Impact of Stringent Regulation on Ratings Market: Evidence from Death of a Rating Agency *

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Abstract

Do strict regulatory sanctions, such as banning a rating agency and reducing competition in the rating market, improve rating quality? Or does the suspension of an agency lead to unintended consequences of downward biased ratings? Exploiting a rare instance of a regulator-sanctioned forced exit of a credit rating agency (CRA) in India, I examine the impact on rating standards of other agencies. Using a difference-in-differences design, I find that the ban on rating services of a CRA leads to a one-notch rating downgrade in one out of five impacted firms. The results are robust to the use of the Ordered logistical regression model. Further, the deflation of ratings is associated with a 30% decline in type I errors (missed defaults) but is also accompanied by an unintended 154% increase in type II errors (false warnings). My findings are consistent with the "pessimistic behavior" hypothesis, where incumbent raters issue downwardly biased ratings to mitigate higher regulatory costs. Further, the decline in ratings leads to real consequences of an increase in borrowing costs for firms that solicit ratings. These findings highlight the unintended consequences of regulator-led forced rating agency exits.

Keywords: Credit rating, Regulation, Rating quality

JEL Codes: G24, M41, M48, G28

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"...It is totally unacceptable, given the evidence of credit rating agency abuses in our 2010 hearings and the S.E.C.'s own inspection reports, that proposed rules (Dodd-Frank Act) to stop the conflicts of interest and inflated ratings have been stalled for three years, wrapped up in bureaucratic red tape. Worse, the proposed rules aren't tough enough to cure the problems..."

Senator Carl Levin
Member of Senate's Subcommittee on Investigations (2014)

1 Introduction

Credit ratings are integral to the functioning of financial markets. Credit rating agencies (CRAs) act as gatekeepers in the financial industry by assessing creditworthiness and providing a trusted evaluation of risk for borrowers and financial instruments. They are utilized by banks in lending decisions, incorporated in investment strategies and fund mandates to manage portfolio risks, and employed in determining regulatory capital requirements under Basel capital adequacy rules.[1] Given the heavy reliance on credit ratings, failure of ratings to predict insolvency can be potentially costly, as evidenced by rating deficiencies observed during the global financial crisis (Benmelech and Dlugosz (2009); Griffin and Tang (2011); He et al. (2012)), Enron crisis (Bedendo et al. (2018), Hill (2011)), and in the bankruptcy of Silicon Valley Bank.[2]

Despite the regulator's efforts to address rating failures through reforms such as the Credit Rating Reform Act (CRA reform ACT) and the Dodd-Frank Wall Street Reform and Consumer Protection Act (Dodd-Frank Act), the general consensus is that the measures have failed to bring about meaningful changes in the rating market (see for example Hill (2004), White (2010),Hill (2011), Opp et al. (2013), Partnoy (2017)). Moreover, the regulators have been accused of providing regulatory immunity to rating agencies through exclusive licensing, such as the nationally recognized statistical rating organization (NRSRO) designation in the US, which incentivizes complacency on the part of CRAs in safeguarding their reputational incentives (Mathis et al. (2009), Partnoy (2017)). Not surprisingly, the extant regulatory actions in the credit rating markets have been limited to monetary penalties and oversight.

[1] See for e.g., Holthausen and Leftwich (1986), Diamond (1991), Hand et al. (1992), and Graham and Harvey (2001)

[2] In an article in Forbes, the author asks "Why did it take a stock price collapse beginning March 6, 2023, for credit rating agencies to downgrade SVB?". The article is available at https://www.forbes.com/sites/shivaramrajgopal/2023/03/15/svb-is-one-more-example-of-a-governance-crisis-that-seems-to-be-only-foretold-by-short-sellers-despite-plenty-of-red-flags-hiding-in-plain-sight/?sh=59f3fad11f63

The inadequacy of past regulatory actions begs the question, "Do stricter sanctions, such as banning the offending rating agency, discipline the rating market and improve the accuracy of ratings?". A ban on a rating agency is significantly different from other regulatory actions that are usually limited to monetary fines and warnings. Moreover, a ban on a rating agency decreases the competition in the rating market, and it is not obvious whether the decline in competition leads to more accurate ratings.

On the one hand, the suspension of a CRA and the subsequent reduction in competition can induce higher reputation incentives, potentially resulting in higher rating quality (Becker and Milbourn (2011)). Additionally, the forced exit of a CRA on grounds of low-quality ratings can signal a strong intent of the regulator to impose severe penalties in the event of rating deficiencies. As a result, agencies may invest in rating methodology, process due diligence, and internal controls to minimize the likelihood of issuing a low-quality rating and facing suspension by the regulator. Consequently, forced exit can lead to a disciplining effect on the rating agencies and ultimately lead to an improvement in the quality of ratings.

On the other hand, Bae et al. (2015) suggests that lower competition may not necessarily lead to improvement in the quality of ratings. For instance, the CRA reform act advocated for the entry of new players in the rating market to stimulate innovation in rating practices and foster healthy competition. More importantly, a 'forced' exit is different from other types of exits that are driven by market forces and may not necessarily lead to improvement in rating standards. Specifically, a forced exit may signal a significant increase in costs of misratings for the rating agencies, potentially inducing a more pessimistic behavior by these agencies. Given that regulatory penalties are asymmetric in the direction of rating bias (Goel and Thakor (2011), Dimitrov et al. (2015)), forced exit may prompt CRAs to issue downward biased ratings to mitigate the risk of being suspended. Consequently, this could lead to lower-than-optimum rating levels and a decline in rating quality. Thus, it is unclear whether a rating agency's forced exit improves or deteriorates rating quality and needs to be examined empirically.

Moreover, examining the aforementioned hypothesis empirically is challenging due to the rarity of such stringent regulatory sanctions. For example, despite several episodes of rating disasters, none of the CRAs operating in the US have ever faced suspension by the Securities and Exchange Commission (SEC). The primary reasons are the oligopolistic nature of the ratings market and the market powers of existing raters derived from exclusive regulatory licenses. Therefore, to examine the effect of the forced exit of a rating agency on rating standards, one needs a setting where the regulator revokes the license of the offending rating agency.

Fortunately, the Indian ratings market provides a unique setting to test the thesis. The Indian regulator, the Securities Exchange Board of India (SEBI), which oversees CRAs in India, suspended one of the rating agencies – Brickwork Ratings (henceforth, Brickwork)– in 2022. Brickwork was banned due to severe rating deficiencies unearthed by SEBI during periodic inspections. Specifically, SEBI highlighted that Brickwork has failed to follow proper rating processes and due diligence, delayed monitoring of ratings and failed to address conflicts of interest, among other deficiencies. Moreover, SEBI recommended suspension on the grounds that Brickwork fared poorly in rating stability compared to other rating agencies, and the actual probability of defaults of ratings from Brickwork fell below the benchmarks specified by SEBI.[3] Note that, like most other jurisdictions, India has never witnessed the forced exit of a rating agency, and the regulatory sanctions have been largely restricted to monetary penalties. Thus, the forced exit of Brickwork was unanticipated and provides an ideal setting to study the effects of stringent regulatory enforcement.

Further, the Indian ratings market is well-developed and representative of other well-established ratings markets (Baghai and Becker (2018)). First, Indian banks rely heavily on external ratings to determine the risk-weight of loans, aligning with globally accepted Basel capital standards. Second, the Indian ratings market is dominated by the Big-3 global agencies – S&P, Moody's, and Fitch – ensuring adherence to global rating standards. Third, the market operates as an oligopoly, follows an issuer-pay model, and faces regulatory barriers to entry, similar to the US and other well-known ratings markets. Lastly, India's large economy and widespread debt market make it an intriguing case study to examine the impact of stricter regulatory sanctions on rating agencies.[4] Thus, inferences drawn from this study can provide valuable insights for other economies.

In this paper, I exploit the forced exit of Brickwork to implement a difference-in-differences (DID) research design and examine the effects on rating standards. Since the SEBI inspection report that recommended suspension of the license of Brickwork was released in April 2021, I denote

[3]SEBI report documents that the average default rate of securities rated AAA by Brickwork is higher than the tolerance level specified by SEBI.

[4]India is one of the fastest growing economies in the world largely aided by robust bank lending market of nearly 50% of the size of the GDP. Source `https://www.livemint.com/news/india/how-indian-banking-is-growing-in-five-charts-11674496516908.html`

the year-quarters after April 2021 as post-intervention period.[5] For identification, I assign the firms belonging to industries with a higher market share of Brickwork during the pre-intervention period as treated firms. The intuition is that industries where Brickwork has a higher market share in the pre-period experience a larger decline in competition. Therefore, I divide the industries into terciles based on the market share of Brickwork in each industry in the pre-period. The firms belonging to the top (bottom) tercile of industries are classified as treated (control) firms.

I collect the credit ratings data from the Centre for Monitoring Indian Economy (CMIE) Prowess database.[6] I then follow Baghai and Becker (2018) to arrange the data at a firm-CRA-quarter level and assign numeric rating score corresponding to each rating grade. A higher rating score indicates a lower credit rating (e.g., AAA denotes a rating score of one, whereas CCC denotes a rating score of 19.). I also use the CMIE data to download other firm-level financial variables from their audited financial statements.

To assess the quality of ratings, I download the loan repayment data of firms from Transunion CIBIL. CIBIL is the largest credit information repository in India that maintains the track record of loan delinquencies of firms at a quarterly frequency. I manually match the firm names between CMIE and CIBIL to create a firm-CRA-quarter level data set having rating scores and future (one-year look ahead period) loan defaults.

Before examining the impact of the forced exit of CRA on rating quality, I first examine the effect on the levels of credit ratings. Given the widespread use of ratings in investment mandates and the calculation of regulatory capital in banks, stability of ratings through the course of the business cycle is desirable. Thus, any unwarranted change in rating level can amount to instability in ratings. I test whether rating levels are impacted due to the suspension of Brickwork using a DiD specification. Results show that credit ratings worsen significantly following the forced exit of a CRA. Specifically, I find that the exit of the rating agency leads to a one-notch downgrade for one out of five treated firms. My results are robust to the use of firm, CRA, and year-quarter level fixed effects. Further, the rating downgrades are not due to firm characteristics that are known to impact the ratings of a firm, such as interest cover ratio, leverage, debt-to-EBITDA ratio, and

[5] See the news article `https://economictimes.indiatimes.com/markets/stocks/news/sebi-issues-notice-to-brickwork-ratings-india-over-lapses/articleshow/82316678.cms?from=mdr`

[6] The CMIE Prowess database has been used extensively for empirical research on Indian markets and has been cited in prominent papers including De Loecker et al. (2016), Manchiraju and Rajgopal (2017), and Baghai and Becker (2018)

profit margins. Thus, ratings of firms have declined significantly following the demise of a CRA.

A drawback of the above empirical design is that it assumes that the numerical rating scores corresponding to the rating letter grades are continuous in nature. However, in reality, credit ratings act as step functions that assign different levels of relative credit risk to each rating grade. To address the above issue, I employ an ordered logistic regression (ologit) model (Dimitrov et al. (2015)). I find that that the ologit results are consistent with the OLS results. Specifically, I find that the odds of a downgrade are 1.12 times higher after the exit of the CRA.

Next, I examine whether the rating deflation is associated with improvement in rating quality or it is caused by the pessimistic behavior of rating agencies. I examine two different aspects of rating quality: False warnings and Missed defaults.

A false warning (type II error) is an event where the rating agency downgrades the firm to below investment grade (lower than BBB rating), and the firm does not default on debt obligations within the next one year of the downgrade. Specifically, false warnings measure whether the downgrades reflect a higher likelihood of future loan defaults. I use the DiD specification with firm, CRA, and time-level fixed effects to test the above. I also account for the observed firm-time level characteristics that can impact the credit ratings of firms. I find that the exit of the CRA leads to a higher probability of false warnings. Specifically, the probability of false warnings increases by 2.9% in a DID sense. Given that the unconditional rate of type II error is 1.88%, the coefficient represents a 1.54 times increase in the probability of false warning.

Next, I focus on missed defaults or type I errors. Missed default is defined as an event where the firm receives a rating upgrade from the rating agency but defaults on loan repayments within the next year. Thus, type I errors potentially represent optimistic or inflated credit ratings. I run a similar DID specification and find that type I error reduces significantly. In terms of economic magnitude, missed defaults reduce by 30%. The above results suggest that the forced exit of the CRA leads to rating deflation, which results in 30% lower type I errors but also results in 154% higher type II errors.

