-regulation period.

In sum, the results of empirical tests conducted in this section provide strong evidence for the argument that the regulation caused bottom4_rating firms to issue less securities and suffer more downgrades because of more disclosures by CRAs mandated by the regulators (leading to heightened scrutiny post-regulation). There is also modest evidence supporting the fact that these firms started engaging with more CRAs in the post-regulation period, when compared to the non-bottom4_rating firms. These results provide some suggestive evidence of a strategic response by these firms in the post-regulation period in order to preserve the pooling equilibrium, by deciding to issue less securities (and therefore having to go through the due diligence procedure less frequently) or engage with multiple CRAs (possibly those that award their securities preferential ratings). This leads us to conclude that the regulation forced a rethink of the financing decision by the bottom4_rating firms.

5.4 Heterogeneity analysis

The impact of the regulation on bottom4_rating firms should not be homogeneous across all firms that are part of that group. Even though a majority of firms that are part of the bottom4_rating group must be of the bad type when it comes to the degree of information asymmetry, some firms may have consciously decided to get their issues rated from bottom 4 CRAs with the intention of providing good quality disclosures. This is possible due to reasons like lower rating cost, prior relationship with these CRAs or merely the persisting trend among the peers in the industry. In that case, one should not expect these types of firms to be as adversely affected due to the regulation as a firm which is actually of a bad type. To further uncover these other signals that might possibly complement in revealing the type of the firm in conjunction with them being part of bottom4_rating group, I undertake a heterogeneity analysis exercise.

Specifically, I look at 4 other proxies that signal the type of the firm, in addition to their choice of CRA firms- listing status, number of non-independent directors on the board, auditing firm reputation and accruals. It has been well established in literature that firms listed on the exchange have lower degree of information asymmetry as compared to unlisted firms, owing to high disclosure requirements, shareholder scrutiny and regulator's oversight. Therefore, bottom4_rating firms which are listed should experience a smaller decrease in their number of issues in the post-regulation period as compared to the control group since they would have good quality information disclosures in the pre-regulation period (good type). To test this argument, I create a dummy variable for listed firms, that takes the value 1 for listed firms and 0 for unlisted firms. On similar lines, firms that have a greater number of non-independent directors on their board have a higher degree of information asymmetry due to higher conflicts of interests, limited external oversight and more opaqueness in flow of communication. Hence, bottom4_rating firms which have a high proportion of non-independent directors on their board should experience a larger decrease in their number of issues in the post-regulation period as compared to the control group since they would have bad quality information disclosures in the pre-regulation period (bad type). To test this argument, I create a dummy variable called 'high_non_independent', that takes the value 1 for firms that have greater than median proportion of non-independent directors on their board in the pre-regulation period, and 0 for the other firms. Extending this line of thought, firms which get their financial statements audited from Big 4 auditors (Ernst and Young, Deloitte, Price Waterhouse Coopers and KPMG) should have a lower degree of information asymmetry due to reputational concerns of these auditors and stricter due diligence requirements. Following this argument, bottom4_rating firms which get their securities rated from a Big 4 audit firm should experience a smaller decrease in their number of issues in the post-regulation period as compared to the control group since they would have good quality information disclosures in the pre-regulation period (good type). To test this argument, I create a dummy variable called 'big4', that takes the value 1 for firms that get their statements audited from a Big 4 firm in at least 1 year in the pre-regulation period, and 0 for firms that never get their statements audited from a Big 4 auditor in the same period. Finally, accruals have been widely used in accounting literature as a measure of earnings management (or low quality financial information disclosure). Since accrual is a non-cash asset, and involves substantial subjectivity in its recognition, it is prone to manipulation by the management as a tool to inflate earnings. Therefore, bottom4_rating firms which have a high proportion of accruals in their balance sheet should experience a larger decrease in their number of issues in the post-regulation period as compared to the control group since they would have bad quality information disclosures in the pre-regulation period (bad type). I create a dummy variable called 'high_accruals_75', that takes the value 1 for firms that have average accruals as a proportion of sales (calculated across the 3 years in the pre-regulation period) in the top 25 percentile of all firms in the sample, and 0 for the remaining firms.

I employ a triple-interaction setup to disintegrate the effect of the regulation on these different categories of firms within the treatment group on their number of security issuances. Specifically, I interact the bottom4_rating $\times$ post with the dummy variables discussed above in a similar setup as equation 1. The regression specification for this test is as follows:

$$Y_{ijt} = a_0 + a_1(Treat \times Post \times Category) + a_2 X + \beta_i + (\gamma_j * \delta_t) + \epsilon_{ijt} \quad (3)$$

where i , j , t indexes for firm, industry and time respectively. The outcome variable Y_{ijt} is number of issues; X is a vector of the list of firm control variables, which are: log(total assets), log(sales), leverage, tangibility, NWC, EBIT, RE, NCF, ncra, avg_risk_score and avg_cra_score. Post is a dummy variable that takes the value 1 for the period FY 2015-2017 and 0 for the period FY 2018-2020. Treat is a dummy variable that takes the value 1 for bottom4_rating firms and 0 for non-bottom4_rating firms. Here, category is one of the 4 discussed heterogeneity analysis variables- listed, big4, high_non_independent, high_accruals_75.

The results of the heterogeneous effect estimation are shown in Table 6. Consistent with the listing status argument, Column 1 in Table 6 indicates that listed firms that were part of the bottom4_rating firms group suffered a significantly subdued impact on their number of security issuances in the period following the implementation of the regulation, as compared to their unlisted peers. The coefficient on bottom4_rating × post indicates that unlisted firms experienced a decrease in number of security issuances of around 27% while the same impact on listed firms is only around 21%, which is brought about by the coefficient on the triple interaction term. Therefore, listing status helps negate some of the negative impact of the regulation on the bottom4_rating firms' security issuance activities, thus acting as a valid signal of the better quality of disclosures (or lower information asymmetry) of these firms.

Column 2 in Table 6 indicates that high_non_independent firms that were part of the bottom4_rating firms group suffered a significantly inflated impact on their number of security issuances in the period following the implementation of the regulation, as compared to other firms that had greater than median independent directors on their board. The coefficient on bottom4_rating × post indicates that firms with greater than median proportion of independent directors on their board (high_non_independent=0) experienced a decrease in number of security issuances of around 22% while the same impact on high_non_independent firms is much greater, at around 28%, which is brought about by the coefficient on the triple interaction term. Therefore, consistent with my hypothesis, board composition acts as a valid signal of the type of firm, in the sense that firms with lower independent members on their board suffer from high information asymmetry firms and may thus typically be bad firms. As a result of this, they become much more cautious and issue less securities in a bid to avoid more stringent due diligence by CRAs mandated by the regulation.

Column 3 in Table 6 indicates that among firms that were part of the bottom4_rating firms group, those that got their financial statements audited from the big 4 auditors suffered a significantly muted impact on their number of security issuances in the period following the implementation of the regulation, as compared to other firms that did not get their financial statements audited from big 4 firms. The coefficient on bottom4_rating × post indicates that non-big4 firms (big4=0) experienced a decrease in number of security issuances of around 27% while the same impact on big4 firms is much lesser, at only around 8.5%, which is brought about by the coefficient on the triple interaction term. Therefore, consistent with my hypothesis, auditor choice acts as a valid signal of the type of firm. Firms that decide to get their statements audited from Big 4 firms are inherently firms with high quality of disclosures (thus signalling their good type) and hence can access the credit markets for issuing securities much more easily than their counterparts in the post-regulation period.

Finally, Column 4 in Table 6 indicates that among firms that were part of the bottom4_rating firms group, those that had accruals in the top 25 percentile suffered a significantly muted impact on their number of security issuances in the period following the implementation of the regulation, as compared to the bottom 75 percentile firms. The coefficient on bottom4_rating × post indicates that bottom 75 percentile firms (high_accruals_75=0) experienced a decrease in number of security issuances of around 24% while the same impact on high_accruals_75 firms is much lesser, at only around 15%, which is brought about by the coefficient on the triple interaction term. This is inconsistent with my hypothesis. However, this is not unreasonable, as small, growth firms are also likely to have high accruals on their balance sheet, which might be more a signal of their growth prospects rather than earnings management activities. Therefore, solely looking at accruals says little about the type of firm.

In sum, the tests examining heterogeneous effects of the regulations on the treatment group's number of security issuances provide indicative evidence of other firm signals that work in conjunction with the bottom4_rating categorization to reveal the nuances of firm type better. While listing status, board composition and auditor choice are all effective as signals of firm quality (in the expected direction), accruals unadjusted for growth prospects may not have concrete certification value as a signal of firm type. A similar analysis is conducted for number of downgrades and number of unique CRA relationships, the other two primary dependent variables, with the same 4 signal choices. The results are reported in the Appendix in Table A2 and Table A3. The results show that audit firm choice of the bottom4_rating firms has a significant impact on the differential impact of this regulation on their number of downgrades. Specifically, bottom4_rating firms with any of the big4 audit firms as auditors suffered significantly lesser downgrades, thus proving the strength of auditor choice as a signal of firm type. In the analysis on number of unique CRA relationships, although none of the coefficients except the one for accruals are statistically significant, the table shows direction of relationships consistent with hypothesis for listing status (negative for listed), board composition (positive for high_non_independent) and auditor choice (negative for big4), it is opposite to the predicted direction for accruals (negative for high_accruals_75), like in my main analysis on number of security issuances.

5.5 Additional analyses: Were bad type firms successful in preserving the pooled equilibrium?

In a previous section, the primary analysis hinted towards two choices through which the bad type firms attempted to defend themselves in the post-regulation period, in order to conceal their firm type and hence preserve the pooling equilibrium- a) by decreasing the frequency of security issues and b) by increasing the number of unique CRA relationships. However, it is still unclear whether they were successful in concealing their firm type from the market. In this section, I look at firms' interaction with two key financial institutions that play an influential role in its financing choices- credit rating agencies and banks. These institutions, along with firms themselves, are critical stakeholders in the credit market and are therefore expected to be themselves significantly impacted by this regulation. While banks would benefit from an improved disclosure environment in the post-regulation period, CRAs would have to incur additional compliance costs initially to comply with the regulation but can protect themselves from reputational concerns in the future by institutionalising a more stringent due-diligence process.

Specifically, I look at 3 secondary variables to explore the question posed above- a) average risk score, b) average CRA score and c) firm debt. As mentioned in the Data section, the variable average_risk_score takes values from 1 to 8, with 1 indicating least risky and 8 indicating most risky. As this is a firm-year variable, it can be construed as proxying for the riskiness of a firm as perceived by CRAs (through their evaluation of all securities they rate during that year) in a specific year. Similarly, average_CRA_score takes values from 1-7, with CRISIL being assigned the score 1 and IVR being assigned the score 7, based on their size and dominance in the Indian credit ratings industry. Again, this is a firm-year variable and hence tracks the evolution of firm-CRA relationships over the years, with a lower score indicating firms initiating relationship with better CRAs. Firm debt is calculated as log(debt), to scale the magnitude of debt.

