Does Observability of Ratings Shopping Improve Ratings Quality?*

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[December 2022]

Abstract:

Ratings shopping is a well-documented cause for ratings inflation by credit rating agencies (CRAs). But the extent of ratings shopping by issuers, and the CRA's propensity to cater to the demand of inflated ratings by issuers is unobservable, making it difficult for market participants to undo it. In this paper, we exploit a unique setting in India, a regulation that requires CRAs to disclose ratings unaccepted by issuers. We ask whether these disclosures influence ratings shopping, and consequently ratings inflation. We find that the disclosure requirements result in a decline in ratings shopping, defined as a practice wherein issuers seek ratings from multiple CRAs and then strategically decide whether to report their ratings. However, we also find that, in the post-regulation period, issuers are more likely to approach a smaller CRA as such CRAs that will give them a better rating. These results are consistent with the view that the enhanced disclosure requirements produced unintended effects, and that they did not achieve their objectives of reducing shopping and ratings inflation.

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We thank Viral Acharya, Christine Cuny (discussant), Apoorv Gogar, Kose John, Nirupama Kulkarni, Partha Mohanram, Suraj Srinivasan, Shiheng Wang (discussant) and the seminar participants at MIT Asia Conference, NSE-NYU Conference, University of Western Australia, ISB Accounting Conference, CAFRAL for their helpful comments and suggestions.

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"CRAs work towards maximising the shareholder value by way of increasing revenues from issuers, while trying to provide independent ratings for investor consumption. Since all rating agencies approach the same set of clients, they have little bargaining power in terms of selecting the instruments to rate. Regrettably, on many occasions, the CRA quoting the lowest price or quite shockingly promising an investment-grade rating beforehand, wins the mandate." Dhiraj Relli, CEO HDFC Securities, India

1. Introduction

Credit rating agencies (CRAs) play an important role in the functioning of debt markets.[1] However, in several instances, notably in the financial crisis of 2007–2009, CRAs have failed to provide sufficient forewarning about impending defaults, thereby raising questions about the quality of these credit ratings.[2] Prior research on credit rating identifies *ratings shopping* as an important factor that adversely affects the ability of CRAs to provide reliable credit ratings (e.g., Sangiorgi et al., 2009; Skreta and Veldkamp, 2009; Bolton et al., 2012; Sangiorgi and Spatt, 2017). Ratings shopping broadly refers to the phenomenon whereby the issuer receives preliminary opinions from multiple CRAs but reports only the most favorable rating(s).[3] Since ratings shopping induces selection bias, observed ratings are more likely to be inflated on average. This suggests that if all ratings, favorable or unfavorable, were to be disclosed, then ratings quality will improve.[4]

In this paper we use a regulation in India to examine if requiring CRAs to disclose all ratings – favorable or unfavorable can indeed improve rating quality. The Securities Exchange Board of India (SEBI), the regulatory body that oversees the functioning of India's capital markets, pioneered a regulation in November 2016 that requires CRAs to give details of ratings

[1] See White (2010) and Roychowdhury and Srinivasan (2019) for an overview.
[2] For instance, CRAs are often blamed for issuing inflated ratings to structured finance products, which led to the rapid growth and the subsequent collapse of the subprime mortgage business, eventually provoking the financial crisis of 2007–2009. [See "Triple-A-Failure", by Roger Lowenstein, *New York Times Magazine*, April 27, 2008 https://www.nytimes.com/2008/04/27/magazine/27Credit-t.html]
[3] For instance, Brian Clarkson, former President and Chief Operating Officer of Moody's Investor's Service said "*There is a lot of rating shopping that goes on. . . What the market doesn't know is who's seen certain transactions but wasn't* hired to rate those *deals."*
[4] For this reason, the Dodd-Frank Act directed the SEC to make such a rule, but SEC is still studying the issue.

that they provided but that issuers rejected.[5] Before the regulation these ratings would not have been disclosed, but after the effective date of the regulation, 1 January 2017, the CRAs publicly disclose details of both accepted and unaccepted (or rejected) ratings including the name of the issuer, name/type of instrument, size of the issue, rating and outlook assigned, and other details. In this paper we use the enhanced disclosure regulation of India as a natural experiment and provide empirical evidence on whether disclosure of unfavorable ratings improves ratings quality.