These findings collectively suggest that the forced exit of the credit rating agency (CRA) leads to a deflation in ratings, resulting in a 30% reduction in type I errors. However, it is also accompanied by an undesirable 154% increase in type II errors. Consequently, the findings are consistent with the view that the decline in ratings is driven by the pessimistic behavior of CRAs and does not necessarily represent an improvement in the quality of ratings.[7]

A major concern with the DID inferences is that the empirical results merely reflect pre-existing trends of an increase in type II error. To mitigate this concern, I test for parallel trends between the treated and control groups in the year-quarters preceding the regulatory intervention. I find that my results are robust to the test for parallel trends in the pre-period.

In the second part of the paper, I address several endogeneity concerns and conduct robustness tests to address them. One significant concern is the influence of self-selection bias, whereby firms may deliberately choose a rating agency for endogenous reasons, making the selection into the treatment or control group non-arbitrary. I address the above concern partially by conducting a robustness test where I limit the sample to firms that have ratings from at least two rating agencies. Thus, I drop the firms that have exclusive rating relations with only one CRA and possibly are involved in collusive behavior for biased ratings. I find that, even with this reduced sample, the conclusions drawn from the analysis remain largely unaffected.

Another concern is that the smaller rating agencies are significantly different from the larger rating agencies and, therefore, may behave differently to regulatory intervention. A skeptic may argue that large CRAs are unlikely to be suspended because the exit of a large CRA could disrupt the ratings market significantly. Consequently, the observed effects could be driven by the pessimistic reaction of the smaller and relatively inexperienced CRAs, who are at a higher perceived risk of being decommissioned. To address the above concern, I rerun the tests on the sample of firms that are rated by the top three rating agencies (combined market share of 65%). Despite the reduction in the size of the sample and the decrease in the power of the test, the inferences remain unchanged. That is, larger rating agencies also react pessimistically despite having a lower likelihood of being banned.

A third concern could be that the ratings of Brickwork, the offending agency, are significantly biased and not comparable to ratings from other agencies. As a result, the observed downgrade of ratings is driven by firms that had exclusive rating relations with Brickwork. Moreover, one may argue that the exit of Brickwork leads to information loss in the firms that are dependent on

[7] Rating quality is evaluated by considering both type I and type II errors. An improvement in rating quality can be ascertained under three scenarios: (i) type I error reduces, and type II error remains unchanged; (ii) type II error reduces and type I error remains unchanged, and (ii) both the types of errors reduce. However, if type I error reduces, but type II error simultaneously increases, it cannot definitely be classified as an improvement in rating quality.

Brickwork during the pre-intervention period. Consequently, the lower ratings are due to the lack of information available to the new entrant CRAs in the post-intervention period for the above firms. I mitigate the above concern by showing that the effect of lower ratings is also prevalent after excluding the brickwork ratings. Overall, my findings are consistent with the pessimism hypothesis, which suggests that rating agencies respond to higher regulatory costs of misratings by issuing downwardly biased ratings.

Finally, I examine whether the pessimistic ratings have any real effects on the firms. Ratings are an integral part of lending activities. Therefore, I examine the implications of lower ratings on the price of loans to firms. Banks in India apply the standardized approach (Basel capital rules) for risk-weighting loans and, therefore, depend on external credit ratings. Thus, lower ratings due to the exit of the CRA can lead to higher risk-weighted assets for banks. In order to maintain the capital adequacy ratios, banks may increase the required return on the loans (Van Roy (2005)). Consistent with the above prediction, I find that a decline in ratings has adverse real effects on firms in the way of a 25% increase in the borrowing cost of firms.

In summary, my study examines the impacts of forced exit and reduced competition on rating standards. However, a caveat is in order here. The paper does not provide an exhaustive assessment of the costs and benefits associated with regulator-driven forced exit of a CRA. Specifically, it does not analyze whether the costs of an increase in type II errors are outweighed by the benefits of an equivalent reduction in type I errors. Nevertheless, the findings can potentially inform the regulators and policymakers to adopt a judicious approach and weigh the costs and benefits while imposing strict regulations in credit rating markets.

The rest of the paper is organized as follows. Sections 2 and 3 provide a review of the related literature. Section 4 to 8 provides details about the institutional setup, data, research setting, and hypothesis. Section 9, 10, and 11 describe the empirical results and robustness tests. This is followed by a discussion on the real effects, and the paper concludes with a summary and discussion.

2 Features of ratings market

In this section, I briefly explain two distinct features of the ratings market that can help understand the theoretical predictions of my hypotheses: issuer pay model and low competition.

2.1 Issuer pay model

The issuer pay model, commonly adopted by credit rating agencies (CRAs) in rating agency markets, introduces a notable feature that can lead to conflicts of interest. Under this model, CRAs may be incentivized to inflate ratings in order to generate higher revenues and retain their clients, discouraging them from seeking ratings from alternative agencies (Skreta and Veldkamp (2009), Jollineau et al. (2014)). Although reputation risks can partially mitigate these conflicts (Smith and Walter (2002), Covitz and Harrison (2003), Goel and Thakor (2011)), numerous studies provide empirical evidence of persistent conflicts of interest and rating shopping behavior. For instance, Flynn and Ghent (2018) reveal that incumbent rating agencies tend to provide biased and favorable ratings in an effort to secure more business after the entry of new players in the structured finance products rating markets. Complementing these findings, Kronlund (2020) demonstrates the prevalence of rating shopping behavior in corporate bond markets. Similarly, Cornaggia et al. (2023) shed light on how conflict of interest can distort credit ratings in municipal bond markets.

Baghai and Becker (2018) expand the literature by examining the ratings market in India, and showing that non-rating revenues are a potential source of conflicts of interest. Finally, Baghai and Becker (2020) provides evidence that rating agencies can issue favorable ratings to regain lost market shares.

The ratings market in India has not been immune to the presence of rating shopping behavior. For instance, in the Brickwork episode, SEBI has accused the rating agency of compromising its independence by failing to segregate roles of rating committee members and business development.

Overall, the extensive evidence from existing literature underscores the existence of moral hazard incentives that contribute to the inflation of ratings. I contribute to the above literature by showing that strict regulatory action in the form of removal of the offending CRA resulted in a notable deflation in ratings. The finding may also suggest a potential reduction in conflicts of interest arising from issuer pay incentives.

2.2 Oligopolies with exclusive licensing

The ratings market in the US and in most other countries is largely characterized by a few players dominating the ratings business. This is because of regulator aided exclusive licenses to a select few raters. Most notably, in the US, the SEC awarded the NRSRO (Nationally Recognized Statistical Ratings Organization) designation to S&P, Moody's, and Fitch in 1975, thereby providing them with significant market power in the ratings businesses (Frost (2007)). The intuition is that, in a highly competitive ratings market, there may be increased pressure on rating agencies to attract clients and generate revenue. This competition for the revenue share can potentially compromise the independence and objectivity of ratings, as agencies may be tempted to provide favorable ratings to please clients and secure business relationships (Becker and Milbourn (2011)). Using a theoretical framework, Skreta and Veldkamp (2009) show that increased competition among raters worsen the problem of rating shopping behaviour. Becker and Milbourn (2011) provide empirical evidence on adverse effects of competitions in ratings market by showing that entry of Fitch into the US ratings market led to lower quality ratings.

However, lower competition can have adverse effects as well. Since the NRSRO designation restricted the entry of new players in the rating agency markets for decades, it is widely blamed for granting an implicit too-big-to-ignore status to the Big 3 raters (White (2010), Behr et al. (2018)). Particularly, Behr et al. (2018) demonstrate that the market power derived SEC regulations in 1975, that restricted the ratings market to a select few players, resulted in ratings inflation. On a similar note, Mathis et al. (2009) find that regulatory protection under NRSRO designation can induce complacency on part of the incumbent raters to protect their long run reputation. Not surprisingly, the special status also ensured that the three big agencies had a wide acceptance in other jurisdictions and became the three largest raters in terms of global market share. Although the NRSRO designations were relaxed after the Enron crisis, it was still difficult for new raters to challenge the incumbency of the existing raters (Hill (2011)).

Like SEC in the US, the Securities and Exchange Board of India (SEBI) regulates the ratings market and provides licenses to raters to operate in India. In India, there are 7 official rating agencies including the subsidiaries of the Big-three global rating agencies. Unlike other important jurisdictions, India is the first country where the regulator suspended a rating agency due to poor quality ratings. Thus, I contribute to the literature by studying how an unexpected and a strict regulatory action impacts behavior of incumbent rating agencies.

3 Related Literature and Contribution

In this section, I provide a detailed review of the literature surrounding the functioning of ratings market and the contribution of this study to the literature.

3.1 Role of inflated credit ratings in economic crises:

Since CRAs serve an important role as gatekeepers in financial markets, failure of ratings can lead to crisis situations. I discuss a few major episodes where CRAs were criticized for reacting slowly to financial distress of firms, and potentially leading to crisis situations.

(1) Enron scandal: In 2001, Enron went into bankruptcy owing to fraudulent accounting activities and misleading reporting. However, the credit ratings of Enron securities were rated as investment grade up until five days before the bankruptcy. The ratings agencies were accused of optimistic ratings and failing to recognize the deteriorating financial condition of Enron (Frost (2007), Healy and Palepu (2003), White (2010), Bedendo et al. (2018)).

(2) WorldCom bankruptcy: Rating agencies also played a role in WorldCom bankruptcy in 2002, where they failed to assess the worsening financial condition of WorldCom (White (2010), Bedendo et al. (2018)). These failures led to several discussions and hearings by the government and regulators, where they recognized the lack of oversight of operations of rating agencies and existence of conflict of interests in ratings businesses.

(3) Global Financial Crisis (GFC): The most infamous scandal related to rating agencies came to the fore during the Global Financial Crisis (GFC). The CRAs were accused of providing inflated ratings to mortgage-backed securities, that fuelled the subprime crisis (White (2010), Benmelech and Dlugosz (2009), Scalet and Kelly (2012)).[8] Further, He et al. (2011) finds evidence in support of rating agencies providing inflated ratings to large issuers, specifically during period of high economic growth. In a postmortem, the rating agencies were also accused of being involved in designing and marketing of these structured products (Josephson and Shapiro (2020)).

(4) IL& FS crisis: More recently, CRAs were held responsible for not highlighting credit risk related to the collapse of IL&FS, a non-banking financial institution in India. The collapse of IL&FS

[8] On the contrary, DeHaan (2017) argues that there was no decline in qualtiy of credit ratings during the subprime mortgage crisis, and the rating failures were caused by inability of CRAs in assessing credit ratings of structured mortgage products.

threatened to spiral into systematic risk for the entire financial system. In subsequent probe, SEBI imposed monetary penalties on the accused CRAs for failing to highlight the risks of debt securities adequately in the rating reports.[9]

These episodes, among others, highlight concerns about the timeliness, accuracy, and independence of credit ratings. In response to these criticisms, several regulatory reforms have been implemented to enhance the accountability, transparency, and governance of credit rating agencies. However, as I will discuss in the next section, most regulatory changes were insufficient to address the issues. Therefore, it is crucial to study whether stricter regulatory intervention and enforcement can have a desired effect on quality of credit ratings. In this paper, I study the effects of a novel regulatory intervention in the Indian credit rating market on rating inflation.

3.2 Inadequate regulatory costs on CRAs:

Although credit rating agencies have faced reputation risks that can hedge the conflict of interests faced by them, there is little evidence of improvement in rating quality following regulatory interventions. Literature cites several kinds of regulatory interventions in the ratings market in the US and documents their implications on rating standards. For instance, following the collapse of Enron and WorldCom, the regulators and stakeholders acknowledged the potential conflict of interests arising out of the issuer pays model, and discussed ways to limit such conflicts and improve reliability of ratings. Subsequently, the Credit Rating Agency Reform Act (CRA reform act) was introduced to address drawbacks in the ratings market. The CRA reform act aimed to ease the entry of new rating agencies to encourage healthy competition and to improve transparency of rating process (Bedendo et al. (2018), Scalet and Kelly (2012)).

However, White (2010) notes that the CRA reform was largely ineffective because SEC did not have much powers to oversee the incumbent raters and influence their models or practices. Further, the easing of issuing NRSRO licenses was too late to challenge the advantages secured by the "Big 3's" incumbency (Hill (2011), White (2010)).

The biggest reforms in the ratings industry were introduced in the wake of the GFC. The US enacted the Dodd-Frank Wall Street Reform and Consumer Protection Act (Dodd-Frank Act) in

[9] See https://www.livemint.com/news/india/sebi-penalises-care-and-icra-on-lapses-in-rating-il-fs-11577373033951.html

2010. The Dodd-Frank Act allowed SEC to impose sanctions on rating agencies and aimed to reduce overreliance of financial institutions on credit ratings. However, the interventions were insufficient to deter the incumbency of the large players and their implicit monopoly in the ratings market (Opp et al. (2013); Partnoy (2017); Hill (2011)).