The results of the analysis for the impact of the regulation on average risk score of the bottom4_rating firms based on the estimation of Eq. 1 are presented in Table 7. The results in Table 7 indicate that relative to the control group of non-bottom4_rating firms, bottom4_rating firms enjoyed a significant decrease in their average risk scores in the period following the implementation of the regulation. The coefficients are significant at the 5% level. In terms of economic magnitude, as indicated by the coefficient of bottom4_rating × post, the impact on average risk score is that of around 0.05 to 0.055 units lower average risk scores (as indicated in columns (1)-(3)) for the bottom4_rating firms, when compared to that for the non-bottom4_rating firms (in both pre and post period) and bottom4_rating firms themselves in the pre-regulation period. Although statistically significant, this is not economically a very drastic change, given that the mean of avg_risk_score is 4.27. However, the implication of this result is substantial in the context of the regulatory environment described above in the post-regulation period. Given that the regulation was intended to create a separating equilibrium by forcing firms to reveal their type through good quality disclosures, the fact that bottom4_rating firms did not experience a significant increase in their average risk scores suggests that they may have been successful in concealing their type.

Figure 8 shows the coefficient plot (only for the coefficients corresponding to financial years) for estimation of equation 2, with the same dependent variable and control variables as described above. The estimation results in the coefficient plot indicate a significant negative impact on the average risk scores of the bottom4_rating firms in the year the identified regulation was implemented and in the next year compared to that of non-bottom4_rating firms. For instance, the average risk scores of the treatment firms are lower by around 0.15 units in the immediate two years following the year in which the regulation was implemented. The coefficient for FY20, though negative, is statistically insignificant. This may be the case because of many reasons but two prominent ones are- a) twin balance sheet issue coming into light in FY2020 which led to higher rating downgrades for firms across the board, but more so for bottom4_rating firms and b) lag effect in CRAs identifying the type of firms due to access to better quality information post regulation. Additionally, the coefficient plot shows that the coefficients for FY16 and FY17 are negative and significant. This points to a negative trend in the evolution of average risk scores of the bottom4_rating firms even before the regulation which was only exacerbated post the regulation. In sum, bad type firms were able to get favourable ratings for 2 years immediately following the regulation, but this trend was reversed in 2020, when their average risk scores spiked drastically.

The results of the analysis for the impact of the regulation on average CRA score of the bottom4_rating firms based on the estimation of Eq. 1 are presented in Table 8. The results in Table 8 indicate that relative to the control group of non-bottom4_rating firms, bottom4_rating firms chose to engage with one notch better or same CRAs in the period following the implementation of the regulation. The coefficients are significant at the 1% level. In terms of economic magnitude, as indicated by the coefficient of bottom4_rating × post, the impact on average CRA score is that of around 0.135 to 0.14 units lower average CRA scores (as indicated in columns (1)-(3)) for the bottom4_rating firms, when compared to that for the non-bottom4_rating firms (in both pre and post period) and bottom4_rating firms themselves in the pre-regulation period. Although statistically significant, this is not economically a very drastic change, given that the mean of avg_CRA_score is 2.45.

However, the implication of this result is substantial in the context of the regulatory environment described above in the post-regulation period. I can't rule out the argument that there is stickiness in firm-CRA relationships (which is evident from the low magnitude of changes in average CRA score for firms YoY). However, the fact that firms choose to engage with same CRAs and even if they do 'rating shopping', engage with CRAs one notch higher than their existing CRAs may reflect a strategic choice by the firms. This is because in the post-regulation period, if a firm chose to initiate a new CRA relationship with a CRA which had a lesser reputation than the CRAs it already had a relationship with, it would send a signal to the market about the firm being of a bad type. Since every rating has two primary components to it- riskiness of security and the firm, and degree of information asymmetry, the choice of getting their securities rated from slightly better CRAs would eliminate concerns about the information asymmetry component about a firm's ratings. However, coupled with previous evidence about average risk scores, this evidence suggest that firms were able to get similar or marginally better ratings by engaging with same or slightly more reputed CRAs in the post-regulation period. Taken together, this solidifies the claim about bottom4_rating firms being able to preserve the pooling equilibrium through strategic choices, at least for a few years post the regulation.

Figure 9 shows the coefficient plot (only for the coefficients corresponding to financial years) for estimation of equation 2, with the same dependent variable and control variables as described above. The estimation results in the coefficient plot indicate a significant negative impact on the average CRA scores of the bottom4_rating firms in the year the regulation was put in place and in the two following years compared to that of non-bottom4_rating firms. For instance, the average CRA scores of the treatment firms are lower by around 0.25 units in the immediate two years following the year in which the regulation was implemented. The coefficients in the post-regulation period, though positively statistically significant, clearly show an increasing trend till 2017, which was reversed exactly when the post period started. Additionally, the coefficient plot shows that the coefficients for FY16 and FY17 are positive and significant, they are much higher than the coefficients for the post period. This points to a trend of increasingly engaging with less-reputed CRAs in the pre-period by the bad type firms, a trend which was reversed with these firms starting to engage with more reputed CRAs post the regulation.

If bottom4_rating firms engaged with same or better reputed CRAs in the post regulation period and were yet able to retain the same average risk scores they had pre-regulation, they must have been able to send the false signal to the market that they are of good type. Another strategic choice that they made to conceal their type is to issue less securities (see Table 3). One test of their success in sending the false signal is if they could act on it through their financing choices. Specifically, if the bad type firms were able to increase their debt by accessing the credit markets in a more stringent disclosure environment (post-regulation period), they must have been successful in preserving the pooling equilibrium.

The results of the analysis for the impact of the regulation on debt levels (log of firm debt) of the bottom4_rating firms based on the estimation of Eq. 1 are presented in Table 9. The results in Table 9 indicate that relative to the control group of non-bottom4_rating firms, bottom4_rating firms enjoyed a significant increase in their debt in the period following the implementation of the regulation. The coefficients are significant at the 5% level. In terms of economic magnitude, as indicated by the coefficient of bottom4_rating $\times$ post, the impact on firm debt is that of around 7.6 to 8.2 percentage higher debt (as indicated in columns (1)-(3)) for the bottom4_rating firms, when compared to that for the non-bottom4_rating firms (in both pre and post period) and bottom4_rating firms themselves in the pre-regulation period. This is economically a very drastic change, given that the mean of firm debt for the bottom4_rating sample is 5941 million. This further solidifies the claim that bad type bottom4_rating firms were able to conceal their type. Further, they were able to send a strong yet false signal to the market of their type due to- i) experiencing no significant increase in their average risk score ii) even after being evaluated by the same (or marginally better reputed) CRA iii) in the existence of a regulation that intended to reduce information asymmetry.

Figure 10 shows the coefficient plot (only for the coefficients corresponding to financial years) for estimation of equation 2, with the same dependent variable and control variables as described above. The estimation results in the coefficient plot indicate a significant positive impact on firm debt of the bottom4_rating firms in the year of regulation implementation and subsequently, in the next two years compared to that of non-bottom4_rating firms. For instance, the firm debt of the treatment firms is higher by around 9% in 2018 and around 11.5% in 2019 and 2020. Additionally, the coefficient plot shows that the coefficient for FY17 is also positive and significant. This points to a positive trend in the evolution of firm debt of the bottom4_rating firms even before the regulation which was only exacerbated post the regulation. In sum, bad type firms were able to increase their firm debt for 2 years following the regulation, but this trend stabilized in 2020, when the increasing pattern in their debt levels came to a halt.

The bigger picture that this analysis paints is that of bottom4_rating firms being able to conceal their type for at least 2 years post the regulation by (i) issuing less securities and (ii) getting their new issues rated from similar CRAs with almost similar average risk scores. While the first strategy may have helped them to avoid stringent due diligence by CRAs, the second strategy helped them to send a false signal to the market about their type. This interpretation is consolidated by the fact that their debt levels grew faster than the control group in the post-regulation period. However, the analysis also gives some suggestive evidence that the bottom4_rating firms weren't able to play this game for long. The results show that the number of downgrades and average risk scores of bottom4_rating firms spiked in 2020, with their firm debt also reaching a plateau in this year, when compared to the non-bottom4_rating firms. Taken together, these results suggest that CRAs may have been able to reveal the actual firm types of firms and create the separating equilibrium that the regulation intended to create, only in FY 2020.

6 Robustness Checks

To establish the strength of the findings presented in this paper, I conduct a set of robustness tests. First, I re-estimate Equation 1 using observations of only long-term security issuances as it might be argued that short-term security ratings primarily reflect the riskiness of the security, rather than the firm itself to a major extent, which long-term securities are better able to capture. Second, I run a Poisson regression model in place of log1plus regressions to check if the primary findings of this paper, which are about count outcomes with positively skewed distributions (number of initial ratings, downgrades and unique CRA relationships), are sensitive to the model specification. Subsequently, Equation 1 is recalculated using a propensity score matched sample to assess the consistency of the results. Finally, a placebo estimation is conducted to ascertain whether the reported findings in this paper are attributable to an artificially induced crisis.

6.1 Only long term securities

While the rating for long-term securities assigns a substantial component to firm level risk and a relatively smaller component to security risk, ratings for short-term securities are primarily driven by the riskiness of the security itself rather than that of the firm. In other words, while a firm's ability to service repayments continually matter for long term securities ratings, its solvency and liquidity position matters more for short-term security ratings. Recent studies (Baghai and Becker, 2018) on credit ratings sometimes retain only long and medium-term securities for analysing firm-level outcomes. To address concerns about my results being driven by short-term securities, I filter and retain only long-term securities and redo the entire analysis on this sub-sample.

Table 10 shows the results related to the impact of the regulation on primary firm outcomes estimated for the filtered sub-sample of long-term security issues only. I report results only for the most saturated model for brevity (firm and industry interacted with year fixed effects with standard errors clustered at the firm level). Consistent with the result from baseline regressions for the full sample, the results from this table show that the number of issues, downgrades and unique CRA relationships decreased, increased, and increased respectively for the bottom4_rating group firms in the post regulation period compared to the non-bottom4_rating group (in both pre and post periods) and the bottom4_rating group themselves pre-regulation. Specifically, Column (1)-(3) of Table 10 show that the number of issues, number of downgrades and number of unique CRA relationships of bottom4_rating group firms in the post regulation period was lower, higher and higher respectively by around 22%, 5% and 3.5%. These results are statistically significant at a 1% level, but more importantly, they have the same direction of relationship as the baseline regressions (although the magnitude is smaller).

Similarly, for the dependent variables used in additional analysis, Column (4)-(6)

show that the average risk score, average CRA score and firm debt of bottom4_rating group firms in the post regulation period was lower, lower and higher respectively by around 2%, 13% and 7%. Except for the result for average risk score, which is statistically insignificant, the results for other outcomes are significant at a 1% significance level. The insignificant result for average risk score shows that bottom4_rating firms were able to issue long-term securities in the post-regulation period with a similar rating as in the pre-regulation period, which is still consistent with the baseline results (see Section 5.1, 5.2, 5.3 and 5.5). Overall, the results from the analysis of the subsample of long-term securities are consistent with the baseline results, thus reinstating the robustness of the results of this paper.