The regulators' intended outcome was that since issuers cannot hide unfavorable ratings from investors under the enhanced disclosure regime, the ratings shopping exercise would possibly become moot, and this would relieve the pressure on CRAs to cater to issuers' preferences, thereby improving the overall quality of credit ratings. We term this conjecture as the *disciplining* hypothesis. The regulation also has other provisions to bring about greater transparency in the way CRAs assign ratings, and thereby facilitate the ease of understanding of such ratings by investors.[6] Collectively all these provisions provide further credence to the disciplining hypothesis.

However, an alternative possibility is that issuer firms migrate to a lower-quality CRA, possibly increasing the pressure on higher-quality CRAs to lower their standards as well, and this reduces the ratings quality overall. By going to a lower-quality CRA, issuers get the benefit of potentially more favorable rating, but at some sacrifice in the reputational benefit of going to a high-quality CRA. Since the new disclosure requirement increases the cost of having to publicly disclose an unfavorable rating, without necessarily increasing the benefit of getting a rating from a reputed CRA, the equilibrium could shift in favor of lower-quality CRAs. In such a scenario, optimal selection of CRA will shift to a new equilibrium wherein issuers choose a

[5] The regulation can be referred to at https://www.sebi.gov.in/sebi_data/attachdocs/1477999985100.pdf.
[6] We describe these provisions in section 3.1.

lower-quality CRA and thereby get a lower benefit in terms of reputation, but face lower cost of receiving a potentially unfavorable rating. Under this *strategic selection* hypothesis, issuers will directly choose the CRAs that will give them a better rating instead of doing what they did in the old regime, which is to first obtain ratings from multiple CRAs including high-quality ones, and then strategically decide whether to report these ratings or not. In response, CRAs could inflate ratings in order to retain customers and avoid missing out on business opportunities, a phenomenon popularly called as *ratings catering*. Strategic choice of CRAs by issuers, and the increased pressure on CRAs to cater, together could reduce ratings quality.

We test these contrasting hypotheses on a sample comprising of 57,478 unique ratings for 12,094 Indian firms from the period 2014-2019. We evaluate changes in ratings quality following the introduction of enhanced ratings disclosure requirements. Since the enhanced ratings disclosures came into effect beginning January 2017, our sample period covers three years before (*PRE* period) and after (*POST* period) this date. In our analysis, we control for time-invariant firm characteristics by including firm fixed effects. We also include macroeconomic control variables such as GDP growth, risk free rate, and aggregate defaults to control for time specific trends. Finally, in certain specifications that we detail later in this paper, we also control for differences in the inherent quality of various CRAs by including rating agency fixed effects.

We begin our empirical analysis by examining whether the instance of ratings shopping declines under the enhanced disclosure regime. Following prior research (e.g., Benmelech and Dlugosz, 2010; Griffin et al., 2013; He et al., 2016), we consider an issuing firm to have engaged in ratings shopping if its debt instrument is rated by only one CRA rather than by multiple CRAs. This construct assumes that the ratings for debt instruments with only one rating are more likely to reflect the presence of selection bias due to ratings shopping, as issuers would strategically choose to disclose only their best (i.e., most favorable) rating and to hide unfavorable ratings. We find that in the *PRE* period, 85% of all instruments were reported to be rated by only one CRA. However, in the *POST* period, 81% of all instruments were rated by a single CRA. These statistics show that the enhanced disclosure requirement leads to a decline in ratings shopping.

To examine whether the quality of ratings improves in the *POST* period, we use three proxies: the overall level of ratings, incidence of investment grade rating, and incidence of Type 1 error. First, we find an increase of approximately 6.25% in the level of ratings in the *POST* period, where rating level is an ordinal scale that takes a value of 19 for the highest rating possible, and a value of 1 for the lowest rating possible. Second, the incidence of instruments receiving an investment grade rating also increases by 23.2% in the *POST* period. Finally, we examine whether such inflated ratings lead to Type 1 prediction errors. Following Cheng and Neamtiu (2009) and Baghai and Becker (2018) a rating agency is defined to have made a Type 1 error if, after it assigns an investment grade rating to an issuing firm in the year *t*, that firm defaults in the year *t+1*. Examining changes in incidences of Type 1 errors is important because these types of errors attract adverse investor and regulatory attention, and are costly for CRAs (Cheng and Neamtiu, 2009). We find no significant change in the incidence of Type 1 errors in the *POST* period, suggesting that on average CRAs care about their reputation losses.