Partnoy (2017) notes that the Big 3 continue to garner huge profits in the rating business without any significant improvement in ratings quality. In a theoretical setting Opp et al. (2013) find that quasi-regulatory dependence of financial institutions on CRAs continues after the Dodd-Frank Act. As a result, the DFA regulation did not seem to improve the quality of credit ratings (Partnoy (2017), Baghai and Becker (2020), Hill (2011)).

Echoing similar concerns, Senator Carl Levin, a member of the subcommittee on investigation of rating failure, expressed strong dissatisfaction with the proposed rules, which he believed fell short in tackling conflicts of interest and inflated ratings. Senator Carl Levin explicitly stated the following.

> *"...It is totally unacceptable, given the evidence of credit rating agency abuses in our 2010 hearings and the S.E.C.'s own inspection reports, that proposed rules (Dodd-Frank Act) to stop the conflicts of interest and inflated ratings have been stalled for three years, wrapped up in bureaucratic red tape. Worse, the proposed rules aren't tough enough to cure the problems..."*

In somewhat contradictory evidence, Dimitrov et al. (2015) does find that the Dodd-Frank Act lead to lowering of ratings by the CRAs. However, the pessimistically biased ratings also led to lower rating quality. Moreover, the setting in my papaer is different from their's because I study a forced exit of a CRA which is different from other regulatory actions. Finally, Baghai and Becker (2020)show that CRAs continue to compromise their standards and issue optimistic ratings to regain market shares. Overall, there is enough evidence to suggest that existing regulatory actions have done little to improve the ratings standards.

The ineffectiveness of the regulatory actions is mainly due to the unique market structure and the regulatory framework of the ratings market (refer section 2.2). Rating markets operate as oligopolies drawing powers from the exclusive licenses from regulators (NRSRO designation in US, or SEBI registration in India). Thus, the barriers to entry in the ratings market are not limited to natural factors such as economies of scale, experience, expertise, and reputation, but also constitute artificial barriers created by the regulators (Behr et al. (2018)). White (2010) argues that the NRSRO designations did not allow a level playing field for new players to compete and allowed the incumbent rating agencies to evolve into too-big-to-ignore players (Big 3).

The exclusive membership of the large players and the implicit regulatory protection of NRSRO can lead to complacency on part of the agencies to protect their long-run reputations (Mathis et al. (2009)). The quasi-immunity from the rating regulators is evident from the fact that, despite their involvement in several episodes of misrating scandals, none of the rating agencies' licenses were revoked. Partnoy (2017) observes that these regulatory barriers and the ensuing oligopoly immunity in the rating market facilitated the subprime mortgage crisis.

To comprehend the low regulatory costs on CRAs, I draw parallels between the workings of the rating agencies market and the markets for other gatekeepers such as auditors and underwriters. For example, the Enron crisis saw the exit of Arthur Andersen – the accountable auditor and one of the big players in the audit market. However, the rating agencies which were responsible for inaccurate ratings did not face similar consequences. Lack of such actions may encourage complacency on the part of credit rating agencies because they face lower economic losses than other players in the event of misratings and financial scandals (White (2010)).

Since the regulatory actions have been limited to litigation and regulatory penalties and have not yielded desired results, it is crucial to examine whether a stricter regulatory sanction, such as forced exit of an incumbent player, can impact the quality of ratings. A forced exit is different from other regulatory actions, and therefore it may have a different effect than earlier regulatory action. I address the above gap in the literature, by studying the effects of cancellation of license of an incumbent rating agency in India on rating characteristics.

3.3 Entry and Exit in ratings market:

There is a large literature that studies the effects of entry of rating agencies and market share of agencies in the ratings market on rating standards. As discussed earlier, ratings markets are universally less competitive and operate as oligopolies. The artificially lower competition is mainly due to the few players authorized by regulators to operate in the rating market. So, entry into ratings market is rare. The motive is that lower competition can discourage conflict of interests between issuer and CRA arising out of the competition from garnering a higher market share (Becker and Milbourn (2011)). On the other hand, opponents of higher concentration in the rating market have argued that lower competition may not lead to higher quality ratings (Bae et al. (2015); Behr et al. (2018)). Specifically, the CRA reform Act encouraged entry of new players into the ratings market to improve rating standards.

The extant literature has relied on the listing of a new agency as an exogenous shock to the rating market to analyze effects of change in competition on rating characteristics. Specifically, most work in the change in ratings market have focused on the inclusion of Fitch in the US bond ratings market. For example, Becker and Milbourn (2011) show that the entry of Fitch into the ratings market dominated by S&P and Moody's coincides with inflated ratings by the incumbents. However, Bae et al. (2015) document that entry of Fitch may not have lea to inflated ratings. Dimitrov et al. (2015) exploits the exogeneity of the Fitch market share to suggest that entry of Fitch lowered future economic rents of the incumbents, leading to deterioration in rating quality of incumbents. Note that all the above studies exploit the entry of Fitch to determine effects of entry of a third rater in an industry on rating standards. In a global study, Hung et al. (2022) extends the literature to study new NRSRO designations of local CRAs in Japan. Since their setting involves an entry of new CRA in the global CRA market, they are able to deduce inference about rating quality across 26 countries.

Unlike the above studies that revolve around the addition of new NRSRO designations (entry of new players) into the ratings market., exit of CRAs is unheard of. Moreover, exit of a CRA can potentially have different effects than other forms of change in competition. I contribute to this literature by addressing how rating standards change when there is a forced exit of a CRA. Specifically, I study a novel regulatory intervention of decommissioning of an authorized rating agency to answer the above question.

4 Institutional Background

I study the exit of a rating agency in the Indian setting. The rating market in India is characterized by presence of seven accredited rating agencies: ACUITE, BRICKWORK, CARE, CRISIL, ICRA, INDRA, and IVR.[10] Among these agencies, CRISIL, ICRA, and INDRA are fully owned subsidiaries of global credit rating agencies SP, Moody's, and Fitch, respectively, while the others are domestic credit rating agencies.

In terms of market share, CRISIL holds the largest share at 30%, followed by CARE and ICRA, each with nearly 20% market share. BRICKWORK, INDRA, and ACUITE provide ratings for 11%, 10%, and 8% of the rated loan facilities, respectively. IVR, which is new entrant in the ratings market has a market share of less than 1% and caters to very few industries. Therefore, I drop the ratings issued by IVR from the sample.

Companies in India seek credit ratings for variety of loans and credit facilities. Bank related lending products dominate the rated offerings. While credit ratings are also extended to bonds and commercial papers in India, it is worth noting that the market for these securities is thinly traded and is predominantly controlled by a small number of listed firms. However, loan ratings facilities serve both large and small companies, including unlisted firms. I provide the list of top twenty credit facilities that are rated by CRAs in Table A.3 of the online appendix.

The ratings market in India is regulated by the Securities Exchange Board of India (henceforth, SEBI), which issues certificate of registration to rating agencies operating in India. Further, the RBI – the central bank of India – provides accreditation to the rating agencies. This accreditation enables banks in India to utilize the ratings from accredited agencies to determine the risk weight of their claims for the purpose of capital adequacy under Basel III requirements. Consequently, credit ratings play a vital role in determining the regulatory capital requirements for banks in India, ultimately impacting the cost of loans for firms (Asquith et al. (2013)).

4.0.1 Forced exit of Brickwork

As discussed earlier, SEBI regulates the ratings markets in India. SEBI conducts periodical inspection to oversee functioning of rating agencies. The inspections are carried out to ensure that the rating agencies follow the rating methodologies and the prescribed rules and guidelines diligently while assigning credit ratings. SEBI also verifies whether the rating firms have adequate processes and internal controls to mitigate conflict of interests arising out of payments from issuers. In case of adverse findings during the inspections, SEBI imposes monetary penalties and issues directives to

[10] The list has been revised in 2023 from 7 to 6 members, after exit of Brickwork

rectify the violations.[11] Some of the regulatory actions in the recent past were related to deficiencies discovered in rating processes related to failure of non-banking financial institutions in India (e.g., failure of IL&FS and DHFL in India). On several cases, rating agencies appealed against the imposed fines as well.

In the case of Brickwork, the SEBI initiated an enquiry proceeding in September 2020 to review any violations by Brickwork. The enquiry, that was completed in April 2021, noted several lapses in rating process by Brickwork.[12] Brickwork was accused mainly on two counts: lack of independence in rating committee and failure in following processes while rating instruments. Specifically, SEBI in the detailed report notes that Brickwrok (i) had failed to follow proper rating process and due diligence while dispensing ratings; (ii) did not produce adequate records and trails supporting its ratings; (iii) delayed monitoring of rating of some issuers; (iv) did not follow timelines prescribed in earlier enquiry reports; (iv) made inaccurate disclosures related to some issuers in press releases announcing credit ratings; and (iv) failed to address conflict of interest by assigning business development roles to rating committee members.

Moreover, SEBI observed that there were repeated instances of deficiencies in rating processes in Brickwork found during consecutive reviews in 2020 and 2022 (see Table A.1 of Online Appendix). Finally, SEBI also compared the transition of stability rates of ratings for each rating category across all the rating agencies. The one-year stability rate of a rating category is the percentage of ratings remaining in the same category at the end of one year. SEBI notes that Brickwork fares poorly among all the rating agencies in terms of stability of their ratings (see Table A.2 of online appendix).

Based on the above findings the regulator recommended cancellation of certificate of registration of Brickwork in April 2021. Although there have been several instances of enquiry proceedings against rating agencies in the past, this was the first review which recommended cancellation of registration of a rating agency. Following the findings of the enquiry, Brickwork contested the decision by appealing against it in High-Court court in India, but the Supreme Court (apex court

[11]For example, SEBI has imposed fines on ICRA and CARE in 2020 owing to deficiencies found in rating processes. See `https://www.sebi.gov.in/enforcement/orders/dec-2019/adjudication-order-in-respect-of-icra-limited-in-the-matter-of-rating-of-ncds-of-ilandfs-_45480.html` Note that the rating agencies are allowed to contest the penalty in courts.

[12]SEBI notification on cancellation of Brickwork is available on their website. `https://www.sebi.gov.in/enforcement/orders/oct-2022/order-in-the-matter-of-brickwork-ratings-private-limited_63749.html`

in India) ruled in favor of SEBI's decision. Finally, in October 2022 SEBI passed an order to Brickwork to wind down its operations within a period of 6 months.

Note that the final order was passed in October 2022 after the Supreme Court decided against the appeal by Brickwork, but the recommendation of cancellation of Brickwork was passed on April 2021. Thus, following the enquiry recommendation in April 2021, the markets anticipated the exit of brickwork.[13] The above is evident from the fact that Brickwork lost its market share rapidly from 11% in April 2021, when SEBI recommended cancellation, to 1% when the final order was passed in October 2022 (see figure 4). Thus, April 2021 is considered as the event date for the exit of Brickwork in my study.

5 Hypothesis Development

The objective of this study is to document the effect of forced exit of a rating agency on rating standards. Existing literature has predominantly focused on the effects of regulatory measures such as litigation penalties, warnings, and heightened regulatory oversight on rating standards, as seen in the CRA Reform Act and the Dodd-Frank Act. Although, regulatory authorities possess the authority to decommission a rating agency, instances of revoking the license of a CRA is very rare.

For example, despite several instances of wrong doings by the CRAs in the past, none of the rating agencies were decommissioned by the regulators in any of the major economies. Therefore, the actual real-world enforcement of forcing a non-compliant CRA to exit can produce different outcomes compared to the theoretical threat of decommissioning of the CRA. Since exits of CRAs are very rare, not surprisingly, existing literature mostly documents the effects of entry of a new rating agency in the ratings market. Whereas, there is no notable study on the exit of a player from the ratings market.

Moreover, the exit of a rating agency is qualitatively different from the entry of a CRA. It is not clear how rating standards will change following exit of a CRA. On one hand, the exit of a CRA can lead to more accurate ratings due to decrease in competition. Specifically, decline in competition can increase reputational incentives for incumbent CRAs to improve the quality of ratings (Becker and Milbourn (2011)). Moreover, the removal of a CRA can signal strong intent of

[13] See financial newspaper article `https://economictimes.indiatimes.com/markets/stocks/news/sebi-issues-notice-to-brickwork-ratings-india-over-lapses/articleshow/82316678.cms?from=mdr`

regulator to impose regulatory costs in the event of misratings, and therefore can have a disciplining effect on the rating agencies. As a result, it can disincentivize tendency to issue inflated ratings owing to conflicts of interests. Additionally, the regulatory action can coerce rating agencies to invest in rating methodology, process due diligence, and internal controls, subsequently leading to improvement in rating quality.