6.2 Poisson regression

Cohn et al. (2022) show that log1plus regression suffers from concerns about heteroscedasticity, non-linearity between explanatory-predictor and predictor-predictor variables, and addition of an arbitrary constant, which may bias the coefficients of the variable of interest. They show that the bias may be so high in some cases that the coefficients may be estimated to have wrong sign in expectation when compared to the direction of relationship in the population. Poisson regression, on account of- i) its distribution being able to naturally fit the distribution of count outcomes which are positively skewed, and ii) being agnostic to violations of heteroscedasticity, is able to produce unbiased estimates with high precision in most circumstances. Therefore, for my primary dependent variables, I estimate the following equation:

$$Y_{ijt} = exp(a_0 + a_1(Treat \times Post) + a_2X + \beta_i + (\gamma_j * \delta_t) + \epsilon_{ijt}) \tag{4}$$

where i , j , t indexes for firm, industry and time respectively. The outcome variable Y_{ijt} is one of the discussed outcome variables corresponding to the 3 hypotheses (number of issues, number of downgrades and number of unique CRA relationships) in subsequent regressions. X is a vector of the list of firm control variables. Post is a dummy variable that takes the value 1 for the period FY 2015-2017 and 0 for the period FY 2018-2020. Treat is a dummy variable that takes the value 1 for bottom4_rating firms and 0 for non-bottom4_rating firms.

Table 11 shows the results related to the impact of the regulation on primary firm outcomes estimated using a Poisson regression. Again, I report results only for the most saturated model for brevity. Consistent with the result from log1plus regressions, the results from this table show that the number of issues, downgrades and unique CRA relationships decreased, increased, and increased respectively for the bottom4_rating group firms in the post regulation period compared to the non-bottom4_rating group (in both pre and post periods) and the bottom4_rating group themselves pre-regulation. Specifically, Column 1 of Table 11 indicates that relative to the control group of non-bottom4_rating firms, bottom4_rating firms decided to issue around 31% percent lesser number of securities in the period following the implementation of the regulation. Furthermore, Column 2 of Table 11 indicates that relative to the control group of non-bottom4_rating firms, bottom4_rating firms suffered downgrades around 27% percent higher in the period following the implementation of the regulation. Finally, Column 3 of Table 11 indicates that relative to the control group of non-bottom4_rating firms, bottom4_rating firms initiated unique CRA relationships around 4% percent more in the period following the implementation of the regulation. All coefficients are significant at a 1% significance level. If anything, these coefficients indicate stronger effects than reported by the log1plus regressions. Table A4 in Appendix presents the results of similar analysis extended to the dependent variables in the additional analyses section. All coefficients in the variable of interest are statistically significant and are estimated with directions consistent with the baseline results.

6.3 Propensity score matching (PSM) analysis

Next, I use the PSM technique to compare the firm-level outcomes discussed in this paper in the post-regulation period for the treatment group and a matched control sample of firms. The aim of Propensity Score Matching (PSM) is to address the non-random selection of firms opting to have their issued securities rated exclusively by bottom 4 Credit Rating Agencies (CRAs), acknowledging that this choice is influenced by specific characteristics of the firms. Propensity Score Matching (PSM) aids in alleviating asymptomatic biases arising from endogeneity or self-selection. Matching, therefore, serves as a robustness test for the regression analysis (Roberts and Whited, 2013). While this technique does not completely eliminate endogeneity or self-selection biases, it effectively addresses endogeneity issues stemming from functional form misspecifications (Shipman et al., 2017).

To do this, I follow the methodology proposed by Al Guindy (2021) and Bharath and Dittmar (2010), and conduct PSM analysis as described below. First, I run a logistic regression to estimate the likelihood of a firm being a part of the bottom4_rating firms group based on its characteristics (control variables used in the study). Since I have 3 years in the pre-period, I use the values of control variables in the year 2017 only (the year just before the treatment) for this segment of the estimation. This segment of the methodology measures the probability or propensity of a firm getting its securities rated from a bottom 4 CRA, based on its characteristics in 2017. Then, I match firms that are part of the bottom4_rating group with firms that are part of the non-bottom4_rating group, but which have homogeneous firm characteristics except for their treatment group status. This provides a way to compare firms that have a similar propensity or are equally likely to be part of the treatment group so that one firm is of the bad type and the other is of the good type.

Table A5 in the Appendix shows the results related to the PSM analysis. In Table A5, columns (1), (2), (3), (4), (5) and (6) show the results for number of issues, number of downgrades, number of unique CRA relationships, average risk score, average CRA score and firm debt respectively, as the dependent variable. The results suggest that bottom4_rating group firms issued less securities, suffered more downgrades, initiated more unique CRA relationships with better reputed CRAs and issued more debt in the post-regulation period relative to the pre-regulation period. These results are consistent with the baseline findings, except for the result for average risk score, which is insignificant for the matched sample. Nevertheless, this does not change the conclusion that bottom4_rating firms were able to get similar average risk scores in the post-regulation period as the pre-regulation period.

6.4 Placebo estimation

To further validate my main findings, I construct a falsification test with a placebo implementation year set at an alternate time point when a similar regulation which was aimed at enhancing disclosure standards by CRAs was implemented by SEBI. Baghai and Becker (2018) study a 2010 regulation by SEBI that mandated CRAs to disclose details of non-rating services revenues it receives from every issuer. They find that firms that pay more revenues for non-rating to a particular CRA are awarded more favourable rating from that CRA. I define the placebo sample period starting from FY 2008 and ending in FY 2013, comprising the implementation of the pseudo-shock regulation exactly in the centre of this timeline. Post-placebo period equals 1 for the period starting from FY 2011 and lasts till FY 2013 and is 0 otherwise. Like this paper's baseline estimates, the pre period spans a total of 3 years and similarly, the post period also spans a period of 3 years. Several corporate finance studies have adopted a similar approach (Dutordoir et al., 2022; Hu et al., 2023; Xu et al., 2016).

Table A6 in the Appendix shows the results related to placebo estimation. In Table A6, columns (1), (2), (3), (4), (5) and (6) show the results related to number of issues, number of downgrades, number of unique CRA relationships, average risk score, average CRA score and firm debt, respectively, as the dependent variable. I do not find any significant results related to the impact of the regulation on the number of issues and number of unique CRA relationships initiated by bottom4_rating firms during the pseudo shock period. However, the placebo test results show that number of downgrades decreased for the bottom4_rating group firms in the post-placebo period as compared to the pre-placebo period. Nevertheless, this is in stark contrast to the increased number of downgrades for the bottom4_rating group firms used in the primary analysis in this study. Therefore, these results are not consistent with my primary analysis results of the impact of the regulation on the treatment group on their number of issues, number of downgrades, and number of new CRA relationships initiated in the post-regulation period relative to the pre-regulation period.

Next, I find that the results for the effect of placebo regulation on average risk score and firm debt of the bottom4_rating group firms to be statistically insignificant. These results are in contrast to the results shown in Table 7 and Table 9. However, I find that the average CRA score of the bottom4_group firms decreases in the post-placebo period, consistent with my baseline results presented in Table 8. Although I can't conclusively state why this is the case, this may be because CARE recorded extraordinary growth during the phase 2011-2013, during which time it would have been a small growing CRA (CRISIL and ICRA were the top 2 CRAs at that time). The arguments that I make for the bottom CRAs in this paper must hold true for CARE during that period. But because CARE is given a score 2 to create this variable, and many bottom4_ratings firms must have initiated relationship with CARE during this period, their average CRA score must have declined. Overall, I do not find any consistent results for the impact of the regulation on firm-level outcomes during the pseudo shock period. This shows that my baseline findings are not induced by an artificially induced crisis.

7 Conclusion

In this study, I investigate a firm's strategic response (and related firm outcomes) to being exposed to a stringent due-diligence requirement business environment mandated by regulation, especially if it is of bad type, or a firm with poor disclosure quality and high information asymmetry. Using Indian firms' data and exploiting a regulation implemented by SEBI in 2018 aimed towards improving disclosure quality for CRAs rating actions, I study the effect of the regulation on a firm's number of security issuances, number of unique CRA relationships it initiates, and number of rating downgrades it suffers in the post-regulation business climate. I find strong evidence of a substantial decrease in the number of new security issuances by bad type firms, and strong evidence of a modest increase in number of unqiue CRAs these firms get their securities rated from post the implementation of regulation. I also find that these firms suffer more rating downgrades in the post-regulation period, consistent with the idea that their firm type is revealed to the CRAs because of stringent due-diligence mandated by the regulator. These results imply that bad type firms attempted to conceal their firm type in the post-regulation period through some strategic responses, but they were ultimately caught out in due time.

Additionally, I find that even among bad type firms, some firms suffered less in terms of their decrease in security issuances, owing to them sending a signal about their type through other channels. Specifically, I find that a firms listing status, board independence and auditor choice act as strong signals of a firm's type, which they use to signal that among the bad type firm pool, they are less worse than the others. Finally, I find that in the post-regulation period, the bad type firms were able to get similar ratings by similar or slightly larger (and more reputed) CRAs, thus taking advantage of the infrequent nature of rating revisions and lag with which a CRA would know the firm's real type. By doing this, they were able to send a false signal to the market, atleast for a short duration, about their type. This is evidenced by the relative greater increase in firm debt for bad type firms in the post-regulation period as compared to the good type firms. However, they were not able to play this game for long and suffered increasing risk scores (higher occurrences of rating downgrades) and decreasing firm debt once their real type was uncovered by CRAs. I find that these results are largely consistent when only long-term issuances are considered and are also robust to alternate estimation techniques, especially the Poisson estimation technique.

Overall these findings suggest that when regulators step in to increase the quality of disclosures, it results in some strategic responses by bad type firms which want to conceal their type and hence maintain a pooling equilibrium. A separating equilibrium only evolves overtime, as it takes time for CRAs to gather good quality information from these type of firms, because i) they interact infrequently with the firms because of the infrequent nature of rating revisions and ii) bad type firms want to avoid due diligence by issuing less securities. This study adds to the understanding about the critical role of CRAs and regulatory bodies in establishing a separating equilibrium based on the quality of firm's disclosures, and the strategic responses that bad type firms make to exacerbate the pooling equilibrium. Future studies can help to uncover other strategic actions that these type of firms take to conceal their type, and the economic costs of the same to shareholders, lenders and in the extreme scenario of a default, to the taxpayer.