We then examine the cross-sectional variation in our results relating to ratings inflation. We argue that the change in ratings inflation in the *POST* period will vary depending on the relative bargaining power of the CRA vis-à-vis the issuer. Consistent with this logic, we expect that everything else being equal, the prospect of future business opportunities induces CRAs to give bigger issuers (as opposed to smaller issuers) more favorable ratings. Further, smaller CRAs, as opposed to larger CRAs are more likely to cater since the potential reputation loss is likely to be lower in smaller CRAs. Hence ratings issued by smaller CRAs will be more inflated. Results of our cross-sectional analysis support these hypotheses.

We argue that the need for public disclosures is another dimension along which our results will vary cross-sectionally. All debt instruments can be broadly classified as public (bonds) versus private (bank financing). Need for additional disclosure is lower in private debt since banks can perform their internal due diligence and can also seek information directly from the issuer. Hence the enhanced disclosures will be more beneficial for the public debt holders. Consequently, we expect to see lower ratings inflation in public debt instrument. Our results are consistent with these expectations.

Overall, our results suggest ratings inflation increases in the *POST* regulation period, suggesting that enhanced disclosures relating to unaccepted ratings seem to have an unintended consequence. To investigate if indeed the strategic selection hypothesis can explain the decline in rating quality in the *POST* regulation period, we compare the likelihood of an issuer selecting small and less reputable CRAs in the *PRE* versus *POST* period. We find that while 17% of all instruments are rated by smaller CRAs in the *PRE* period, this frequency increases to 27% in the *POST* period. We attribute this increase to the fact that smaller CRAs (rather than larger CRAs) are more likely to cater to issuers' demands for an inflated rating, and issuing firms are thus more likely to solicit them in the *POST* period.

As mentioned before, the SEBI Circular not only required disclosure of unacceptable ratings but had other provisions as well. While it is not possible to empirically disentangle the effect of other provisions on CRAs from that of unaccepted rating disclosures, those provisions tightened the requirements on CRAs and therefore should increase ratings quality. On the other hand, our results show that ratings quality decreased; therefore they are unlikely to be attributable to those other provisions. This leaves the strategic selection hypothesis, that can be seen as a rational response by issuer to the unaccepted rating disclosure requirement, as the most likely explanation for our findings.

Our results should be of interest to academics, regulators, and market participants. Tendency of firms to shop for inflated ratings and willingness of CRAs to provide such inflated ratings has been a key concern highlighted by both academics and regulators. So, understanding the role that disclosures may play in this credit rating process is important. The Dodd-Frank Act proposed a provision for disclosing rejected ratings, but this prospective disclosure requirement remains under consideration. Our results are timely for policy makers across the globe who are considering regulations such as enhanced disclosures with the aim to enhance the quality of credit ratings. Our results suggest that legislation demanding disclosures of rejected ratings may not resolve conflict of interest issues in CRAs.

This paper contributes to the credit rating literature in a number of ways. First, we add to the literature examining the impact of regulatory changes on credit ratings properties (Jorion et al., 2005; Cheng and Neamtiu, 2009; Goel and Thakor, 2011; Dimitrov et al., 2015). Our results suggest that regulatory changes can produce unintended consequences, and that the quality of credit ratings, which regulatory changes seek to improve, might, in fact, decline, owing to intensified competitive pressure resulting from the regulation. Second, we contribute to the stream of literature studying determinants of credit rating quality. While one body of work (e.g., Becker and Milbourn, 2011; Griffin et al., 2013; Kraft, 2015; He et al., 2016; Cornaggia et al., 2017; Baghai and Becker, 2018; Gopalan et al., 2019) provides evidence that competitive pressure produces inflated ratings for firms, another stream of research (e.g., Bonsall IV, 2014; Xia, 2014; Bonsall IV et al., 2017; deHaan, 2017) suggests that the CRA's reputational concerns keep ratings inflation under check. We contribute to this debate and our findings suggest that disclosure requirements are also likely to have an impact on credit rating quality. Finally, this paper contributes to the broader literature about the real effects of disclosure regulation (Leuz and Wysocki, 2016). This literature examines situations in which firms and intermediaries change their behavior in the real economy because of mandated disclosure, and more specifically, in response to regulatory changes. We add to this literature by exploiting a particular case of a regulatory change and its effects in India. We document the changes in the competitive landscape for CRAs following an obligation to disclose unaccepted ratings.