On the other hand, a reduction in competition resulting from the exit of a credit rating agency (CRA) may not necessarily result in increased rating accuracy, as suggested by Bae (2015). Furthermore, Brickwork's exit is a forced one, and thus, it may not yield the same outcomes as a normal CRA exit. Moreover, regulatory penalties are asymmetric in nature, because the regulator usually penalizes optimistically biased ratings but may not levy a similar penalty for pessimistically biased ratings (Goel and Thakor (2011)). Therefore, the decline in competition due to the forced exit of Brickwork can induce pessimistic behavior in rating agencies, leading to excessive downgrades and lower quality rating. Thus, the effect of the forced exit of CRA is not clear ex-ante, and needs to be examined empirically.

6 Data

In this section I describe the sample selection procedure and the summary statistics of the main variables. I obtain data on credit ratings of loans and debt securities of firms from the Prowess database maintained by the Centre of Monitoring Indian Economy (CMIE). CMIE has been used in several prominent studies such as Baghai and Becker (2018), Lilienfeld-Toal et al. (2012), and Vig (2013). It has data about credit ratings issued by all the rating agencies that are licensed by SEBI and RBI and maintains the credit rating at a 'firm − rating agency − debt instrument type' level. The data has rating information for roughly 60 different debt instruments. Table A.3 of the online appendix lists the top twenty commonly rated debt securities in our sample. Not surprisingly, the most commonly rated debt securities include bank debt products such as term loans and cash credit.

Like the global ratings scale, the credit ratings of debts in India also have a scale ranging from AAA, the highest credit rating, to D that corresponds to default rating. Following existing literature, I convert each of the credit rating categories to a numerical scale that represents the ranked order of creditworthiness of debts (Baghai and Becker (2018)). The rating AAA is assigned a rating score of 1, which represents the highest or safest possible credit rating. Subsequently, I assign higher numbers in the increment of one to identify lower or riskier credit ratings. For example, AA+, AA, and AA- correspond to rating scores of 2, 3, and 4, respectively. Thus, the rating scores from 1 to 10 represent 'investment grade' ratings from AAA to BBB-, whereas the rating scores from 12 to 20 represent 'speculative grade' ratings from BB+ to D. The list of rating categories and their numerical scales are presented in Table 1.

My sample period comprises of fourteen quarters from 2020Q3 to 2023Q4.[14] In the above sample period, there are 107,062 ratings available at an instrument type- firm- CRA level for 5,784 firms and 6 rating agencies.

Note that the dataset provides rating at an instrument type level but does not provide the instrument identifier. Therefore, following Baghai and Becker (2018) I coalesce the rating information to a 'firm – rating agency' level panel data. That is, I create the variable *mean_rating* that is calculated as the average of rating scores of all the securities rated by a CRA for a firm in a year-quarter. For example, if firm A has three bank loans that are rated as AAA, AA, and A by CRISIL in 2nd quarter of year 2020, then I assign a *mean_rating* of 2 (mean of 1, 2, and 3) to the firm A by CRISIL in 2020Q2. For robustness, I also determine the firm-CRA level credit rating by taking median and maximum (or worse) scores of ratings of debt securities of the firm rated by the CRA in that year-quarter. I create the variable *median_rating* (*max_rating*), which is calculated as the median (maximum) of the rating scores of all securities rated by the CRA for the firm in the year-quarter.

After arranging the data at a firm – CRA – quarter level, I have 27,728 observations. The mean and median value of the *mean_rating_score* is 8.3 and 7, respectively. Thus, on average, a CRA issues a BBB+ rating to a firm. Out of the 27,728 observations, 38% of the ratings are speculative grade. As expected, the *max_rating* has higher average and median values of 8.9 and 8, respectively.

I derive the market share of a rating agency by calculating the ratio of credit ratings that are issued by the rating agency in an industry to the overall credit ratings issued by all rating agencies

[14] Financial year in India is from April 1 to March 31st.

in that industry.[15] I plot the time trend of market share of each of the rating agency in Figure 4. As evident from the above figure, CRISIL, the subsidiary of S&P, has the highest market share followed by CARE and ICRA (subsidiary of Moody's). Brickwork ratings have an average market share of 11% before the event.

As discussed in the 1, I determine a firm as a treated firm if it belongs to the industry that lie in the top tercile in terms of market share of Brickwork ratings during the pre-period. In other words, I sort the market share of brickwork across all industries during the pre-intervention period. I then assign any firm that belong to the top (bottom) tercile of the industries in terms of market share of Brickwork as treated (control) firms. The intuition is that industries that have larger presence of Brickwork in the pre-intervention period, experience a larger decline in competition in ratings market.

I analyze the rating scores to investigate whether there is a change in levels of ratings following the regulatory action. However, to determine the quality of ratings, I map rating changes to future default by firms. I obtain the loan performance data about firms from CIBIL, the largest credit information company in India. CIBIL maintains a record of all corporate loans of over Rupees 10 million, where the bank has initiated legal recovery proceedings against the firm. The central bank mandates banks and financial institutions to report the list of such delinquencies to CIBIL at a quarterly frequency. I download the data from the CIBIL website and manually match the name of the firms with firm names in Prowess. I then determine whether the firm that receives a rating from a rating agency in a year-quarter has defaulted on debt repayments in the year (next four quarters) after it received the rating.

Since my rating data is available only up to 2023-Q4, I do not have the future loan default data for ratings issued after 2022-Q4. Therefore, for tests pertaining to ratings quality which requires (one-year) future debt default data, I limit my sample from 2020-Q3 to 2022-Q4.[16] During the above period, the average debt default rate is 5.6%.

I also retrieve other firm level variables from audited financial statements available in Prowess. Following prior literature, I control for liquidity, leverage, and firm performance in my specifications.

[15] Industry refers to the two-digit NIC code of the industry the firm belongs to. There are 41 distinct industries in the sample.

[16] Studies in the literature usually apply a two year or three year look ahead period to determine debt defaults by rated firms. However, due to constraints of availability of observations up to 2023Q4, I am using a stringent look ahead period on one year only.

I calculate the interest cover ratio as the ratio of Earnings before interest and tax (EBIT) and the interest expense of the firm in the year. The ICR denotes the capability of the firm to repay its interest obligations. A higher ICR denotes higher liquidity of the firms. In the sample, the mean ICR stands at 16.3. I calculate leverage of the firm as the ratio of debt of the firm to the total assets of the firm in a year, expressed in percentages. The average (median) leverage of the firm is 43.1% (36.7%).

Further, I also derive performance of the firms by calculating the ratio of operating profit of the firm to the sales of the firm in the year. On average, a firm has 6.4% profit margin during the observation period. Finally, I calculate EBITDA to DEBT ratio, which measures the proportion of the debt the firm can repay before it can cover for interest, depreciation, amortization, and taxes. Specifically, I calculate the ratio of EBITDA (Earnings before interest tax depreciation and amortization) and debt of the firm. The summary statistics of all the variables are presented in Table 2 (Panel B).

7 Research Setting

Extant literature points out at insufficient regulatory actions towards disciplining of credit ratings by CRAs. Although, reputational costs of agencies impose self-discipline on rating agencies, it has largely been insufficient to address deficiencies in ratings quality. Subsequently, investors have called for stricter regulations and penalties to curb loss of independence of CRAs and improve reliability of credit ratings. Thus, there is a need to study whether harsh regulatory actions can improve the quality of credit ratings. Specifically, it is not known whether strict regulatory enforcement such as derecognition or delicensing of erring CRAs can discipline the incumbent rating agencies to provide superior quality rating. Although, forced exit of a rating agency can decrease competition and boost reputational incentives of incumbent CRAs to provide more accurate ratings. The decline in competition may lead to pessimistic behavior of incumbent CRAs, due to threat of regulatory sanction.

To explore the aforementioned question, one needs to examine the effects of forced exit of an incumbent CRA on grounds of misratings on the rating standards of other CRAs. Unfortunately, agencies in most geographies have never faced such dire consequences. Furthermore, the culprit agencies have not faced credible threats of delicensing in response to substantial misratings by their organizations.

I address the above question by exploiting a unique setting where the regulator suspends a poorly performing designated rating agency from the ratings market. Specifically, the SEBI, which issues licenses and regulates CRAs operating in India, recommended suspension of license of Brickwork Ratings to operate in the Indian ratings markets in April 2021. In their inspection, SEBI noted that Brickwork Ratings had failed to exercise proper skill, care, and diligence in dispensing its duty as a credit rating agency, and that the quality of its ratings were significantly poor than deemed fit by SEBI. The ban on the CRA is an extreme step by SEBI and stands out from previous regulatory penalties that were imposed on CRAs.

I exploit the above unanticipated regulatory action to examine the impact on rating standards. The Indian setting is ideal to derive inferences on the effect of forced exit of a CRA because of several reasons. First, the role of rating agencies in India is representative of role of rating agencies in other major jurisdictions. For instance, like firms in developed economies, firms in India are also highly reliant on external credit ratings to issue debt. Moreover, Indian banks comply with globally accepted Basel III norms, and therefore the debt market and provisioning requirements in Indian banks and debt markets attest to globally accepted standards. Since, Basel regulations allow the use of external ratings for determining regulatory capital and loan provisioning, the use of credit ratings in the Indian debt market provide a generalizable setting to study effects of regulations.

Second, the Indian rating market is dominated by the global Big 3 rating agencies – S&P, Moody's, and Fitch. The three global rating agencies account for more than 60% of the total ratings in India, and therefore, it is reasonable to assume that the rating practices in India are comparable to those of other large economies.

Third, the dynamics of the ratings market in India are like those of ratings market in the western and other developed countries. For instance, like NRSRO designations issued by SEC in the US, the SEBI in India authorizes rating agencies to participate in the ratings market. Thus, there are barriers to entry in the rating market in India. Further, like global agencies, the agencies in India operate on the issuer pay model. Fourth, the Indian debt markets are representative of the broad financial debt markets globally, and, therefore, any inference drawn from the study is relevant elsewhere (Baghai and Becker (2018)). Finally, the Indian financial market is a compelling case study that merits attention. India is the fifth largest economy in the world with a nominal GDP of over $ 3.7 trillion as on March 2023 and market capitalization of nearly $ 3 trillion.

In summary, the Indian context encompasses factors such as the important role of rating agencies, significant presence of global agencies, comparable rating market dynamics, representative debt markets, and the significance of the Indian financial market, which collectively make it an ideal setting for studying the effects of regulatory measures on credit ratings.

8 Empirical Design

SEBI recommended cancellation of license of Brickwork rating in April 2021. Note that Brickwork had presence in almost all rating businesses prevalent in India. Since SEBI ordered cancellation of entire rating business of Brickwork, it is difficult to identify the treated list of firms based on specific debt instrument types that were affected more than others. Thus, the exit of brickwork does not provide us any natural discontinuity to study the causal effects.

To overcome the above shortcoming, I exploit the variance in market share of Brickwork during the pre-intervention period to identify firms that are comparatively more impacted by the exit of Brickwork Ratings. Brickwork had a presence in almost all the industries and its market share varied from near zero percent to 24 percent during the pre-period. I segregate the industries into treated and controlled based on whether Brickwork had a high or low market share in those industries in the pre-period, respectively.

The identification is based on the premise that industries where Brickwork has significant presence experience higher decline in competition than other industries due to exit of Brickwork. Moreover, since the regulator has uncovered a greater number of rating inconsistencies in companies within the industries with higher Brickwork market share, and considering that regulators often contend with limited resources, it is reasonable to expect higher regulatory scrutiny towards these industries. That is, the companies within the sector of Brickwork's specialization are perceived as compromised entities and have a higher likelihood of regulatory inspection.

Therefore, I denote an industry as a treated industry, and the firms in those industries as treated firms, if Brickwork's market share in that industry lies in the top tercile of market shares across all industries in which Brickwork operated. Similarly, I designate an industry as a control industry if the Brickwork's market share in that industry lies in the bottom tercile of industries in terms of market share. To avoid any look ahead bias, I ensure that the market share of Brickwork is calculated only for the year-quarters before the SEBI recommendation was made.

I then use a difference-in-differences (DID) framework to estimate the effect of the forced exit on ratings level and ratings quality of firms. I denote the year-quarters after April 2021 as the 'post' event period. I argue that the event of SEBI recommending cancellation of Brickwork's license is exogenous and was largely unanticipated due to two reasons. First, a licensed CRA being suspended by the regulator was unheard of, and it was the first known instance of license of a CRA being cancelled in a developed or a developing economy. Second, the number of firms which availed credit rating facilities on loans from Brickwork did not see a significant decline in the year-quarter preceding the ruling. However, the market share of brickwork declined monotonically in the post SEBI ruling period (see figure 4). Thus, the move by SEBI was largely unexpected from the perspective of credit rating markets and can be characterized as an exogenous shock.