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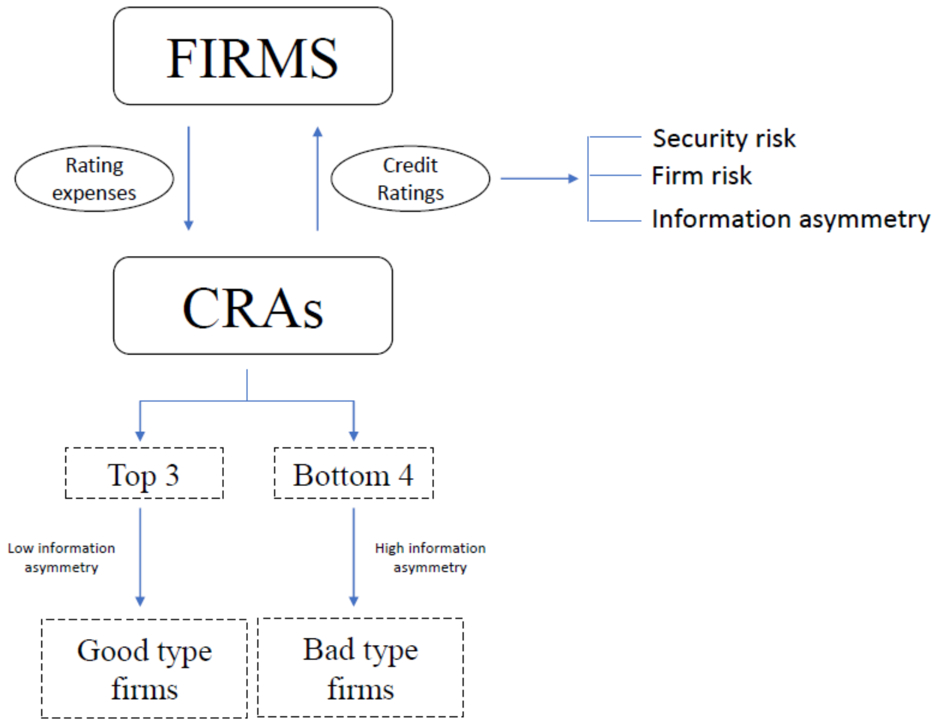


Figure 1: Firm-CRA relationship and firm-type

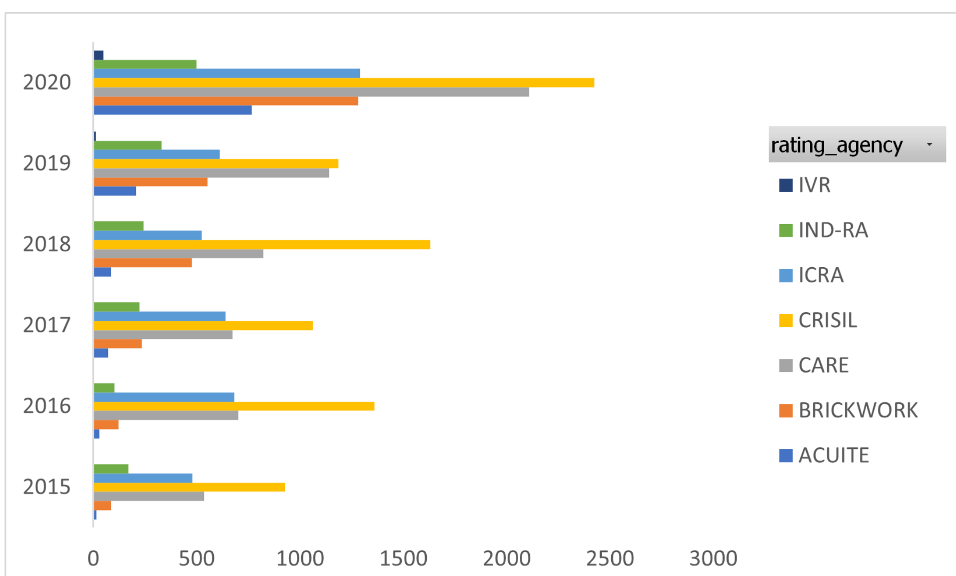
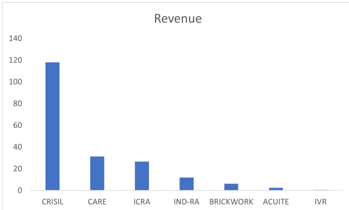
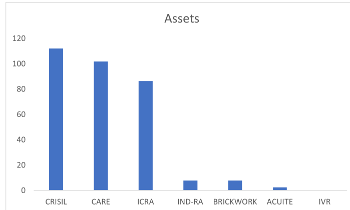


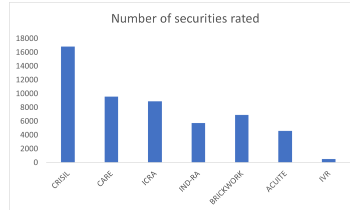
Figure 2: Number of downgrades by CRAs in 2015-2020