The rest of the paper is organized as follows. In section 2 we review the related literature. Section 3 describes the regulatory change and lays out our hypotheses. Section 4 describes our research design and data. Section 5 presents our empirical analysis and results. Section 6 offers our conclusions.

2. Literature Review

Credit ratings are important in assuring investors about the credit quality, and more specifically, the likelihood of default, of debt issuers. They allow uninformed investors to assess the risk characteristics of security issuances using a widely adopted scale. Credit ratings enable corporations and government entities to raise capital, and they facilitate the investment choices of investors and fiduciaries. Beginning in the 1930s in the United States, financial regulations have mandated that ratings be the primary measure for evaluating the credit quality of bonds. For instance, regulators of commercial banks, insurance firms, money market mutual funds, and pension funds have established minimum capital requirements in their portfolios that are based on credit ratings.[7] Taken together, the quality of ratings is a key factor for the successful functioning of debt markets.

Several factors affect the quality of the ratings provided by credit rating agencies. A significant discussion surrounds the possible conflicts of interest engendered by the issuer-pay model used by credit rating agencies, whereby the entity issuing debt also pays the rating

[7] See Sy (2009) for a discussion of the Basel Committee on Banking Supervision analysis of the regulatory uses of credit ratings from 26 regulatory agencies across 12 different countries. Sy (2009) concludes that credit ratings are an essential part of the regulatory process across jurisdictions for identifying assets that are eligible for investment purposes and for determining capital requirements.

agency to rate the issuance. Under this model, the rating agency is predisposed to satisfy the issuer by biasing its rating upward, owing to the pressure to both generate business and avoid losing a customer. This raises questions about the quality of the ratings produced. However, issuing low-quality ratings can lead to reputational costs for the rating agencies involved. This may incentivize them to provide accurate ratings for an issuer's credit quality and future prospects, despite the commercial risks this entails (Smith and Walter, 2002; White, 2010; Becker and Milbourn, 2011). A large body of research examines the influence of this dilemma on ratings quality. Several studies offer evidence that poorer-quality ratings result from the issuer-pay model (Becker and Milbourn, 2011; Cornaggia and Cornaggia, 2013; Griffin et al., 2013; He et al., 2016; Baghai and Becker, 2018). Another stream of research suggests that long-run reputational concerns for rating agencies supersede the pressures of this model and incentivize higher ratings quality (Covitz and Harrison, 2003; Bonsall IV, 2014; Xia, 2014; Bonsall IV et al., 2017; deHaan, 2017). Bolton et al. (2012) model the conditions in which reputational concerns dominate over commercial pressures, and vice versa. Their model suggests that CRAs are more prone to giving poor quality ratings when reputational costs are lower and when the proportion of investors that take the ratings at face value is larger. Conversely, the model suggests that when reputational costs are greater and there is a higher proportion of sophisticated investors doubtful of credit rating accuracy, CRAs are more likely to provide accurate ratings of credit quality.[8] Other studies examining ratings quality document a temporal trend revealing that credit ratings have become more conservative over time (Baghai et al., 2014).

[8] Similarly, Mathis et al. (2009) model the trade-off, and demonstrate that CRAs truth telling incentives are weaker, with higher likelihood of issuing inflated ratings, when the CRA generates revenue primarily from complex products. On the other hand, reputational effects should dominate when CRAs generate revenue primarily from transparent issuers, such as firms with audited financial statements.

In addition to studies examining ratings quality, a related stream of literature has examined ratings bias, and specifically, ratings inflation. Ratings inflation is widely seen as resulting from two related practices: ratings shopping and ratings catering. The often-cited practice of ratings shopping refers to the scenario in which the issuer solicits preliminary ratings from multiple CRAs but strategically purchases and reports only the most favorable rating(s) (e.g., Mathis et al., 2009; Sangiorgi et al., 2009; Skreta and Veldkamp, 2009). Ratings catering refers to the phenomenon whereby CRAs, in anticipation of ratings shopping by their clients, relax their credit rating standards to match their more lenient competitors in order to attract or keep clients, and to avoid missing out on revenues or market share. This intensified competition leads to CRAs catering to the demands of the issuers, and particularly, leads to CRAs issuing higher ratings (see Griffin et al., 2013). It is important to recognize that ratings shopping and ratings catering have different underlying drivers, but that these phenomena are not mutually exclusive.