A major concern in the above empirical design could be that the effects observed in the treated industry in the DID specification are due to the characteristics of the firms belonging to that industry rather than due to the exit of the CRA. I address the above concern by using firm level fixed effects that absorb both industry level heterogeneity as well as firm level differences. Thus, the results documented in this paper cannot be on account of spurious correlation due to any observable or unobservable firm level factors.

Moreover, a critique may argue that rating agencies may vary in the way they react to regulatory action and, therefore, any changes in observed ratings could be due to the characteristics of rating agencies. To address the above concern, I also include agency level fixed effects, which absorbs observed and unobserved agency level characteristics. I explain the empirical specification in more details in the next section.

9 Impact on Rating Level

My main research question is whether exit of a rating agency impacts the credit rating standards. First i examine the impact on ratings level because stable interpretation of credit ratings is important for use in capital calculation or managing investment mandates (Becker and Milbourn (2011)).

Moreover, as shown in Table A.2, the regulator is concerned about rating stability, and expects credit ratings to be stable over the short term period (typically one year). An overall decline in rating levels (higher rating scores) without any corresponding decline in creditworthiness of borrowers can indicate poor quality of ratings.

As discussed in section 5, exit of Brickwork can lead to less competition for client revenue share and thus incentivise CRAs to provide more accurate ratings. However, higher quality ratings may not lead to change in rating levels, because a decline in 'false warnings' can lead to increase in rating levels (rating upgrades), whereas decline in 'missed defaults' can lead to decline in rating levels (rating downgrades). Thus, it is possible that rating levels do not change significantly.

On the contrary, forced exit of Brickwork can also signal a significant increase in regulatory costs for incumbent CRAs, resulting in pessimistic behavior of CRAs. That is, the CRAs may now resort to pessimistic grading of debt securities to safeguard themselves from the threat of forced exit. As a result, rating levels may decline due to the forced exit of Brickwork. Therefore, the impact of forced exit of rating agency on rating levels is an empirical question and needs to be examined.

9.1 Forced exit and Rating deflation – OLS model

I empirically examine whether ratings of firms changed due to the forced exit of Brickwork by using two different empirical models. First, I use the OLS based model.

$$Y_{i,j,t} = \alpha + \beta_1 * post_t * treated_i + \beta_2 X_{j,t} + \gamma_i + \delta_j + \theta_t + \epsilon_{i,j,t} \tag{1}$$

Here, $Y_{i,j,t}$ represents the rating score of firm i issued by agency j in year-quarter t. The variable *post* is a time dummy which is set to one for year-quarters from 2022-Q2 onwards, and zero otherwise. The variable *treated* is set to one for firms belongs to an industry where Brickwork Ratings has high market share in the pre-period, zero otherwise. The variable of interest is the interaction term between *post* and *treated.* The coefficient of the interaction term provides the DID estimate of effect of the regulatory action on rating levels of firms.

As discussed earlier, one concern could be that the firms in the treated group are significantly different from firms in control group, and the systematic differences between the firm characteristics drive observed changes in rating scores. I address the above concern in two ways. First, I employ firm level fixed effects (γ_i) that absorbs the time-invariant industry and firm level heterogeneity. Second, I include the lagged values of firm-time level control variables that are known to impact the ratings of the firms. I account for several firm-time level characteristics that can determine credit rating of the firm – interest cover ratio (ICR), leverage, debt coverage ratio , and profit margins. The above variables are the commonly used ratios to determine the credit ratings of firms.[17] All the control variables are defined in section 6.

Additionally, I also include rating agency level fixed effects. Since the rating agencies differ vastly in terms of their expertise and their reputation, the agency level fixed effects help absorb heterogeneity at the CRA level. Finally, I also add time level fixed effects to control for time trend in rating scores. Standard errors are adjusted for heterogeneity and clustered at the Industry $\times$ time level.

Results are presented in Table 3. In columns 1 and 2 I use the *mean_rating* as the dependent variable. Whereas, in columns 3 and 4 (5 and 6) I use the *median_rating* (*max_rating*) as the dependent variable. Firm, CRA, and time level fixed effects are included in all the specifications. The even numbered columns also include the control variables mentioned above.

In column 1, I find that the coefficient of the DID term is positive and significant, which suggests that the *rating_score* of the firms increases in DID sense. The value of the coefficient stands at 0.19, which is economically significant. It indicates that one out five treated firms experience a one notch rating downgrade (or one notch increase in *mean_rating*) after the exit of Brickwork. In column 2, I include the control variables and find that my results do not change significantly.

For robustness, I also verify my results using the median or the worst *rating_scores* of the firm. Across columns 3 to 6 in Table 3 I find that the result remain similar economically as well as statistically. Thus, the ratings of firms seem to have worsened after the regulatory action against Brickwork.

[17]CRISIL recognizes the financial ratios and their variations to determine credit rating of debt facilities of firms. See `https://www.crisil.com/mnt/winshare/Ratings/SectorMethodology/MethodologyDocs/criteria/CRISILs%20Approach%20to%20Financial%20Ratios.pdf`

9.2 Forced exit and Rating deflation – Ordered logistic regression model

All the results discussed in the previous section pertain to OLS models. A drawback of using OLS regression is that it assumes that the rating scores are continuous measure of underlying creditworthiness of firms. However, the rating levels actually indicate thresholds of relative creditworthiness of firms measured in an ordinal scale. Therefore, for robustness, I follow Blume et al. (1998) and Dimitrov et al. (2015) to employ an ordered logistic regression model (ologit). Here, the ordinal scale of credit rating ranging from 1 to 20 serves as the dependent variable. The ologit specification takes the following form.

$$\log\left(p/1-p\right) = \alpha + \beta_1 * post_t * treated_i + \beta_2 X_{j,t} + \eta_k + \delta_j + \theta_t + \epsilon_{k,j,t} \tag{2}$$

Here, the data is arranged at a firm-agency-time level. The dependent variable is the logarithm of odds of a rating agency issuing an accurate rating to the firm. My main independent variables *post* and *treated* carry their usual meaning. I also use the same set of control variables that have been sued in Equation 1. As before, I employ agency and time fixed effects to control for CRA level time varying heterogeneity and time trends in changes in ratings. However, unlike specification Equation 1 I am unable to use firm fixed effects. The reasons is that statistical packages (stata) are incompatible with computing estimates using a large array of fixed effect structure. Nevertheless, following Dimitrov et al. (2015), I employ industry level fixed effects (η_k) in the ologit model. The coefficient of interest is β_1. A positive coefficient would indicate that ratings have worsened after the regulatory shock.

Results are presented in Table 4. In column 1 (2) (3) I use the mean (median) (maximum) rating_score of the firm-rating agency pair in the year-quarter. I include control variables across all the columns. The coefficient of the interaction term in column 1 is 0.11 and is statistically significant. The result suggests that treated firms have a higher likelihood of having a lower credit rating (or higher *rating_score*) due to the forced exit of brickwork. The proportional odds ratio corresponding to 0.11 is 1.12 ($= \exp^{0.11}$). Thus, the odds of having a lower rating are 1.12 times higher for the treated firms. Results presented in columns 2 and 3 are also economically and statistically similar to results presented in column 1.

Overall, the inferences from the OLS and the ologit models suggest that firms experience rating deflation due to forced exit of a CRA. Moreover, note that Brickwork represents a market share of roughly 11% in the pre-period. Thus, the magnitude of rating deflation documented above underestimates the potential effect when a larger rating agency with a higher market share is forced to exit.

10 Impact on Ratings Quality

As discussed in section 5, it is not clear whether exit of a rating agency will discipline the incumbent rating agencies to improve their rating quality. CRAs may improve their ratings due to higher reputational incentives, following the decline in competition in the ratings market. Subsequently, false warnings and missed defaults may reduce. However, it is also possible that CRAs adopt a pessimistic approach due to the real threat of forced exit in the future. Therefore, they may resort to deflating ratings, to protect themselves from regulatory sanction. Such deflated ratings may actually increase the likelihood of false warnings.

Moreover, the previous findings in section 9 show that the exit of a CRA is associated with rating deflation. However, it remains unclear whether this regulatory action actually improves the quality of ratings. I examine this explicitly by estimating the effect of exit of Brickwork on *missed defaults* and *false warnings*.

10.1 Forced exit and false warnings

To empirically test the effect on rating quality, I analyze two critical indicators of rating quality: "missed defaults" and "false warnings." First, I discuss impact on *false warnings* in this section.

False warnings occur when a rating agency downgrades the credit rating of a firm from above-investment grade to speculative grade rating, but the firm does not experience a subsequent loan default within one year of the downgrade. False warnings represent *type II errors*, where the rating agency provides overly pessimistic ratings that do not align with the actual credit performance of the borrower (Cheng and Neamtiu (2009)). I test effect on false warnings using the following specification.

$$False\_warning_{i,j,t} = \alpha + \beta_1 * post_t * treated_i + \beta_2 X_{j,t} + \gamma_i + \delta_j + \theta_t + \epsilon_{i,j,t} \quad (3)$$

Here $False\_warning_{i,j,t}$ is a dummy variable set to one if the firm i experiences a rating downgrade from above investment grade to below investment grade by agency j in the year-quarter t, but does not default on loan repayments in the next four quarters. All the other variables on the right side of the equation carry their usual meanings, as explained in section 9.1. Note that data on loan defaults is available up to 2023Q4. Since the above test requires at least one year of look-ahead period for assessing future loan defaults from the year-quarter of rating downgrade, I restrict the credit rating data to 2022Q4. Thus, I use 6 quarters around the regulatory event (2021Q2 to 2022Q4) for the above test.

Results are presented in Panel A of Table 5. In column 2, I present the estimates after including the control variable. Throughout the specifications, I observe that the coefficient on the interaction term is positive and significant. Thus, the forced exit of the agency seems to increase the false warnings from rating agencies. In column 2 the coefficient is 2.9%, which is economically meaningful because it represents 154% of the unconditional rate of type II error (1.88%). My results are in line with the findings of Dimitrov et al. (2015), which note that the Dodd-Frank Act resulted in higher false warnings.

10.2 Forced exit and missed defaults

Having shown that regulatory enforcement leads to an undesirable increase in false warnings, I now examine whether agencies now have lower missed defaults. I denote "missed default" as an event when a rating agency upgrades the rating of a firm, but the firm subsequently defaults on its loan repayments within one year of the rating upgrade. These errors are considered type I errors, highlighting the deficiencies of the CRA in accurately assessing credit loss events (Cheng and Neamtiu (2009)).

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By examining the occurrence of missed defaults, I aim to assess whether the forced exit of a CRA and the ensuing decline in competition leads to a reduction in type I errors and an improvement in

[18] I also define type I error as an event where the rating agency upgrades the firm from below invest grade to above investment grade in the eyar-quarter, and the firm defaults on loan repayments within the next one year. However, this definition is very restrictive, because there are very few instances of change in rating from speculative grade to investment grade. Moreover, in the few instances of rating upgrade, the ex-ante probability of loan defaults within a year is very low (0.02%). Thus, the definition results in very low power of test. In order to overcome this issue, I examine type I error as the event where the firm experiences an upgrade (not limited from below investment grade to above investment grade) and defaults on loan repayments in the future.

rating quality. I test the above conjecture by using a regression specification similar to Equation 4.

$$Missed\_default_{i,j,t} = \alpha + \beta_1 * post_t * treated_i + \beta_2 X_{j,t} + \gamma_i + \delta_j + \theta_t + \epsilon_{i,j,t} \tag{4}$$

Here, the dependent variable is 'missed default.' It is a dummy variable set to one if the firm i receives a rating upgrade from agency j in the year-quarter t, but defaults on loan repayments within the next four quarters. All the other variables are the same as explained earlier. Again, due to data availability up to 2023Q4 and the need to have one year look ahead period for measuring future loan defaults, I restrict the data from 2021Q2 to 2022Q4.

I present the results in Panel B of Table 5. The layout of Panel A is similar to that of Panel B. Across all columns of Panel B, I find that the coefficient of the interaction term is negative and statistically significant. In other words, the type I errors seem to be reduced due to the forced exit of CRA. Moreover, the effect is economically significant because it represents a 30% decline compared to the unconditional probability of missed defaults (1.69%).

Thus, my results suggest that the forced exit of a rating agency and deflation in ratings leads to lower type I errors. Although the above result shows that regulatory sanction leads to lower type I errors, the results should be interpreted together with changes in type II errors. Together, the increase in false warnings and the decrease in missed defaults are consistent with the view that the rating deflation is due to the pessimistic behavior of CRAs. That is, CRAs tend to understate credit ratings to mitigate regulatory costs, which leads to lower type I errors but also increases type II errors.