(a) Total revenues by CRA

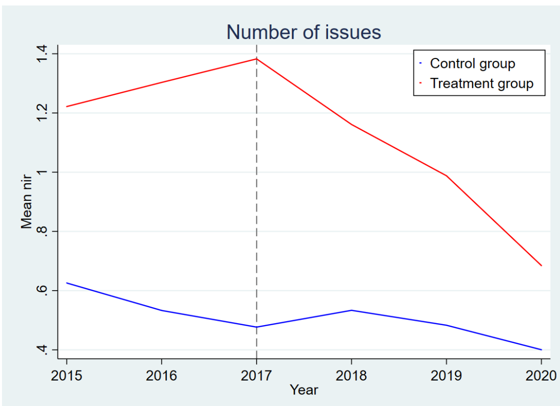


(b) Total assets by CRA

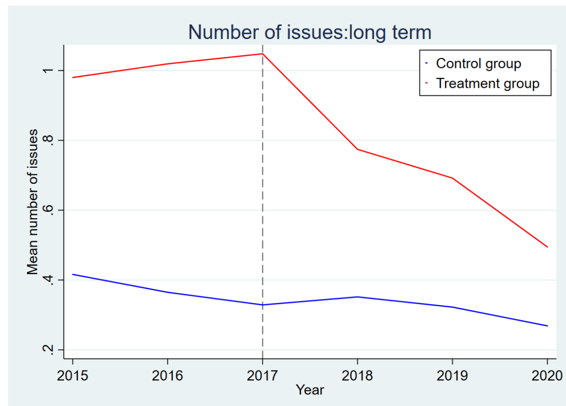


(c) Rating activity by CRA

Figure 3: Size of Indian CRAs



(a) Total issues



(b) Only long-term issues

Figure 4: Parallel trends- Number of issues

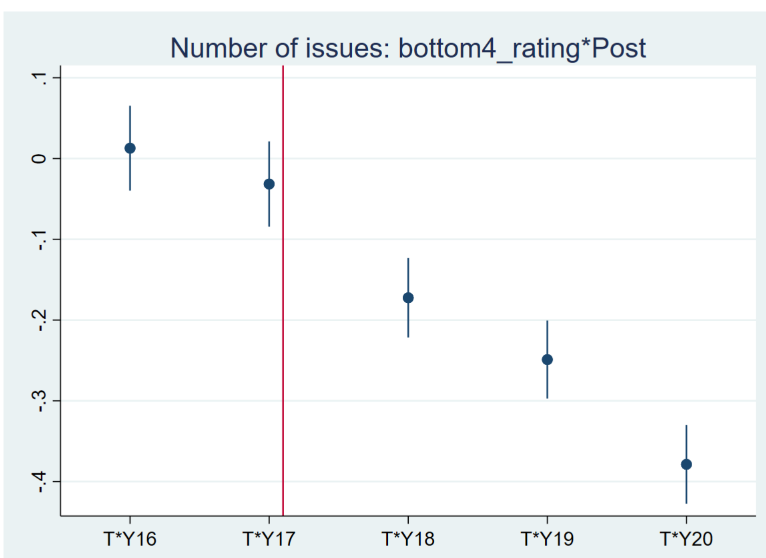


Figure 5: Coefficient plot-Number of issues

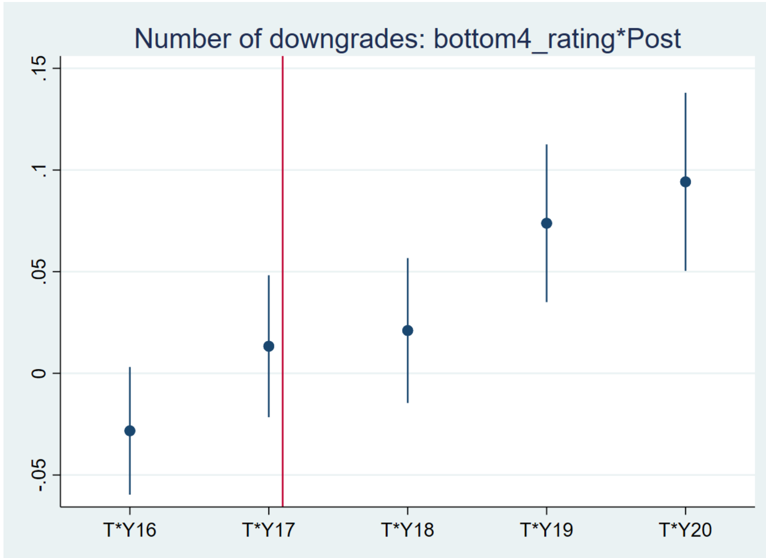


Figure 6: Coefficient plot-Number of downgrades

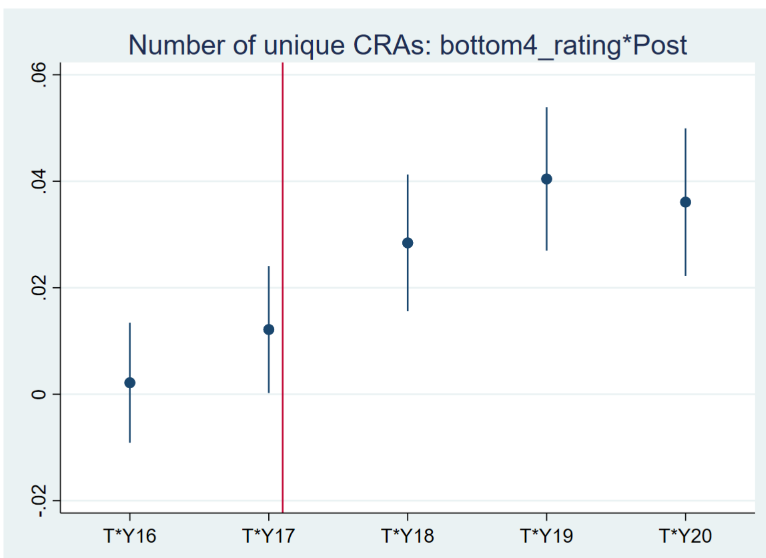


Figure 7: Coefficient plot-Number of unique CRAs

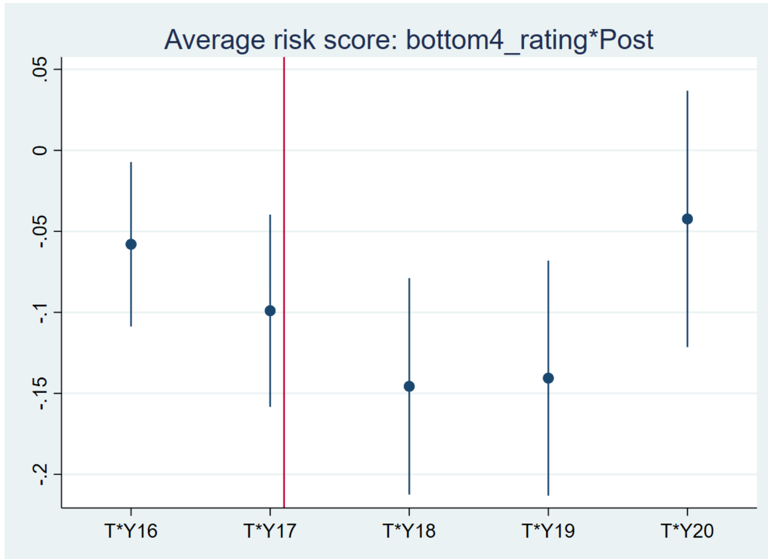


Figure 8: Coefficient plot-Average risk score

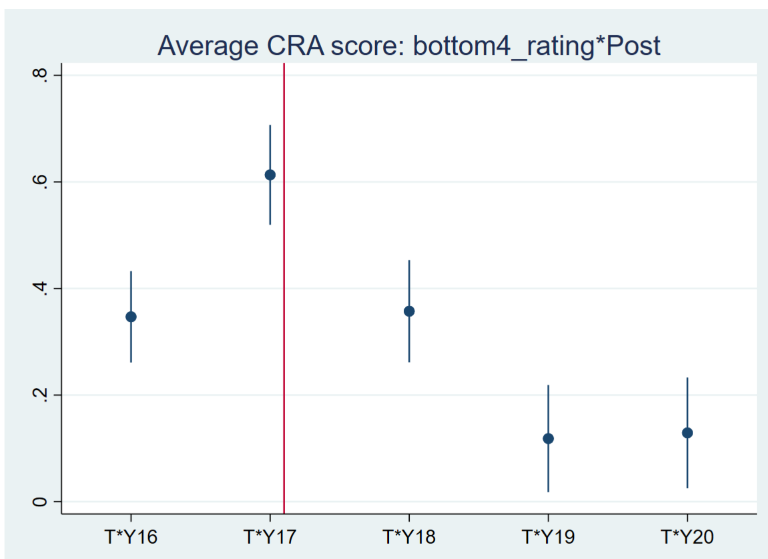


Figure 9: Coefficient plot-Average CRA score

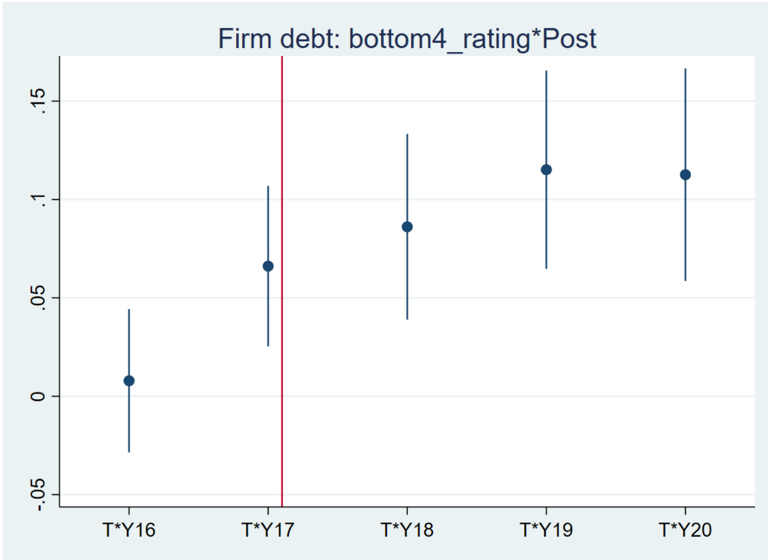


Figure 10: Coefficient plot-Firm debt

Table 1: Variable description

Variable	Variable definition	Variable calculation
Dependent variables		
nir	Number of new security issues by a firm in a financial year	log(1+number of issues)
ndg	Number of security downgrades suffered by a firm in a financial year	log(1+number of downgrades)
ncra	Number of unique CRA's a firm gets its securities rated from in a financial year	log(1+number of unique CRAs)
average_risk_score	Average riskiness of a firm based on ratings awarded to its issued securities in a financial year	$\frac{\text{Total riskiness score}}{\text{Number of securities outstanding}}$, with AAA getting a rating 1 and D getting a rating 8
average_CRA_score	Average reputation of CRA's the firm gets its securities rated from in a financial year	$\frac{\text{Total CRA score of issued securities}}{\text{Number of securities outstanding}}$, with CRISIL getting a rating 1 and IVR getting a rating 7
logD	Total debt of firm as of the last date of the financial year	log(debt)
Independent variables		
logTA	Totals assets of firm as of the last date of the financial year	log(total assets)
NCF	Net cash flow of a firm in a financial year	$\frac{\text{Net cash flow}}{\text{Total assets}}$, where net cash flow= CFO+CFF+CFI

Continued on the next page

Table 1 – continued from previous page

Variable	**Variable definition**	**Variable calculation**
leverage	Proportion of debt in the capital mix of a firm, as of the last date of a financial year	$\frac{\text{Debt}}{\text{Total assets}}$
tangibility	Proportion of fixed assets in total assets of a firm, as of the last date of a financial year	$\frac{\text{Fixed assets}}{\text{Total assets}}$
logS	Total sales of the firm in a financial year	log(sales)
NWC	Net working capital of a firm, as of the last date of a financial year	$\frac{\text{Net working capital}}{\text{Sales}}$
EBIT	Profit before interest and tax for a firm in a financial year	$\frac{\text{EBIT}}{\text{Sales}}$
RE	Proportion of retained earnings from profit after tax for a firm in a financial year	$\frac{\text{Retained earnings}}{\text{PAT}}$

Table 2: Summary statistics

Variable	**Mean**	**SD**	**p25**	**p50**	**p75**	**p90**	**N**
no_of_ir	0.683733	1.65611	0	0	1	3	50919
nDG	0.424812	1.680122	0	0	0	2	50919
nuir	1.115497	0.499337	1	1	1	2	50919
avg_risk_score	4.270753	1.699099	3	4	5.5	6	50919
avg_cra_score	2.454139	1.371114	1	2	3	5	48356
leverage	0.427633	0.87774	0.212035	0.374375	0.553229	0.748141	49346
total_assets	11337.73	33940.78	706.2	1946.3	6109.8	20712.1	50919
tangibility	0.29569	0.23527	0.10159	0.25279	0.43803	0.63609	50191
net_cash_flow	16.87427	402.3314	-14.1	0.2	19.7	122.3	45463
net_fixed_assets	3497.011	12178.12	101.8	384.9	1490	5673.6	50191
sales	7173.945	18527.85	612.4	1764.25	5007.1	14538.7	49690
net_working_capital	32.96891	4261.372	-52.4	90.1	428	1568.3	50918
ebit	730.7753	2440.238	25.9	111.5	412.6	1444.7	50803
retained_profits	115.3426	1069.911	-0.2	22.1	127.8	501.5	50803

Table 3: Effect of regulation on number of issues of treatment group

	DV: Number of initial ratings		
	1	**2**	**3**
post	-0.14866***		
	[0.00618]		
bottom4_rating × post	-0.25228***	-0.25034***	-0.25549***
	[0.01432]	[0.01442]	[0.01463]
logTA	-0.08273***	-0.02397*	-0.0184
	[0.01350]	[0.01359]	[0.01398]
NCF	0.01725	-0.00036	0.00336
	[0.05228]	[0.05132]	[0.05242]
uir	0.49670***	0.50504***	0.50178***
	[0.01147]	[0.01144]	[0.01143]
leverage	0.00094	0.00838	0.00678
	[0.01291]	[0.01266]	[0.01292]
tangibility	-0.02897	-0.03481	-0.02342
	[0.03482]	[0.03492]	[0.03556]
logS	0.00869	0.00245	-0.00138
	[0.00605]	[0.00603]	[0.00626]
NWC	-0.00002	0.00001	0.00001
	[0.00006]	[0.00006]	[0.00006]
EBIT	0.00006	-0.00001	0.00007
	[0.00051]	[0.00050]	[0.00050]
RE	0.00022***	0.00021***	0.00020***
	[0.00007]	[0.00007]	[0.00007]
avg_risk_score	-0.07125***	-0.06582***	-0.06909***
	[0.00468]	[0.00472]	[0.00481]
avg_cra_score	0.07989***	0.08718***	0.08831***
	[0.00511]	[0.00524]	[0.00527]

Continued on next page

Table 3 – Continued from previous page

	1	**2**	**3**
Constant	0.54897***	0.00122	-0.00085
	[0.10790]	[0.10977]	[0.11248]
N	39161	39161	39108
Adjusted R^2	0.22496	0.23766	0.23619
Fixed effects			
Firm	Y	Y	Y
Year	N	Y	N
Industry $\times$ Year	N	N	Y

Table 4: Effect of regulation on number of downgrades of treatment group

	DV: Number of downgrades		
	1	**2**	**3**
post	0.02536***		
	[0.00705]		
bottom4_rating × post	0.06329***	0.06315***	0.06544***
	[0.01336]	[0.01334]	[0.01339]
logTA	0.17549***	0.13919***	0.14418***
	[0.01297]	[0.01325]	[0.01393]
NCF	-0.14364***	-0.14448***	-0.14995***
	[0.03751]	[0.03735]	[0.03791]
uir	0.21936***	0.21130***	0.21300***
	[0.01096]	[0.01085]	[0.01086]
leverage	-0.00386	-0.00729	-0.00737
	[0.01058]	[0.01034]	[0.01085]
tangibility	0.00829	-0.00401	-0.00889
	[0.03265]	[0.03247]	[0.03298]
no_of_ir	-0.03735***	-0.03400***	-0.03309***
	[0.00285]	[0.00275]	[0.00254]
logS	-0.02653***	-0.01970***	-0.01913**
	[0.00753]	[0.00750]	[0.00768]
NWC	0.00016*	0.00014*	0.00013
	[0.00009]	[0.00009]	[0.00009]
EBIT	-0.00043	-0.0004	-0.00047
	[0.00071]	[0.00069]	[0.00072]
RE	0.00021***	0.00021***	0.00023***
	[0.00005]	[0.00005]	[0.00007]
avg_risk_score	0.21093***	0.20677***	0.20830***
	[0.00688]	[0.00673]	[0.00676]

Continued on next page

Table 4 – Continued from previous page

	1	2	3
avg_cra_score	0.01322***	0.00750*	0.00692*
	[0.00392]	[0.00389]	[0.00391]
Constant	-2.16513***	-1.87384***	-1.92383***
	[0.10383]	[0.10657]	[0.11099]
N	39161	39161	39108
Adjusted R^2	0.18764	0.20008	0.20284
Fixed effects			
Firm	Y	Y	Y
Year	N	Y	N
Industry × Year	N	N	Y

Table 5: Effect of regulation on number of unique CRA relationships of treatment group

	DV: Number of unique CRAs		
	1	**2**	**3**
post	0.04611***		
	[0.00187]		
bottom4_rating × post	0.03058***	0.03061***	0.02944***
	[0.00452]	[0.00452]	[0.00455]
logTA	0.02211***	0.01365***	0.01249***
	[0.00390]	[0.00397]	[0.00408]
NCF	-0.01926*	-0.01564	-0.01557
	[0.01017]	[0.01006]	[0.01017]
leverage	-0.00174	-0.00295	-0.003
	[0.00346]	[0.00347]	[0.00350]
tangibility	0.01158	0.01362	0.01343
	[0.00944]	[0.00949]	[0.00961]
logS	0.00946***	0.00996***	0.01084***
	[0.00171]	[0.00170]	[0.00180]
NWC	0.00003**	0.00003**	0.00002**
	[0.00001]	[0.00001]	[0.00001]
EBIT	-0.00019**	-0.00017**	-0.00017**
	[0.00008]	[0.00008]	[0.00008]
RE	-0.00004***	-0.00004***	-0.00002
	[0.00001]	[0.00001]	[0.00002]
avg_risk_score	0.00564***	0.00501***	0.00539***
	[0.00142]	[0.00142]	[0.00143]
no_of_ir	0.02601***	0.02653***	0.02660***
	[0.00183]	[0.00185]	[0.00159]
avg_cra_score	0.00502***	0.00383**	0.00328**