Many empirical studies about ratings inflation provide evidence of ratings shopping.[9] Several papers have studied ratings shopping in the structured securities market by comparing the performance of securities that have one rating with those that have two or three ratings (Benmelech and Dlugosz, 2010; Griffin et al., 2013; He et al., 2016), under the assumption that securities that have just one rating are more likely to reflect ratings shopping. Benmelech and Dlugosz (2010) find that collateralized debt obligations (CDOs) tranches rated only by a single CRA are more likely to be downgraded and have relatively larger ratings decline; Griffin et al. (2013) also consider the CDO market but find that defaults are less common in securities with a single rating. They argue that this is inconsistent with pure ratings shopping, but they

[9] A substantial literature considers ratings catering by examining whether CRAs assign higher ratings (e.g., Griffin and Tang, 2012; Griffin et al., 2013; Kraft, 2015). These papers document that CRAs assign ratings that are higher than the rating model output of the CRA, and that CRAs tend to "adjust" their ratings upwards, suggesting ratings catering.

document evidence consistent with ratings catering. He et al. (2016) focus on the mortgage-backed securities (MBS) market and show that MBSs with only one rating have higher losses over time, with information in the yields reflecting future losses. Kronlund (2020) presents evidence of ratings shopping in the corporate bond market.[10] In Kronlund's view, shopping occurs when issuers choose to engage CRAs that have provided higher ratings in the prior periods compared to other agencies, meaning that published ratings are more likely to represent only the highest average ratings among all agencies sought.

The ratings inflation produced by ratings shopping can influence what information is revealed to investors (debt-holders) about credit ratings, as well as its distribution. This means that investors can be systematically misled about the issuer's true credit risk. Several papers theoretically and empirically consider investors' responses to biased credit ratings. According to the model provided by Skreta and Veldkamp (2009), investors do not sufficiently account for ratings bias, which allows issuers to exploit this winner's curse fallacy and engenders adverse effects in investor demand and pricing. In contrast, Sangiorgi and Spatt (2017) demonstrate that even when investors are rational about ratings inflation and discount bond prices, ratings shopping can persist in equilibrium under particular conditions, such as when investors cannot fully observe issuers disclosing one good rating and withholding one bad rating.[11] Investors may even tolerate (or prefer) inflated ratings because of regulatory distortions; specifically, when prudentially regulated investors such as banks and insurance companies carry bonds with inflated ratings, they can reduce their regulatory capital requirements yet obtain higher yields relative to the rating (Opp et al., 2013; Stanton and Wallace, 2010). Several empirical papers present evidence that investors at least partially

[10] Bongaerts et al. (2012) also examine corporate bonds and find some evidence of rating agency shopping near the investment-grade boundary.

[11] Another way to state is in a pooling equilibrium, when investors cannot exactly infer which bonds have biased ratings.

understand ratings shopping and account for this bias in the pricing (Griffin et al., 2013; He et al., 2016; Kronlund, 2020).

Given the central role CRAs play in the financial markets in the United States and around the world, they have long been subject to scrutiny, particularly after the Asian crisis of the late 1990s, the collapse of Enron and WorldCom in the 2000s, and the 2007-2009 financial crisis (Ferri et al., 1999; White, 2010). Following the Asian crisis and the collapse of Enron, CRAs faced widespread criticism for their lack of timeliness and their failure to predict these bankruptcies. In the case of the 2007-2009 financial crisis, CRAs faced partial blame for providing overly-inflated ratings of mortgage-related securities, stemming from conflicts of interest (Brunnermeier, 2009; White, 2010). These criticisms have resulted in increased regulatory oversight of CRAs. SOX and the Dodd-Frank Act aim to increase transparency, limit conflicts of interest, and increase competition, with the hope of ultimately improving credit rating quality. Jorion et al. (2005) find that the informational content of credit rating upgrades and downgrades increased after Regulation Fair Disclosure (FD) was implemented in 2000, which exempted firms from disclosing nonpublic information to the CRAs. Similarly, Cheng and Neamtiu (2009) investigate the change in properties of credit ratings following the passage of SOX; they find that CRAs improved on the timeliness of downgrades, increased rating accuracy, and reduced rating volatility. On the other hand, in a study of the effect of the Dodd-Frank Act on corporate bond ratings, Dimitrov et al. (2015) find no evidence of the disciplining effect in improving CRA ratings quality. Rather, they find that after the passage of the Dodd-Frank Act, CRAs provide lower ratings, give more false warnings, and issue less informative downgrades, which they attribute to CRAs being more protective of their reputations. These findings are consistent with the model summarized in Goel and Thakor (2011), who show that increasing litigation or regulatory risk in the credit ratings industry is a double-edged sword. On the one hand, CRAs may exert greater due diligence, resulting in more informative ratings, but on the other hand, CRAs may obfuscate their ratings, leading to downward-biased ratings. Our paper builds on this stream of literature by examining the effectiveness of enhanced disclosure requirements in India, under which CRAs now need to disclose ratings that they issued but that were rejected by the issuer.