It is important to note that the increase in type II errors (154%) is significantly larger than the decline in type II errors (30%). However, I acknowledge that it is difficult to directly interpret whether the benefits of a reduction in type I error outweigh the costs of an increase in type II error. I discuss more about these limitations in section 13. Nevertheless, the key takeaway from the findings is that the forced exit of a CRA leads to pessimistic behavior of rating agencies, as evidenced in rating deflation, and does not necessarily result in more accurate ratings.[19]

[19] Although the forced exits lead to some decline in missed defaults, I provide further evidence in section 12 in favor of the argument that the indiscriminate decrease in rating levels have unfavorable real effects on firms.

10.3 Test for existence of pre-trends

A potential concern about the validity of the DID inferences is that the observed increase in false warnings in the treatment group is an extension of the pre-existing patterns before the regulatory intervention. To rule out the above possibility, I employ DID framework and include pre-event time dummies to capture any changes in the difference between treated and control groups prior to the regulatory ruling. The regression model is specified as follows:

$$Y_{i,j,t} = \alpha + \beta_1 * post_t * treated_i + \sum_{n=-3}^{n=-2} \beta_n Pre_n * treated_i + \gamma_i + \delta_j + \theta_t + \epsilon_{i,j,t} \quad (5)$$

Here, the dependent variable denotes either false warnings or missed defaults. The variable Pre_n denotes a time dummy which is set to one for n-quarters before the regulatory intervention. For instance, Pre_1 is set to one for the quarter immediately preceding the implementation of the regulatory sanction, and zero otherwise. By including the interaction term between treatment and each of the pre-event dummies, I capture the effect of any changes in the difference in false warnings between the treated and control groups before the SEBI recommendation came into effect. All other variables in the regression remain the same as shown in equation 1.

The results of this analysis are presented in Table 6. The dataset consists of firm-agency-quarter observations for the sample period spanning from 2021Q2 to 2022Q4. In columns 1 and 2, the dependent variable is 'false warnings,' while in columns 3 and 4, the dependent variable is 'missed defaults.' Control variables are included in the even-numbered columns.

In columns 1 and 2, the DID coefficient remains positive and statistically significant, indicating a significant increase in false warnings following the regulatory intervention. Importantly, the pre-trend coefficients are statistically indistinguishable from zero, suggesting that there is no evidence of a changing trend in false warnings prior to the SEBI ruling. Furthermore, the main coefficient retains a similar magnitude as presented in section 10.1.

In columns 3 and 4, the DID coefficients are negative and significant. This implies that missed defaults decrease due to the pessimistic behavior of CRAs. Overall, the results suggest that the observed effects on false warnings and msised defaults cannot be explained by the presence of pre-existing trends.

11 Robustness Tests

In this section, I conduct three different robustness tests to address concerns related to the research design and the inferences.

11.1 Addressing self-selection bias

One potential concern in interpreting the results of this study is that firms self-select themselves into treated or control group by hiring a rating agency that has the highest likelihood of issuing favorable ratings. For example, a firm may hire a rating agency, that it perceives to have more lenient rating standards compared to other agencies to solicit a higher rating. Moreover, a firm may hire a rating agency and collude (issuer pay conflicts) to obtain higher than optimal rating grade. In the presence of such self-selection bias, it is possible that the observed effects are not solely due to the regulatory actions.

To address concerns of self-selection bias, several steps have been taken in this study. Firstly, I would like to draw the reader's attention to the comprehensive fixed effect structure - fixed effects at the firm level, rating agency level and time level – employed in the tests. This approach helps control unobserved heterogeneity and time-varying factors that may confound the relationship between regulatory action and rating quality.

Furthermore, to alleviate any residual concerns regarding self-selection bias, I conduct a robustness test that ensures each firm in the sample avails rating services from at least two rating agencies. The rationale behind this test is that a firm colluding with a single rating agency to obtain biased and favorable ratings may encounter difficulty in securing inflated ratings when multiple gatekeepers are involved in the rating process. For example, if a firm exclusively relies on Brickwork as its sole rating agency, it may be relatively easier for the firm to solicit an inflated rating. However, if there are multiple CRAs involved it is difficult for the firm to simultaneously collude with multiple raters (Kofman and Lawarrée (1993)).

Additionally, CRAs are known to exhibit herding behavior when they are involved in rating the same entity (Lugo et al. (2015)). Thus, it is unlikely that a biased CRA continues to issue a divergent and significantly higher rating than other raters of the same firm. Thus, by considering firms that engage multiple rating agencies, I aim to provide additional evidence on the effectiveness of regulatory action independent of self-selection biases.

I rerun the main specifications using a sub-sample of firms where firms are associated with at least two rating agencies during the pre-period. I present the results in Table 7. In column 1, I present the estimates for the specification equation 1 using the reduced sample. I find that results remain qualitatively similar. That is, agencies tend to deflate ratings in a DID sense. In column 2 and 3 my results are consistent with rating agencies having more type II errors but lower type I error after the forced exit. Overall, the above robustness test mitigates concerns related to self-selection of firms into treated or control group.

11.2 Large CRAs do not behave pessimistically

Another concern could be that smaller CRAs that are relatively less experienced and have lower reputation risk than their larger counterparts are more likely to issue inflated ratings, ex-ante. Thus, the decline in ratings is due to correction of inflated ratings issued by the smaller CRAs. Moreover, one may argue that the cost of suspending a larger CRA, that controls a large market share in the ratings market, could be too high for the regulator to ignore. For example, consider the rating agency CRISIL (subsidiary of S&P) that accounts for roughly 30% of the overall ratings in India. The decommissioning of S&P can lead to a significant disruption in the financial markets because of their dependency on S&P. Thus, the likelihood of forced exit of a large agency could be lower.

As a result, a skeptic may argue that the decline in ratings is driven by the smaller rating agencies that are more likely to be sanctioned by the regulator. I address this concern by conducting a robustness test where I limit my sample to firms that obtain credit ratings from the top three rating agencies of India (CRISIL, ICRA, and CARE). The big 3 rating agencies account for nearly 70% of the market share of the ratings. I present the results in Table 8. I observe that the results remain similar economically and statistically. Thus, it is unlikely that lowering of ratings is driven only by the smaller and relatively inexperienced CRAs.

11.3 Information loss for clients of Brickwork

Finally, another concern is that the ratings of firms that have exclusive rating relations with Brickwork are significantly more biased than ratings from other agencies. As a result, the downgrade in ratings is due to the decline in ratings witnessed in the above set of firms. Also, one may argue that the firms that were rated exclusively by Brickwork in the pre-intervention period now are forced to approach other rating agencies for availing credit ratings. The newer CRAs may have inadequate information while dispensing ratings for the new clients and may resort to lower and pessimistic ratings. The new CRAs may also be skeptical of providing higher ratings to the clients of Brickwork to avoid attracting regulatory scrutiny. Thus, lower information availability with the new entrant CRAs could drive the lower ratings of such firms.

I address this concern by removing the sample of firms that were rated exclusively by Brickwork in the pre-period, and were possibly subjected to excessive downgrades in the post-intervention period. However, the results presented in Table 9 remain qualitatively similar. That is, the downgrades are not limited to firms that were rated by brickwork.

12 Consequences of Rating Deflation

Finally, I examine whether the excessive downgrades have any real effects on firms. External credit ratings are solicited by banks to assess the risk (risk weight) of loans and, therefore, have a direct bearing on the pricing of bank lending.

Banks typically use standardized approach of Basel capital requirements to assign risk weight to loans depending on their external credit ratings. Thus, a lower external rating of the firm can increase the value of risk weighted asset (RWA) of the loan and, subsequently, reduce the regulatory capital ratios. In order to offset the higher risk of the loans on their books banks can raise the price of the loans (Van Roy (2005)). Therefore, I predict that the firms impacted by exit of the CRA will experience higher cost of borrowings. I test the above hypothesis by using the following regression specification.

$$InterestRate_{i,j,t} = \alpha + \beta_1 * post_t * treated_i + \gamma_i + \delta_j + \theta_t + \epsilon_{i,j,t} \tag{6}$$

Here, "interest rate" is calculated as the ratio of interest expense of the firm to the outstanding amount of bank loans in the previous year, expressed in percentages. All the other variables are the same as used in Equation 1. I present the results in table 10. In column 2, where I also include the control variables. I find that the DID coefficient is 4.47% and is statistically significant. Thus, the cost of borrowing seems to increase in a DID sense. Since the average rate of interest of firms is 17.49%, the effect represents a 25% increase in the cost of borrowing of firms.

Finally, to address the concern of existence of pre-trends in interest rates, I include interaction terms representing pre-period year dummies and treatment. Results are presented in columns 3 and 4 of table 10. Column 4 shows that all the pre-period treatment dummies are statistically indifferent from zero, whereas the DID coefficient remains positive and significant. Thus, the change in interest rates is most likely due to the exit of the CRA and rating deflation.

13 Limitation

The paper finds that forced exit of rating agency leads to rating deflation which in turn results in decrease in type 1 errors, that is usually sought after by the regulator. However, the rating deflation also results in the unintended consequence of higher type II errors. However, this paper doesn't attempt to determine whether the overall effect of lower ratings is beneficial or detrimental for users of ratings. The evidence presented in section 12 highlights one such adverse effect of lower ratings, manifesting as increased borrowing costs for firms.

However, from the regulator's standpoint, one could argue that a reduction in type I errors holds greater benefits, as it can reduce the likelihood of systemic crises triggered by inflated ratings. Assessing the magnitude of such benefits goes beyond the scope of this paper and remains a subject for future research.

14 Conclusion

Credit ratings play a key role in financial markets, and failure of ratings can lead to systemic crisis, as evident during the Global Financial Crisis. Although there have been several regulatory efforts to improve functioning of rating markets, criticisms have been raised regarding their limited effectiveness in bringing about meaningful change. This calls into question whether stricter regulatory actions that reduce competition in ratings market can discipline rating agencies.

In this study, I exploit the forced exit of a rating agency in India to examine whether stricter regulatory sanction, such as suspension of the offending rating agency. I employ a difference-in-differences design to examine whether forced exit of a rating agency leads to improvement in rating standards. The headline result is that the derecognition of a rating agency leads to significant rating downgrades in the ratings market. The lower ratings seem to be pessimistically biased that results in decline in missed defaults, but also lead to undesirable increase in the false warnings of credit ratings. Moreover, the lower ratings cannot be attributed to firm-specific characteristics and the results are robust to a host of alternative explanations. Overall, the findings are consistent with pessimistic behavior hypothesis - rating agencies issue pessimistically biased ratings in the face of extreme regulatory actions. Finally, the excessive downgrades also have real consequences in the form of an increase in cost of borrowing for the affected firms.

The findings are crucial from a policy perspective and emphasize the need for policymakers and regulators to carefully consider the potential negative impacts of stringent regulations on the ratings market. The study's results can contribute to ongoing discussions on improving the regulatory framework and and enhancing the overall reliability and accuracy of credit ratings in financial markets.

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Figure 1: The figure shows the time trend of market share of CRAs in India. The vertical line indicates the regulatory intervention when SEBI recommended exit of Brickwork.

Figure 2: Market Share of CRAs

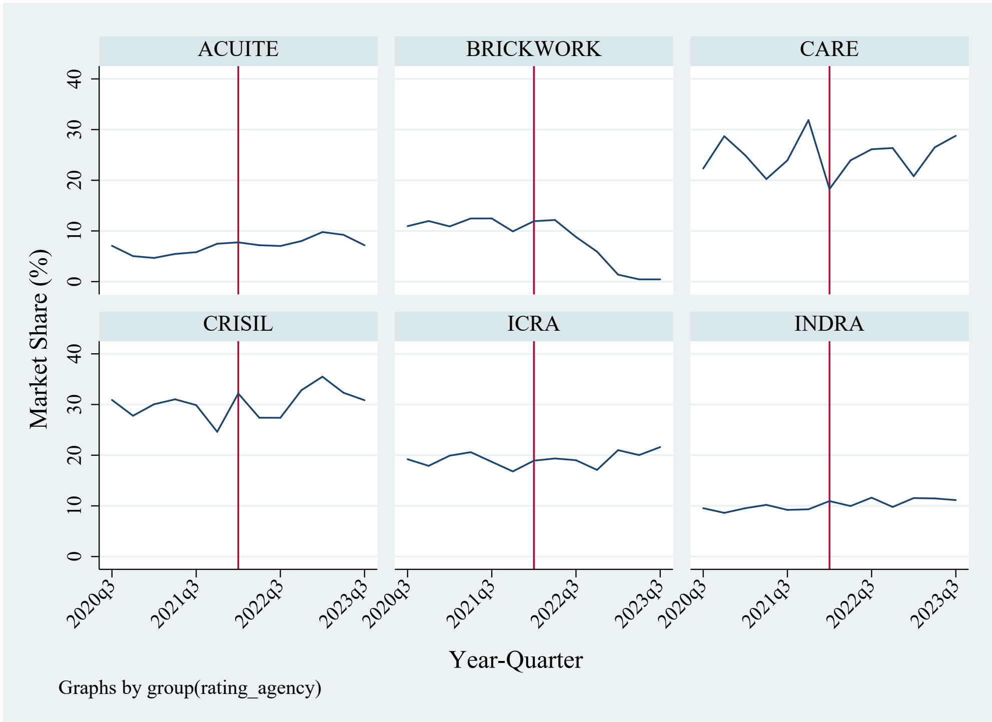

Table 1: Rating Scores

The table provides the mapping of rating letter grades of credit ratings of debt instruments to corresponding rating scores.

rating group	rating grade	rating score
Investment grade	AAA	1
	AA+	2
	AA	3
	AA-	4
	A+	5
	A	6
	A-	7
	BBB+	8
	BBB	9
	BBB-	10
Speculative grade	BB+	11
	BB	12
	BB-	13
	B+	14
	B	15
	B-	16
	C+	17
	C	18
	C-	19
	D	20

Table 2 (Panel A): Sample Construction

The table provides the sample construction..