Continued on next page

Table 5 – Continued from previous page

	1	2	3
	[0.00150]	[0.00151]	[0.00148]
Constant	0.43388***	0.52678***	0.52921***
	[0.03096]	[0.03167]	[0.03249]
N	39161	39161	39108
Adjusted R^2	0.48484	0.48777	0.48635
Fixed effects			
Firm	Y	Y	Y
Year	N	Y	N
Industry $\times$ Year	N	N	Y

Table 6: Heterogeneous effect of regulation on number of issues of treatment group

	DV: Number of initial ratings			
	1	**2**	**3**	**4**
bottom4_rating × post	-0.27635***	-0.22035***	-0.27312***	-0.24418***
	[0.01685]	[0.02171]	[0.01598]	[0.02189]
bottom4_rating × post × listed	0.06317*			
	[0.03265]			
bottom4_rating × post × high_non_independent		-0.06352**		
		[0.03021]		
bottom4_rating × post × big4			0.18708***	
			[0.04344]	
bottom4_rating × post × high_accruals_75				0.09643**
				[0.04438]
logTA	-0.02048	-0.01583	-0.01367	-0.0084
	[0.01398]	[0.01427]	[0.01424]	[0.01805]
NCF	0.00353	0.00774	0.00409	0.04827
	[0.05239]	[0.05314]	[0.05264]	[0.07118]
leverage	0.00712	0.0032	0.00832	0.01625
	[0.01287]	[0.01141]	[0.01338]	[0.01682]
tangibility	-0.02776	-0.03517	-0.01995	-0.06044
	[0.03560]	[0.03657]	[0.03609]	[0.04550]
logS	0.00017	0.00144	-0.00125	0.00796
	[0.00628]	[0.00631]	[0.00638]	[0.00813]
NWC	-0.00001	-0.00001	-0.00001	-0.00006
	[0.00006]	[0.00006]	[0.00007]	[0.00009]
EBIT	0.00005	0.00009	0.00006	0.00024
	[0.00050]	[0.00049]	[0.00050]	[0.00024]

Continued on next page

Table 6 – Continued from previous page

	1	**2**	**3**	**4**
RE	0.00020***	0.00018**	0.00020***	0.00021***
	[0.00007]	[0.00007]	[0.00007]	[0.00007]
uir	0.50178***	0.50183***	0.49853***	0.48403***
	[0.01141]	[0.01165]	[0.01163]	[0.01515]
avg_risk_score	-0.06977***	-0.07119***	-0.06842***	-0.06387***
	[0.00480]	[0.00491]	[0.00490]	[0.00598]
avg_cra_score	0.08830***	0.08777***	0.08864***	0.09279***
	[0.00528]	[0.00539]	[0.00541]	[0.00772]
Constant	0.00248	-0.04954	-0.03868	-0.19233
	[0.11237]	[0.11526]	[0.11455]	[0.15206]
N	39108	37793	38078	23445
Adjusted R^2	0.23693	0.23759	0.23704	0.23571
Fixed effects				
Firm	Y	Y	Y	Y
Year	N	N	N	N
Industry × Year	Y	Y	Y	Y

Table 7: Effect of regulation on average risk score of treatment group

	DV: Average risk score		
	1	**2**	**3**
post	0.08301***		
	[0.01210]		
bottom4_rating × post	-0.05271**	-0.05216**	-0.05487**
	[0.02419]	[0.02420]	[0.02444]
logTA	-0.31052***	-0.33238***	-0.32498***
	[0.02460]	[0.02586]	[0.02594]
NCF	0.29611***	0.29595***	0.29190***
	[0.06613]	[0.06629]	[0.06714]
leverage	0.19992	0.19706	0.17794
	[0.12892]	[0.12904]	[0.12197]
tangibility	0.42408***	0.41481***	0.42738***
	[0.08216]	[0.08232]	[0.08283]
logS	-0.23436***	-0.23010***	-0.22100***
	[0.01530]	[0.01525]	[0.01504]
NWC	0.00035***	0.00034***	0.00030**
	[0.00013]	[0.00013]	[0.00013]
EBIT	-0.00089*	-0.00086*	-0.00056
	[0.00050]	[0.00049]	[0.00050]
RE	0.00029***	0.00028***	0.00025***
	[0.00008]	[0.00008]	[0.00008]
uir	0.05260***	0.04648***	0.04866***
	[0.01347]	[0.01352]	[0.01353]
no_of_ir	-0.03290***	-0.03071***	-0.03263***
	[0.00344]	[0.00339]	[0.00312]
avg_cra_score	-0.02818***	-0.03152***	-0.03206***
	[0.00673]	[0.00680]	[0.00677]

Continued on next page

Table 7 – Continued from previous page

	1	**2**	**3**
Constant	8.17023***	8.37292***	8.25008***
	[0.21414]	[0.22642]	[0.22217]
N	39161	39161	39108
Adjusted R^2	0.85904	0.85943	0.8609
Fixed effects			
Firm	Y	Y	Y
Year	N	Y	N
Industry $\times$ Year	N	N	Y

Table 8: Effect of regulation on average CRA score of treatment group

	DV: Average CRA score		
	1	**2**	**3**
post	0.22077***		
	[0.01173]		
bottom4_rating × post	-0.13881***	-0.13588***	-0.14115***
	[0.03006]	[0.03009]	[0.03061]
logTA	0.05500**	-0.01606	-0.00877
	[0.02586]	[0.02647]	[0.02683]
NCF	-0.09194	-0.06705	-0.05434
	[0.08464]	[0.08543]	[0.08326]
leverage	0.0164	0.00729	0.00723
	[0.01948]	[0.01905]	[0.01939]
tangibility	0.08745	0.10075*	0.07927
	[0.05986]	[0.05973]	[0.06110]
logS	-0.01777	-0.00968	-0.00767
	[0.01130]	[0.01120]	[0.01155]
NWC	0.00002	-0.00001	0.00002
	[0.00009]	[0.00009]	[0.00009]
EBIT	0.00046	0.00052	0.00055
	[0.00054]	[0.00055]	[0.00055]
RE	0.00003	0.00004	0.00004
	[0.00007]	[0.00007]	[0.00010]
avg_risk_score	-0.03866***	-0.04294***	-0.04433***
	[0.00936]	[0.00937]	[0.00947]
uir	0.06977***	0.05336***	0.04586**
	[0.01954]	[0.01965]	[0.01944]
no_of_ir	0.06239***	0.06693***	0.06882***
	[0.00615]	[0.00638]	[0.00573]

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Table 8 – Continued from previous page

	1	**2**	**3**
Constant	2.06161***	2.71259***	2.66073***
	[0.20414]	[0.21339]	[0.21622]
N	39161	39161	39108
Adjusted R^2	0.71029	0.71317	0.71196
Fixed effects			
Firm	Y	Y	Y
Year	N	Y	N
Industry × Year	N	N	Y

Table 9: Effect of regulation on firm debt of treatment group

	DV: Firm debt		
	1	**2**	**3**
post	-0.14171***		
	[0.01023]		
bottom4_rating × post	0.08279***	0.08194***	0.07619***
	[0.01617]	[0.01618]	[0.01657]
logTA	1.00729***	1.03647***	1.04795***
	[0.02597]	[0.02710]	[0.02771]
NCF	-0.29661***	-0.30835***	-0.29738***
	[0.09193]	[0.09190]	[0.09264]
uir	0.00205	0.00816	0.0072
	[0.00902]	[0.00907]	[0.00904]
avg_cra_score	0.00384	0.00800**	0.00543
	[0.00402]	[0.00406]	[0.00413]
tangibility	0.57553***	0.56687***	0.58989***
	[0.05264]	[0.05303]	[0.05372]
logS	-0.04542***	-0.04883***	-0.04265***
	[0.01032]	[0.01037]	[0.01060]
NWC	-0.00009	-0.00007	-0.0001
	[0.00008]	[0.00008]	[0.00008]
EBIT	0.00048	0.00046	0.00041
	[0.00068]	[0.00068]	[0.00068]
RE	-0.00002	-0.00003	-0.00011
	[0.00004]	[0.00004]	[0.00009]
avg_risk_score	0.07931***	0.08104***	0.07547***
	[0.00527]	[0.00532]	[0.00537]
no_of_ir	0.00465***	0.00273*	0.00298*
	[0.00160]	[0.00161]	[0.00167]

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Table 9 – Continued from previous page

	1	**2**	**3**
Constant	-1.44026***	-1.74151***	-1.85445***
	[0.20872]	[0.22040]	[0.22475]
N	39161	39161	39108
Adjusted R^2	0.92558	0.92586	0.92669
Fixed effects			
Firm	Y	Y	Y
Year	N	Y	N
Industry $\times$ Year	N	N	Y

Table 10: Only long term loans analysis

	No. of IR	No. of downgrades	No. of unique CRAs	Average risk score	Average CRA score	Firm debt
	1	**2**	**3**	**4**	**5**	**6**
bottom4_rating × post	-0.21878***	0.04852***	0.03181***	-0.021	-0.13458***	0.06903***
	[0.01218]	[0.01156]	[0.00442]	[0.02401]	[0.03114]	[0.01651]
logTA	-0.01645	0.12165***	0.01020**	-0.29859***	-0.00579	1.04805***
	[0.01192]	[0.01255]	[0.00414]	[0.02507]	[0.02776]	[0.02702]
avg_cra_score	0.07216***		0.00306**	-0.03304***		0.00254
	[0.00430]		[0.00144]	[0.00696]		[0.00422]
NCF	-0.00972	-0.11997***	-0.01389	0.25904***	-0.01979	-0.24805***
	[0.04731]	[0.03518]	[0.01136]	[0.05703]	[0.08981]	[0.08700]
uir_ltl	0.41561***	0.18082***		0.07493***	0.04458**	-0.00081
	[0.00977]	[0.00987]		[0.01403]	[0.01990]	[0.00938]
leverage	0.03085	-0.02188	-0.01035*	0.45815***	0.026	
	[0.02302]	[0.01822]	[0.00607]	[0.09229]	[0.04067]	
tangibility	-0.01435	0.00383	0.01179	0.29975***	0.06249	0.59964***
	[0.03124]	[0.02887]	[0.00975]	[0.07145]	[0.06090]	[0.05140]
logS	-0.00704	-0.01603**	0.01087***	-0.22161***	-0.00766	-0.04423***
	[0.00571]	[0.00693]	[0.00181]	[0.01597]	[0.01249]	[0.00921]
NWC	0.00004	0.00009	0.00002*	0.00033***	0.00003	-0.0001
	[0.00005]	[0.00007]	[0.00001]	[0.00012]	[0.00009]	[0.00007]
EBIT	0.00027	-0.00051	-0.00032**	0.00065	0.00006	-0.00061**
	[0.00086]	[0.00066]	[0.00013]	[0.00044]	[0.00095]	[0.00026]
RE	0.00018**	0.00017***	-0.00002	0.00021**	-0.00004	-0.0001
	[0.00008]	[0.00006]	[0.00002]	[0.00010]	[0.00010]	[0.00009]
avg_risk_score_ltl	-0.07115***	0.17428***	0.00804***		-0.04762***	0.07281***
	[0.00432]	[0.00593]	[0.00148]		[0.01013]	[0.00543]