3. Institutional background and hypotheses

3.1. Credit Rating Agencies in India and their regulation

There are six CRAs registered and regulated in India: CRISIL (incorporated in 1987), CARE (1993), ICRA (1991), BRICKWORK (2007), IND-RA (1996), and ACUITE (2005). CRISIL, CARE, and ICRA are the three largest credit rating agencies in terms of market cap. Several of the Indian CRAs are owned by the American rating agencies. For example, Standard and Poor's Global Inc., holds majority shareholdings in CRISIL, Moody's Corporation owns a 51.86% stake in ICRA, and Fitch Ratings Inc. holds 100% ownership in IND-RA. Consequently, Indian CRAs operate in a manner similar to that of their American parents.

As in the rest of the world, credit ratings play an important role in facilitating debt contracting in India. Credit ratings are also used by various regulatory agencies to safeguard investors. For example, the Employees' Provident Fund Organization (EPFO), India's largest public pension fund with INR 15.69 trillion assets under management (USD 209 billion) as of November 2021,[12] is limited to investing in debt rated AA or higher. Mutual funds are primarily only allowed to invest in bonds that are rated BBB- or above and can invest up to 10% of their portfolio in unrated debt instruments. Insurance companies can invest, at most, 60% of assets in AA or higher-rated corporate bonds. Ratings are also used by the central bank to help determine bank capital adequacy.

[12] https://www.epfindia.gov.in/site_docs/PDFs/Updates/Nirbadh_EPFO_to_e%20EPFO.pdf

Given the increasingly important role played by credit ratings in financial markets, Indian CRAs were brought under regulatory purview in 1999. The Securities and Exchange Board of India (SEBI)[13] regulates Indian credit rating agencies. SEBI issued the first comprehensive regulatory framework through the SEBI (Credit Rating Agencies) Regulations, 1999. These regulations cover the establishment of rating agencies, ratings disclosure, methodology, and conflicts-of-interest. SEBI has on several occasions taken steps to strengthen the process of credit ratings by issuing directives. These directives require the CRAs to increase transparency and to disclose information having material bearing on the ratings.[14]

Like those in the United States, all Indian CRAs face challenges inherent to the issuer-pay compensation model. The Reserve Bank of India (RBI), which is the Indian central bank, has often expressed concerns about the widespread ratings shopping practiced by firms for their long-term bank loans.[15] In its financial stability report RBI highlights several instances in which CRAs gave "indicative ratings" to issuers without entering into written agreements with them. The report further notes that it becomes difficult to identify ratings shopping since such indicative ratings are not required to be disclosed by CRAs on their websites.

With the aim of curbing such ratings shopping and to improve the overall quality of disclosures by CRAs, in 2016, SEBI issued the circular "MIRSD/MIRSD4/CIR/P/2016/119". This regulation imposes additional disclosure requirements to directly address ratings shopping amongst issuers, which we exploit in the empirical analysis in our paper.[16] An important

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[13] SEBI is equivalent to the Securities Exchange Commission or SEC in the US.

[14] For instance, in May 2010, SEBI strengthened regulations through "Circular CIR/MIRSD/CRA/6/2010" by requiring CRAs disclose rating movement and credit rating history on all outstanding securities on their website twice a year. These rules also included requirements that CRAs publish default studies to document credit ratings performance, specific policies regarding conflicts of interests, and disclosure requirements related to rating agency revenue for non-rating services (see Baghai and Becker 2018).