Sample construction table	
For ratings level test	
Observation period for ratings level test	2020Q3 - 2023Q4
Number of credit ratings available at a firm-quarter-CRA-instrument level	107,062
Number of firm-CRA-quarter level ratings available	27,728
Number of unique firms	5,784
For ratings quality test	
Observation period for rating qualtiy tests	2021Q3 - 2022Q4
Number of firm-CRA-quarter level ratings available	11,948
Number of observations where upgrade/downgrade information is available	8,018
Number of observations where control variables are populated	6,001
Number of unique firms	2,967

Table 2 (Panel B): Summary Statistics

The table provides the descriptive statostics of the variables.

	Obs	mean	median	10%ile	25%ile	75%ile	90%ile	std dev
mean_rating	27,728	8.30	7.00	1.38	3.40	13.00	16.00	5.73
median_rating	27,728	8.39	8.00	1.00	3.50	12.50	16.00	5.69
max_rating	27,728	8.93	8.00	2.00	4.00	15.00	18.00	5.66
false warning (%)	6,001	1.88%	0	0	0	0	1	13.59%
missed default (%)	6,001	0.03%	0	0	0	0	1	1.83%
missed default2 (%)	6,001	1.69%	0	0	0	0	1	1.30%
interest_rate (%)	17,161	19.00	9.54	4.43	7.06	12.84	20.89	55.85
Interest_cover_ratio	24,338	16.32	2.62	0.68	1.48	7.20	25.22	69.74
profit margin (%)	24,338	6.45	12.91	-0.58	5.14	47.13	80.95	168.44
Ebitda_to_debt (%)	24,338	289.44	26.64	4.78	13.70	70.59	258.96	1382.80
Leverage (%)	24,338	43.11	36.68	5.12	16.83	63.23	79.42	49.29

Table 3: Forced Exit of CRA and Ratings Deflation - OLS

The table provides the association between forced exit of a CRA and the level of ratings using an OLS specification. The data are at a firm-CRA-quarter level for the period 2020Q3 to 2023Q4. Ratings are normalized into rating scores ranging from 1 to 20, one being the highest rating (refer Table 1). The dependent variable is the credit rating score defined at the firm-CRA-quarter level. The dependent variable in columns 1 and 2 (3 and 4) (5 and 6) is the average (median) (max) rating of the instruments of the firm rated by the CRA in that year-quarter. *Post* is an indicator variable that is set to one for the year-quarters 2022Q2 - 2023Q4, and zero otherwise. *Treated* denotes the firms that belong to industries that lie in the top tercile in terms of market share of Brickwork in industries during the pre-intervention period. I use a set of four control variables in the even numbered columns- Interest cover ratio, profit margin, EBITDA to debt ratio and leverage. All the control variables are defined in Section 9.1. I include firm, CRA and time level fixed effects across all columns. Standard errors are clustered at the industry X time level. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	mean_rating		***median_rating***		***max_rating***	
*Post * Treated*	0.189***	0.119*	0.201***	0.144**	0.178***	0.147*
	(0.060)	(0.072)	(0.061)	(0.071)	(0.063)	(0.077)
Interest cover ratio		-0.011		-0.016		-0.003
		(0.022)		(0.024)		(0.024)
Operating margin		-0.005		-0.005		-0.004
		(0.003)		(0.003)		(0.003)
EBITDA to debt ratio		0.000		-0.000		0.000
		(0.001)		(0.001)		(0.001)
Leverage		0.440***		0.490***		0.477***
		(0.149)		(0.142)		(0.140)
Firm F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Rating agency F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Year-Quarter F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Observations	27,334	20,304	27,334	20,304	27,334	20,304
R-squared	0.934	0.924	0.929	0.917	0.925	0.915

Table 4: Forced Exit of CRA and Ratings Deflation - Ologit model

The table provides the likelihood of rating scores due to forced exit of CRA using an ordered logisitc regression (ologit) model. The data is arranged at a firm-CRA-quarter level. Ratings are normalized into rating scores ranging from 1 to 20, one being the highest rating (refer Table 1). The dependent variable is the credit rating score defined at the firm-CRA-quarter level. In columns 1, 2, and 3 the credit rating score is calculated as the average, median, and maxmimum rating score of all instruments of the firm rated by the CRA in that year-quarter, respectively. *Post* is an indicator variable that is set to one for the year-quarters 2022Q2 - 2023Q4, and zero otherwise. *Treated* denotes the firms that belong to industries that lie in the top tercile in terms of market share of Brickwork in industries during the pre-intervention period. I use a set of four control variables in the even numbered columns- Interest cover ratio, profit margin, EBITDA to debt ratio and leverage. All the control variables are defined in Section 9.1. I include industry, CRA and time level fixed effects across all columns. Standard errors are clustered at the industry X time level. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1) ***mean_rating***	(2) ***median_rating***	(3) ***max_rating***
*Post * Treated*	0.113**	0.114**	0.095*
	(0.057)	(0.057)	(0.058)
Interest cover ratio	-0.189***	-0.190***	-0.184***
	(0.033)	(0.034)	(0.032)
Profit margin	-0.018***	-0.018***	-0.017***
	(0.001)	(0.001)	(0.001)
EBITDA to debt ratio	-0.006***	-0.007***	-0.006***
	(0.001)	(0.001)	(0.001)
Leverage	1.433***	1.403***	1.412***
	(0.148)	(0.148)	(0.146)
Industry F.E.	Yes	Yes	Yes
Rating agency F.E.	Yes	Yes	Yes
Year-Quarter F.E.	Yes	Yes	Yes
Observations	20,757	20,757	20,757

Table 5: Accuracy of Credit Ratings

The table show the effects of forced exit of a CRA on false warnings and missed defaults. The data are at a firm-CRA-quarter level for the period 2021Q3 to 2022Q4. The dependent variable in Panel A is *false warning*, that is an indicator variable set to one if the CRA downgrades the rating of the firm to below investment grade (BB or below) level but the firm does not default on loan repayments in the next one year. The dependent variable in Panel B is *missed default*, that is an indicator variable set to one if the CRA does not downgrade the rating of the firm to below investment grade (BB or below) level but the firm defaults on loan repayments in the next one year. *Post* is an indicator variable that is set to one for the year-quarters starting from 2022Q2, and zero otherwise. *Treated* denotes the firms that belong to industries that lie in the top tercile in terms of market share of Brickwork in industries during the pre-intervention period. I use the set of control variables described in 3 in the even numbered columns. I include firm, CRA, and time level fixed effects across all columns. Standard errors are clustered at the industry X time level. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(1)	(2)
	Panel A		Panel B	
	False warning		***Missed default***	
*Post*Treated*	0.030*	0.029*	-0.006***	-0.005***
	(0.017)	(0.017)	(0.002)	(0.002)
Controls	No	Yes	No	Yes
Firm F.E.	Yes	Yes	Yes	Yes
Rating agency F.E.	Yes	Yes	Yes	Yes
Year-Quarter F.E.	Yes	Yes	Yes	Yes
Observations	4,573	4,573	4,573	4,573
R-squared	0.408	0.408	0.863	0.863

Table 6: Test for pre-trends

The table tests for the presence of pre-trends. The data are at a firm-CRA-quarter level for the period 2021Q3 to 2022Q4. The dependent variable in Panel A is *false warning*, that is an indicator variable set to one if the CRA downgrades the rating of the firm to below investment grade (BB or below) level but the firm does not default on loan repayments in the next one year. The dependent variable in Panel B is *missed default*, that is an indicator variable set to one if the CRA does not downgrade the rating of the firm to below investment grade (BB or below) level but the firm defaults on loan repayments in the next one year. *Post* is an indicator variable that is set to one for the year-quarters starting from 2022Q2, and zero otherwise. *Treated* denotes the firms that belong to industries that lie in the top tercile in terms of market share of Brickwork in industries during the pre-intervention period. *Pre1* and *Pre3*) denote time dummy variables representing one and three quarters before the intervention, respectively. I use the set of control variables described in 3 in the even numbered columns. I include firm, CRA, and time level fixed effects across all columns. Standard errors are clustered at the industry X time level. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(1)	(2)
	Panel A		Panel B	
	False warning		***Missed default***	
*Pre1*Treated*	0.023	0.021	-0.015	-0.015
	(0.030)	(0.031)	(0.010)	(0.010)
*Pre3*Treated*	0.020	0.019	-0.004	-0.004
	(0.029)	(0.029)	(0.005)	(0.005)
*Post*Treated*	0.042*	0.041*	-0.010**	-0.009**
	(0.024)	(0.024)	(0.004)	(0.004)
Controls	No	Yes	No	Yes
Firm F.E.	Yes	Yes	Yes	Yes
Rating agency F.E.	Yes	Yes	Yes	Yes
Year-Quarter F.E.	Yes	Yes	Yes	Yes
Observations	4,573	4,573	4,573	4,573
R-squared	0.408	0.409	0.863	0.863

Table 7: Robustness test: Addressing self-selection bias

The table shows the changes in rating levels and rating quality due to forced exit of CRA in the sample of firms where each firm is rated by at least two rating agecnies. The data are at a firm-CRA-quarter level for the period 2020Q3 to 2023Q4 in column 1 and 2021Q3 to 2022Q4 in column 2. I exclude the firms which are rated by only a single credit rating agecny in the pre-period.. The dependent variables in columns 1, 2, and 3 are *mean rating*, *false warning* and *missed default*, respectively. All the above variables are defined in the text. *Post* is an indicator variable that is set to one for the year-quarters starting from 2022Q2, and zero otherwise. *Treated* denotes the firms that belong to industries that lie in the top tercile in terms of market share of Brickwork in industries during the pre-intervention period.I use the set of control variables described in 3 in the even numbered columns. I include firm, CRA, and time level fixed effects across all columns. Standard errors are clustered at the industry X time level. ***, **, *, and †represent statistical significance at the 1%, 5%, 10% and 15% levels, respectively.

	(1)	(2)	(3)
VARIABLES	***mean_rating***	***false warning***	***missed default***
*Post * Treated*	0.107†	0.055**	-0.007***
	(0.769)	(0.023)	(0.003)
Controls	Yes	Yes	Yes
Firm F.E.	Yes	Yes	Yes
Rating agency F.E.	Yes	Yes	Yes
Year-Quarter F.E.	Yes	Yes	Yes
Observations	18,219	3,011	3,011
R-squared	0.919	0.406	0.824

Table 8: Robustness test: Effects in Larger CRAs

The table shows the changes in rating levels and rating quality due to forced exit of CRA in the sample of firms rated by the larger CRAs. The data are at a firm-CRA-quarter level for the period 2020Q3 to 2023Q4 in column 1 and 2021Q3 to 2022Q4 in column 2. I limit the sample to firms that are rated by at least one of the three large CRAs - CRISIL, ICRA, and CARE - during the pre-period. The dependent variables in columns 1, 2, and 3 are *mean rating*, *false warning* and *missed default*, respectively. All the above variables are defined in the text. *Post* is an indicator variable that is set to one for the year-quarters starting from 2022Q2, and zero otherwise. *Treated* denotes the firms that belong to industries that lie in the top tercile in terms of market share of Brickwork in industries during the pre-intervention period.I use the set of control variables described in 3 in the even numbered columns. I include firm, CRA, and time level fixed effects across all columns. Standard errors are clustered at the industry X time level. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

VARIABLES	(1) ***mean rating***	(2) ***false warning***	(3) ***missed default***
*Post * Treated*	0.165**	0.036**	-0.005***
	(0.075)	(0.017)	(0.002)
Controls	Yes	Yes	Yes
Firm F.E.	Yes	Yes	Yes
Rating agency F.E.	Yes	Yes	Yes
Year-Quarter F.E.	Yes	Yes	Yes
Observations	18,015	4,308	4,308
R-squared	0.923	0.407	0.859

Table 9: Robustness test: Effects in firms not rated by Brickwork

The table shows the changes in rating levels and rating quality due to forced exit of CRA in the sample of firms that are not rated by Brickwork. The data are at a firm-CRA-quarter level for the period 2020Q3 to 2023Q4 in column 1 and 2021Q3 to 2022Q4 in column 2. I limit the sample to firms that are note rated by Brickwork. The dependent variables in columns 1, 2, and 3 are *mean rating*, *false warning* and *missed default*, respectively. All the above variables are defined in the text. *Post* is an indicator variable that is set to one for the year-quarters starting from 2022Q2, and zero otherwise. *Treated* denotes the firms that belong to industries that lie in the top tercile in terms of market share of Brickwork in industries during the pre-intervention period.I use the set of control variables described in 3 in the even numbered columns. I include firm, CRA, and time level fixed effects across all columns. Standard errors are clustered at the industry X time level. ***, **, *, and †represent statistical significance at the 1%, 5%, 10% and 15% levels, respectively.