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Table 10 – Continued from previous page

	1	**2**	**3**	**4**	**5**	**6**
no_of_ir_ltl		-0.04109***	0.04045***	-0.06428***	0.10733***	0.00879***
		[0.00285]	[0.00134]	[0.00458]	[0.00678]	[0.00260]
Constant	0.09479	-1.61333***	0.53213***	8.00634***	2.65255***	-1.80436***
	[0.09626]	[0.09818]	[0.03367]	[0.18947]	[0.22665]	[0.21052]
N	37147	37147	37147	37147	37147	37147
Adjusted R^2	0.23957	0.20223	0.4598	0.84314	0.71333	0.93029
Fixed effects						
Firm	Y	Y	Y	Y	Y	Y
Year	N	N	N	N	N	N
Industry × Year	Y	Y	Y	Y	Y	Y

Table 11: Poisson regression

	No. of IR	No. of downgrades	No. of unique CRAs
	1	**2**	**3**
bottom4_rating × post	-0.36249***	0.31773***	0.04133***
	[0.05214]	[0.10120]	[0.00901]
logTA	0.12203**	1.03118***	0.02611***
	[0.06182]	[0.11256]	[0.00864]
NCF	0.10831	-1.13224***	-0.03746*
	[0.19887]	[0.33534]	[0.02234]
uir	1.22569***	0.99490***	
	[0.03642]	[0.05785]	
leverage	0.03906	0.06782	-0.00825
	[0.05725]	[0.05150]	[0.00819]
tangibility	-0.00892	0.22904	0.03081
	[0.16164]	[0.24318]	[0.02056]
logS	0.06985**	0.02643	0.02228***
	[0.03107]	[0.04117]	[0.00388]
NWC	-0.00021	0.00047	0.00002
	[0.00025]	[0.00079]	[0.00002]
EBIT	0.00044	-0.00145	-0.00022**
	[0.00055]	[0.00357]	[0.00010]
RE	0.00043***	0.00126***	-0.00003
	[0.00014]	[0.00042]	[0.00004]
avg_risk_score	-0.37635***	0.48194***	0.01027***
	[0.02476]	[0.02991]	[0.00300]
avg_cra_score	0.26284***	-0.03342	0.00791***
	[0.01582]	[0.02772]	[0.00293]
no_of_ir		-0.17327***	0.04305***
		[0.02539]	[0.00337]

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Table 11 – Continued from previous page

	1	**2**	**3**
Constant	-2.10224***	-11.89790***	-0.28442***
	[0.50034]	[0.92470]	[0.06929]
N	28152	16697	39108
Pseudo R^2	0.3137	0.3592	0.0414
Fixed effects			
Firm	Y	Y	Y
Year	N	N	N
Industry × Year	Y	Y	Y

Appendix

<u>Annexure-A2: Standard Template for Press Release *(Minimum Information be disclosed)*</u>

Name of the Company

Date of Press Release

Details of Instrument

Name of the instrument	Date of issuance	Coupon rate	Maturity Date	Size of the issue	Ratingassigned, along with Rating Outlook

Rating action (assigned/upgraded/downgraded) for the instrument.

Detailed Rationale justifying the Rating Action/ rating assigned.

List of key rating driversfor the Rating Action i.e. factors justifying favourable assessment (strengths) and factors constituting risk (weakness).

Detailed description of key rating drivershighlighted above.

Analytical approach (wherever applicable) taken by the CRAto assign the rating.

Hyperlink/ reference to the applicable "Criteria" for rating the instrument.

About the Company: Factual details of the company along with the major financial information for the last and current financial year.

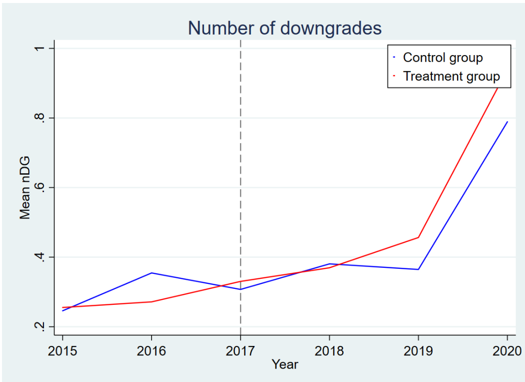
Status of non-cooperation with previous CRA (if applicable): Reason and comments on status of non-co-operation with the previous CRA (if applicable).

Any other information:

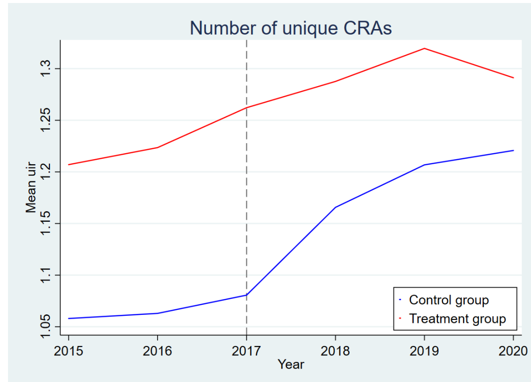
Rating History for last three years:

S.No	Name of Instrument (NCD/ Bank Loan/ Non-Fund based facilities/ Commercial Paper etc.)	Current Rating (Year T)			Chronology of Rating History for the past 3 years (Rating Assigned and Press Release Date) along with Outlook/ Watch, if applicable		
		Type (long term/ Short term)	Amount Outstanding (Rs. Crores)	Rating	Date(s) & Rating(s) assigned in Year T-1	Date(s) & Rating(s) assigned in Year T-2	Date(s) & Rating(s) assigned in Year T-3
1							
2							

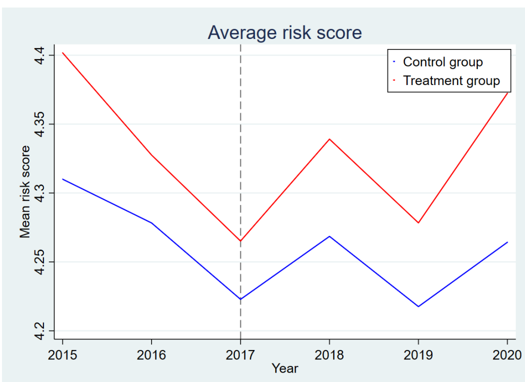
Figure A1: Snapshot of standardized document to be published by CRAs for rating actions



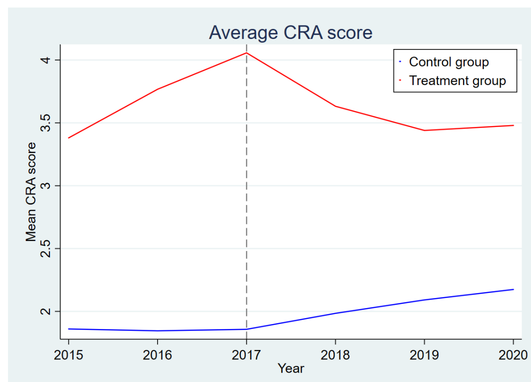
(a) Total downgrades



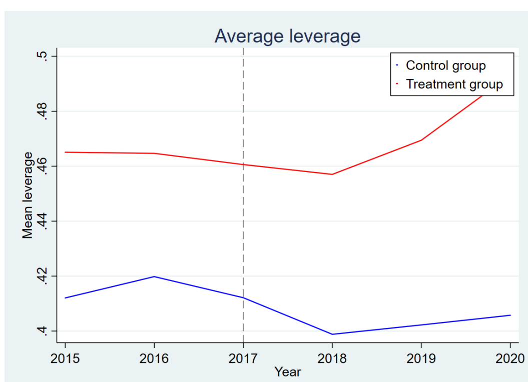
(b) Unique CRAs



(c) Average risk score



(d) Average CRA score



(e) Firm debt

Figure A2: Parallel trends analysis- Secondary hypotheses and additional analyses dependent variables

Table A1: Univariate comparison of treatment and control group before and after the regulation

	bottom4_rating firms		non-bottom4_rating firms	
Dependent variable	Pre	Post	Pre	Post
Number of issues (initial ratings)	1.303	0.932	0.542	0.474
Number of downgrades	0.286	0.603	0.304	0.507
Number of unique CRAs	1.232	1.300	1.067	1.197
Average risk score	4.496	4.313	4.261	4.174
Average CRA score	3.748	3.513	1.855	2.081
Total firm debt	0.463	0.474	0.415	0.402

Table A2: Heterogeneous effect of regulation on number of downgrades of treatment group

	DV: Number of downgrades			
	1	**2**	**3**	**4**
bottom4_rating × post	0.06104***	0.08058***	0.07586***	0.07206***
	[0.01405]	[0.02184]	[0.01459]	[0.02061]
bottom4_rating × post × listed	0.02269			
	[0.03271]			
bottom4_rating × post × high_non_independent		-0.03676		
		[0.02737]		
bottom4_rating × post × big4			-0.10661***	
			[0.04079]	
bottom4_rating × post × high_accruals_75				-0.03573
				[0.04282]

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Table A2 – Continued from previous page

	1	**2**	**3**	**4**
logTA	0.14652***	0.14784***	0.14659***	0.14727***
	[0.01395]	[0.01432]	[0.01414]	[0.01864]
NCF	-0.15015***	-0.14408***	-0.15467***	-0.20359***
	[0.03795]	[0.03774]	[0.03834]	[0.05990]
uir	0.21279***	0.21066***	0.20858***	0.19975***
	[0.01083]	[0.01102]	[0.01101]	[0.01451]
leverage	-0.008	-0.00683	-0.00864	-0.00148
	[0.01093]	[0.01111]	[0.01122]	[0.00915]
tangibility	-0.00378	-0.00095	-0.00888	-0.01161
	[0.03298]	[0.03438]	[0.03355]	[0.04247]
no_of_ir	-0.03287***	-0.03303***	-0.03270***	-0.03105***
	[0.00253]	[0.00262]	[0.00261]	[0.00334]
logS	-0.02070***	-0.02018**	-0.01877**	-0.02246**
	[0.00766]	[0.00793]	[0.00779]	[0.01047]
NWC	0.00013	0.00013	0.00014	0.00017
	[0.00009]	[0.00009]	[0.00009]	[0.00014]
EBIT	-0.00045	-0.00046	-0.00045	-0.00086
	[0.00072]	[0.00072]	[0.00071]	[0.00075]
RE	0.00023***	0.00022***	0.00022***	0.00028***
	[0.00007]	[0.00007]	[0.00007]	[0.00007]
avg_risk_score	0.20880***	0.20816***	0.20738***	0.19221***
	[0.00670]	[0.00697]	[0.00691]	[0.00875]
avg_cra_score	0.00658*	0.00646	0.00724*	-0.00304
	[0.00390]	[0.00403]	[0.00401]	[0.00591]
Constant	-1.92348***	-1.93539***	-1.93706***	-1.81476***
	[0.11100]	[0.11516]	[0.11349]	[0.15395]
N	39108	37793	38078	23445
Adjusted R^2	0.2037	0.20112	0.20148	0.19333

Continued on next page

Table A2 – Continued from previous page

	1	2	3	4
Fixed effects				
Firm	Y	Y	Y	Y
Year	N	N	N	N
Industry × Year	Y	Y	Y	Y

Table A3: Heterogeneous effect of regulation on number of unique CRAs of treatment group

	DV: Number of unique CRAs			
	1	2	3	4
bottom4_rating × post	0.03175***	0.02364***	0.03000***	0.02945***
	[0.00521]	[0.00649]	[0.00490]	[0.00642]
bottom4_rating × post × listed	-0.00732			
	[0.01005]			
bottom4_rating × post × high_non_independent		0.01123		
		[0.00926]		
bottom4_rating × post × big4			-0.01912	
			[0.01439]	
bottom4_rating × post × high_accruals_75				-0.02976**
				[0.01364]
logTA	0.01261***	0.01183***	0.01192***	0.01760***
	[0.00408]	[0.00387]	[0.00420]	[0.00537]
NCF	-0.01558	-0.01423*	-0.01716*	-0.01959
	[0.01017]	[0.00843]	[0.01021]	[0.01433]
leverage	-0.00301	-0.00255	-0.00335	-0.00119
	[0.00349]	[0.00328]	[0.00373]	[0.00335]
tangibility	0.01367	0.01647	0.01293	0.02974**

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Table A3 – Continued from previous page

	1	**2**	**3**	**4**
	[0.00961]	[0.01144]	[0.00977]	[0.01281]
logS	0.01074***	0.01021***	0.01103***	0.00902***
	[0.00179]	[0.00202]	[0.00185]	[0.00236]
NWC	0.00002**	0.00003**	0.00003**	0.00004***
	[0.00001]	[0.00001]	[0.00001]	[0.00001]
EBIT	-0.00017**	-0.00018**	-0.00017**	-0.00011*
	[0.00008]	[0.00009]	[0.00008]	[0.00006]
RE	-0.00002	-0.00001	-0.00002	-0.00001
	[0.00002]	[0.00001]	[0.00002]	[0.00002]
avg_risk_score	0.00544***	0.00541***	0.00499***	0.00231
	[0.00143]	[0.00165]	[0.00146]	[0.00179]
no_of_ir	0.02662***	0.02680***	0.02646***	0.02465***
	[0.00160]	[0.00181]	[0.00162]	[0.00215]
avg_cra_score	0.00329**	0.00336**	0.00298**	0.00447**
	[0.00148]	[0.00158]	[0.00151]	[0.00218]
Constant	0.52885***	0.54384***	0.53495***	0.50602***
	[0.03247]	[0.03392]	[0.03340]	[0.04453]
N	39108	37793	38078	23445
Adjusted R^2	0.48636	0.48805	0.48953	0.53704
Fixed effects				
Firm	Y	Y	Y	Y
Year	N	N	N	N
Industry × Year	Y	Y	Y	Y

Table A4: Poisson regression- Additional analyses variables

	Average risk score	Average CRA score	Firm debt
	1	**2**	**3**
bottom4_rating × post	-0.01334**	-0.08816***	0.01101***
	[0.00577]	[0.00934]	[0.00249]
logTA	-0.07644***	-0.0046	0.15829***
	[0.00609]	[0.01035]	[0.00476]
NCF	0.06404***	-0.01467	-0.04278**
	[0.01426]	[0.03074]	[0.01717]
leverage	0.03332	0.00505	
	[0.02499]	[0.01038]	
tangibility	0.08472***	0.03219	0.07959***
	[0.01937]	[0.02374]	[0.00845]
logS	-0.04277***	-0.00211	-0.00540***
	[0.00306]	[0.00414]	[0.00152]
NWC	0.00006**	0.00001	-0.00001
	[0.00003]	[0.00003]	[0.00001]
EBIT	0.00001	0.00019	0.00001
	[0.00013]	[0.00018]	[0.00006]
RE	0.00008***	0.00002	-0.00001
	[0.00003]	[0.00004]	[0.00001]
uir	0.01368***	0.01879***	0.00085
	[0.00321]	[0.00711]	[0.00131]
no_of_ir	-0.00841***	0.02263***	0.0003
	[0.00070]	[0.00175]	[0.00024]
avg_cra_score	-0.00603***		0.00097
	[0.00144]		[0.00066]
avg_risk_score		-0.01679***	0.01096***
		[0.00354]	[0.00078]

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Table A4 – Continued from previous page

	1	2	3
Constant	2.35615***	1.10613***	0.58605***
	[0.05120]	[0.08431]	[0.04129]
N	39108	39108	39108
Pseudo R^2	0.1602	0.1692	0.1158
Fixed effects			
Firm	Y	Y	Y
Year	N	N	N
Industry × Year	Y	Y	Y

Table A5: Propensity Score Matching (PSM) Analysis

	No. of IR	downgrades	unique CRAs	risk score	CRA score	Debt
	1	**2**	**3**	**4**	**5**	**6**
bottom4_rating × post	-0.22244***	0.07164***	0.01685***	-0.03294	-0.15223***	0.06136***
	[0.01909]	[0.01823]	[0.00617]	[0.03080]	[0.03713]	[0.02184]
logTA	-0.03211	0.11537***	0.02135***	-0.33063***	-0.04349	1.06163***
	[0.02362]	[0.02284]	[0.00750]	[0.04018]	[0.05088]	[0.03973]
NCF	0.05833	-0.20413***	-0.00493	0.41818***	0.10152	-0.60866***
	[0.09074]	[0.07509]	[0.02148]	[0.14233]	[0.15787]	[0.16616]
uir	0.46045***	0.19445***		0.05462***	-0.00843	0.00335
	[0.01500]	[0.01453]		[0.01851]	[0.02523]	[0.01165]
leverage	0.09907***	-0.06365*	-0.01541	0.52611***	0.0498	
	[0.03490]	[0.03734]	[0.01145]	[0.10799]	[0.06102]	
tangibility	-0.05592	0.05795	0.04363**	0.32985***	0.19248*	0.54873***
	[0.05725]	[0.05432]	[0.01807]	[0.11423]	[0.10357]	[0.07341]
logS	0.01836*	-0.02508*	0.01235***	-0.26695***	-0.00168	-0.04811***
	[0.00987]	[0.01348]	[0.00319]	[0.02507]	[0.01854]	[0.01720]
NWC	0.00006	0.00015	0.00002	0.00053***	0.00012	-0.00007

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Table A5 – Continued from previous page

	1	2	3	4	5	6
	[0.00005]	[0.00010]	[0.00002]	[0.00020]	[0.00015]	[0.00007]
EBIT	-0.00131***	0.00028	-0.00024	-0.00023	0.00175	-0.00106**
	[0.00049]	[0.00089]	[0.00023]	[0.00082]	[0.00109]	[0.00047]
RE	0.00023***	0.00021**	-0.00001	0.00027***	0.00005	-0.00016
	[0.00007]	[0.00009]	[0.00003]	[0.00007]	[0.00012]	[0.00012]
avg_risk_score	-0.07217***	0.18684***	0.00672***		-0.04065***	0.08406***
	[0.00761]	[0.01093]	[0.00247]		[0.01535]	[0.00812]
avg_cra_score	0.07237***	0.00157	-0.00542***	-0.01874**		0.00389
	[0.00741]	[0.00542]	[0.00209]	[0.00944]		[0.00552]
no_of_ir		-0.03139***	0.02480***	-0.02702***	0.05565***	0.00612***
		[0.00376]	[0.00218]	[0.00473]	[0.00761]	[0.00221]
Constant	0.00297	-1.54445***	0.48057***	8.51049***	3.29516***	-1.89601***
	[0.20001]	[0.18160]	[0.06239]	[0.32830]	[0.43023]	[0.35135]
N	15871	15765	15723	15804	15577	15780
Adjusted R^2	0.2492	0.19713	0.50679	0.85983	0.65319	0.94001
Fixed effects						
Firm	Y	Y	Y	Y	Y	Y
Year	N	N	N	N	N	N
Industry × Year	Y	Y	Y	Y	Y	Y

Table A6: Placebo estimation- 2008-2013 window

	No. of IR	downgrades	unique CRAs	risk score	CRA score	Debt
	1	2	3	4	5	6
bottom4_rating × post	0.03996	-0.12991***	-0.00086	-0.02942	-0.22180***	-0.03976
	[0.04401]	[0.03576]	[0.01075]	[0.06057]	[0.04465]	[0.03887]
logTA	0.01811	0.13112***	0.01634**	-0.22512***	0.02108	1.23808***
	[0.03241]	[0.02833]	[0.00640]	[0.05204]	[0.02853]	[0.04369]

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Table A6 – Continued from previous page

	1	**2**	**3**	**4**	**5**	**6**
NCF	-0.00115	-0.0868	-0.01704	0.31599**	-0.00729	0.00403
	[0.11647]	[0.07403]	[0.01880]	[0.12372]	[0.07078]	[0.12676]
uir	0.50838***	0.13741***		-0.05414	0.11580***	0.02695
	[0.02804]	[0.02433]		[0.03384]	[0.03120]	[0.01903]
leverage	0.01738	0.29006***	0.00672	0.68933***	-0.04953	
	[0.06655]	[0.06055]	[0.01361]	[0.12325]	[0.05279]	
tangibility	-0.04284	0.14635**	0.01698	0.56563***	-0.05993	0.55221***
	[0.08322]	[0.07363]	[0.01392]	[0.12880]	[0.06065]	[0.09139]
logS	0.01531	-0.04740***	-0.00015	-0.18180***	-0.04523***	-0.01785
	[0.01670]	[0.01547]	[0.00366]	[0.02667]	[0.01373]	[0.02028]
NWC	0.00018	0.0002	0.00004	0.00012	-0.00014	0.00007
	[0.00022]	[0.00016]	[0.00003]	[0.00017]	[0.00014]	[0.00028]
EBIT	0.00037	-0.00067	-0.00014	-0.00069	0.00105	-0.00464*
	[0.00200]	[0.00246]	[0.00028]	[0.00214]	[0.00239]	[0.00277]
RE	-0.00003	0.00042**	0.00002	-0.00025	-0.0001	-0.00048
	[0.00026]	[0.00019]	[0.00003]	[0.00045]	[0.00011]	[0.00031]
avg_risk_score	-0.03115***	0.27044***	-0.00257		0.00801	0.04531***
	[0.00963]	[0.01002]	[0.00179]		[0.00967]	[0.00744]
avg_cra_score	0.01554		0.01656***	0.0229		0.00294
	[0.02297]		[0.00477]	[0.02768]		[0.01155]
no_of_ir		-0.02720***	0.01164***	-0.00753*	0.00008	0.00294
		[0.00558]	[0.00131]	[0.00437]	[0.00362]	[0.00273]
Constant	-0.25157	-1.73284***	0.54801***	6.50710***	2.19265***	-3.42706***
	[0.26018]	[0.23742]	[0.04886]	[0.41709]	[0.23027]	[0.34416]
N	12171	12171	12171	12171	12171	12171
Adjusted R^2	0.26519	0.2743	0.47484	0.85734	0.84475	0.94405
Fixed effects						
Firm	Y	Y	Y	Y	Y	Y

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Table A6 – Continued from previous page

	1	2	3	4	5	6
Year	N	N	N	N	N	N
Industry $\times$ Year	Y	Y	Y	Y	Y	Y