VARIABLES	(1) ***mean rating***	(2) ***false warning***	(3) ***missed default***
*Post * Treated*	0.095†	0.037**	-0.005***
	(0.072)	(0.016)	(0.002)
Controls	Yes	Yes	Yes
Firm F.E.	Yes	Yes	Yes
Rating agency F.E.	Yes	Yes	Yes
Year-Quarter F.E.	Yes	Yes	Yes
Observations	19,003	4,333	4,333
R-squared	0.927	0.416	0.861

Table 10: Cost of borrowing

The table shows the effects of forced exit of CRA and associated changes in credit ratings on cost of borrowing of firms. The data are at a firm-CRA-quarter level for the period 2020Q3 to 2023Q4. The dependent variable is *Interest Rate*, the ratio of interest expenses incurred by the firm to the outstanding amount of bank loans in the previous year, expressed in percentages. *Post* is an indicator variable that is set to one for the year-quarters starting from 2022Q2, and zero otherwise. *Treated* denotes the firms that belong to industries that lie in the top tercile in terms of market share of Brickwork in industries during the pre-intervention period. I use the set of control variables described in 3 in the even numbered columns. I include firm, CRA, and time level fixed effects across all columns. Standard errors are clustered at the industry X time level. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)
		Interest rate		
*Pre2*Treated*			0.705	1.879
			(4.407)	(2.600)
*Pre3*Treated*			0.239	-0.182
			(4.277)	(2.715)
*Post*Treated*	8.238***	4.470**	8.212**	5.542**
	(2.815)	(1.776)	(3.850)	(2.705)
Controls	No	Yes	No	Yes
Firm F.E.	Yes	Yes	Yes	Yes
Rating agency F.E.	Yes	Yes	Yes	Yes
Year-Quarter F.E.	Yes	Yes	Yes	Yes
Observations	16,421	13,961	16,421	13,961
R-squared	0.627	0.796	0.627	0.796

Internet Appendix

Figure 3: The figure compares the actual default rates of debt facilities rated by Brickwork vis-a-vis the benchmark default rate set by SEBI for each of the rating category. In the first three columns, the comparison is shown for one year default rates. The first and second columns provide the average actual default rate on debt instruments rated by brickwork for each rating grade in 2020 and 2022 respectively. The column 3 presents the benchmark probability of default set by SEBI for one year defaults on instruments rated under each rating category. Similarly, columns 4 to 6 present the actual default rates and the benchmark probability of defaults for two year default horizon. Finally, columns 7 to 9 show the comparison for three year default horizon. The data has been sourced from the notification issued by SEBI on cancellation of Brickwork.

Figure 4: Market Share of CRAs

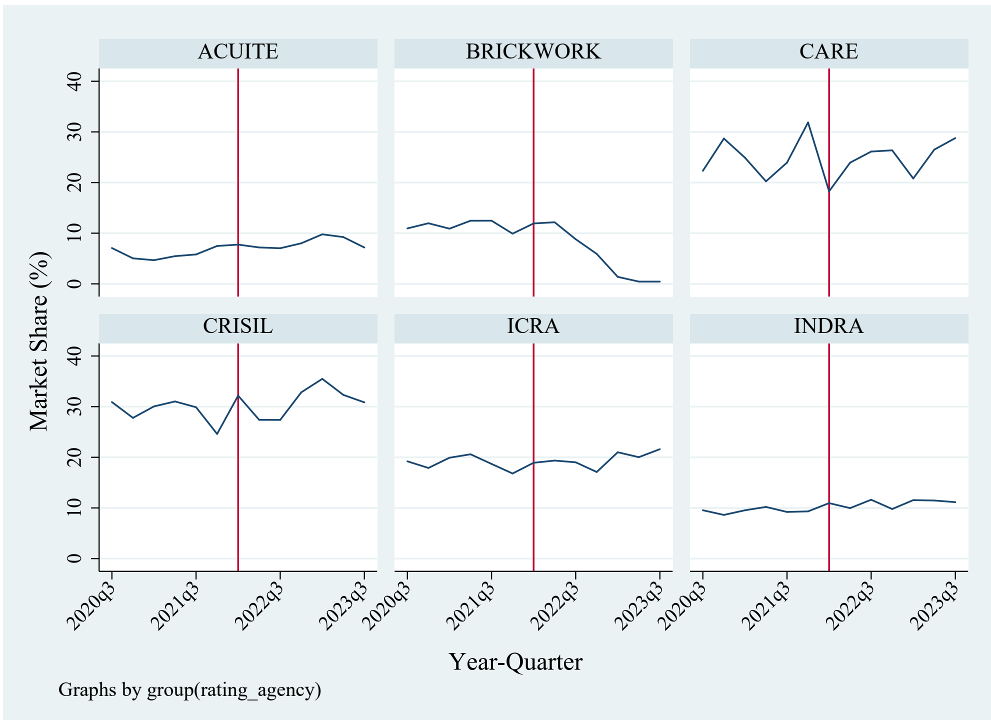

Table A.1: Actual default rate on Brickwork rated securities VS Probability of default benchmark by SEBI

he figure compares the actual default rates of debt facilities rated by Brickwork vis-a-vis the benchmark maximum probability of default (PD) set by SEBI for each of the rating category. In the first three columns, the comparison is shown for one year actual default and PD rates. The first and second columns provide the average actual default rate on debt instruments rated by brickwork for each rating category in 2020 and 2022 respectively. The column 3 presents the benchmark probability of default rate set by SEBI for one year defaults on instruments rated under each rating category. Similarly, columns 4 to 6 present the actual default rates and the benchmark probability of defaults for two year default horizon. Finally, columns 7 to 9 show the comparison for three year default horizon. The data has been directly sourced from the notification issued by SEBI on cancellation of Brickwork.

Period	March 2022	March 2020	Benchmark	March 2022	March 2020	Benchmark	March 2022	March 2020	Benchmark
Rating Category		*One year*			*Two year*			*Three year*	
AAA	0.48%	0.59%	0.00%	1.42%	1.43%	0.00%	2.47%	2.41%	1.00%
AA	0.98%	1.46%	0.00%	2.33%	2.83%	2.00%	3.71%	3.93%	2.00%
A	1.65%	1.79%	3.00%	3.63%	3.67%	3.50%	5.63%	5.49%	5.40%
BBB	2.42%	2.04%	3.30%	5.57%	4.67%	6.00%	8.99%	7.65%	10.50%
BB	2.71%	2.13%	8.70%	5.51%	4.59%	14.40%	8.50%	7.39%	19.60%
B	3.52%	2.89%	17.20%	7.73%	6.14%	33.10%	11.43%	9.54%	45.30%
C	11.52%	11.01%	100.00%	25.22%	20.27%	100.00%	35.52%	30.29%	100.00%

Table A.2: Stability Rates

The table shows the transition rates of each rating category for the years 2019, 2020, and 2022 for each of the rating agency. Transition rate is calculated as one minus the stability rate, where stability rate of a rating category is the percentage of ratings that remain in the same category at the end of one year. The data has been directly sourced from the notification issued by SEBI on cancellation of Brickwork.

CRA	From AAA			From AA			From A		
	2019	2020	2022	2019	2020	2022	2019	2020	2022
ACUITE	NA	0.00%	0.00%	6.50%	4.50%	6.70%	4.40%	8.40%	8.10%
BRICKWORK	7.01%	12.18%	12.31%	5.73%	9.65%	10.70%	4.99%	8.69%	12.81%
CARE	2.93%	4.03%	2.71%	3.98%	7.45%	7.57%	5.11%	9.69%	8.70%
CRISIL	1.31%	1.23%	1.20%	1.91%	2.14%	2.83%	3.97%	4.36%	6.44%
ICRA	1.40%	2.80%	2.10%	2.20%	5.60%	5.60%	3.80%	10.80%	9.90%
INDIA RATINGS	1.65%	2.32%	2.05%	3.22%	3.69%	4.89%	5.69%	6.30%	11.90%

CRA	From BBB			From BB			From B		
	2019	2020	2022	2019	2020	2022	2019	2020	2022
ACUITE	7.00%	10.90%	9.60%	5.00%	7.80%	13.30%	4.30%	8.40%	13.70%
BRICKWORK	5.85%	12.70%	20.73%	5.56%	13.75%	26.75%	4.99%	9.38%	18.87%
CARE	5.50%	10.96%	9.07%	7.40%	12.36%	11.33%	9.66%	23.89%	21.89%
CRISIL	5.05%	5.57%	8.06%	7.00%	7.12%	10.12%	8.29%	9.01%	20.37%
ICRA	4.80%	12.90%	12.40%	5.80%	12.50%	12.90%	5.10%	13.10%	16.40%
INDIA RATINGS	7.00%	8.10%	12.92%	8.02%	10.37%	21.84%	8.20%	8.89%	30.39%

Table A.3: Rated Instruments

The table shows the top twenty rated instruments and the frequency of each of these instruments in the Prowess database.

Security type	**Frequency**
Term loans	16.51%
Cash Credit	15.28%
Non convertible unsecured debentures	8.49%
Bank Guarantee	7.82%
Letter Of credit	6.59%
Long term Loans	6.05%
Non-government debt	5.46%
Fund based financial facility/instruments	4.42%
Working capital loan	4.38%
Non-fund-based financial facility/instruments	4.03%
Commercial paper	3.61%
Debentures / Bonds / notes / bills	2.76%
Pass through certificates	2.40%
Packing Credit	1.63%
Overdraft	1.47%
Short-term loan	1.26%
Others	1.09%
Debt	1.03%
Bill Purchase / Bill Discounting	0.88%
Non-fund based working capital limit	0.84%

Table A.4: Variable definitions

The table provides the definitions of the important variables used in the study.

Variable	**Definition**
rating_score	The numerical rating scale of the credit rating assigned by a credit rating agency to a debt instrument of a firm in a year-quarter. I map the credit rating grades of all the credit rating agencies to rating scales varying from 1 to 20. Rating_score of 1 corresponds to the highest credit rating (example: AAA by CRISIL), whereas the rating_score 20 corresponds to the lowest credit rating or the default rating. I assign the ordinal rating scales following Baghai and Becker (2018).
mean_rating_score	The average rating score of all instruments rated by a CRA for a firm in a year-quarter
median_rating_score	The median rating score of all instruments rated by a CRA for a firm in a year-quarter
max_rating_score	The highest rating score across all instruments rated by a CRA for a firm in a year-quarter
Downgrade	An indicator variable set to one if the rating agency downgrade the credit rating of a firm from investment grade (rating_score less than 11) to below investment grade (rating_score more than or equal to 11) in a year-quarter.
Upgrade	An indicator variable set to one if the rating agency upgrades the credit rating of the firm from below investment grade to investment grade rating in a year-quarter.
Treated	An indicator variable set to one (zero) if the firm it belongs to the industry that lies in the top (bottom) tercile in terms of market share of Brickwork ratings across industries during the pre-period.
Default	An indicator variable set to one if the firm defaults on bank loans within the next year (i.e. next four quarters), zero otherwise.
false_warning	An indicator variable set to one if the credit rating agency downgrades the firm to below investment grade rating in the year-quarter, but the firm does not default on its debt repayments within the next one year, zero otherwise.
missed_default1	An indicator variable set to one if the credit rating agency upgrades the firm to investment grade rating in the year-quarter, but the firm defaults on its debt repayments within the next one year, zero otherwise.
missed_default2	An indicator variable set to one if the credit rating agency assigns an investment grade rating to the firm in the year- quarter, but the firm defaults on its debt repayments within the next one year, zero otherwise.