[15] https://timesofindia.indiatimes.com/business/india-business/rbi-sounds-the-alarm-over-rating-shopping/articleshow/73001629.cms

[16] This regulation also had several other requirements that relate to maintaining an operations manual; disclosure of detailed rating criteria, including on default recognition, and explaining the use of financial ratios; disclosure of eligibility requirements of auditors for conducting internal audits of CRAs; laying out the roles and responsibilities of the rating analysts; policies regarding non-cooperation by the issuer; standardization of press

requirement involves the disclosure of ratings not accepted by the issuer. Each CRA is required to disclose details of all ratings assigned by them on their website, regardless of whether the issuer accepted the rating or not. The CRAs were given sixty days to implement these guidelines following the circular. Appendix A shows screenshots of unaccepted ratings disclosures retrieved from two CRA websites.

In discussing the reasoning behind the regulation, a senior SEBI official, Rajeev Kumar, suggested that the principle of the enhanced disclosure regulation was to increase the transparency and accountability of CRAs. These enhanced disclosure regulations were welcomed by both the ratings agencies and investors. For example, Rajesh Patel, then CEO of India Ratings and Research, remarked, "The guidelines will bring in greater transparency and consistency in ratings process across the industry which will help investors take an informed investment decision."[17] Consistent with rating agencies views, Lakshmi Iyer, Chief Investment Officer at the Asset Management firm Kotak, stated, "The new disclosures are definitely a hygiene check for lenders. This is not the only yardstick we use when processing information, but it is important. I think the new rules on disclosures have disincentivized rating-shopping; it has a certain suasion."[18]

3.2.Hypotheses

We posit that enhanced disclosure requirements can have two opposing effects on the overall quality of credit ratings. We term our first hypothesis the *disciplining* hypothesis. We argue that once CRAs begin to disclose rejected ratings, market participants can compare these presumably unbiased, rejected credit ratings with the higher rating obtained after shopping, thereby making rating shopping a futile exercise. Hence, we expect that the extent of ratings

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release after assigning a rating; publishing rating history of all instruments of the issuer rated by CRA in the past three years and withdrawn ratings.

[17] Retrieved from https://economictimes.indiatimes.com/sebi-enhances-disclosure-rules-for-credit-rating-agencies/articleshow/55189692.cms

[18] Retrieved from https://www.thehindubusinessline.com/companies/648-firms-refuse-to-accept-credit-ratings-given-by-various-agencies/article9724780.ece

shopping will diminish once enhanced ratings disclosures became effective, compared to the pre-regulatory period. Further, we suggest that the disclosure of rejected ratings will relieve the pressure on CRAs to cater. Consequently, under this *disciplining* hypothesis, we expect reduced ratings inflation after enhanced disclosure requirements come in effect.

While the disciplining role of enhanced disclosures is consistent with the objectives of SEBI, it is possible that the new disclosure requirement could change the behavior of the firms issuing debt instruments that seek ratings. Issuers must weigh the benefits, which are associated with obtaining a rating from a reputed rating agency, versus the potential cost of getting an unfavorable rating from them. Since the new disclosure requirement increases the negative cost of having to publicly disclose an unfavorable rating, without necessarily increasing the benefit of getting rating from a reputed CRA, issuing firms might choose to obtain a rating from smaller but less reputable rating agencies, and thereby shift to a new equilibrium based on a lower potential benefit (in terms of reputation) and lower potential cost (receiving an unfavorable rating). Thus, using information provided through informal channels, prior experience, and peers, issuing firms can strategically choose the CRAs most likely to give them a better rating. Furthermore, if reputed rating agencies anticipate this behavioral change on the part of firms seeking credit ratings, they might lower their rating quality in the interest of attracting clients and generating revenue. Hence, under the *strategic selection* hypothesis, we expect higher ratings inflation in the *POST* period compared to the *PRE* period.

Ultimately, it is an empirical question which of these two hypotheses (i.e., the *disciplining* hypothesis or the *strategic selection* hypothesis) will dominate. Hence, we present our first hypothesis in a null form:

H1 – There is no impact of the enhanced disclosure requirement on the overall quality of credit ratings.

While it is difficult to predict the average impact of enhanced disclosure requirements on ratings quality, prior research (e.g. Bolton et al. 2012) clearly identifies conditions in which competitive pressure to generate business is likely to overpower reputational concerns of CRAs. Building on these studies, we expect that the change in ratings inflation in the *POST* period will vary depending on the relative bargaining power of the CRA vis-à-vis the issuer. We posit that CRAs are more likely to cater when they are rating instruments for bigger issuers, as such ratings could solidify business relationships with the issuer and potentially generate higher future revenue. We thus predict that ratings will be more inflated for instruments of large issuers (compared to instruments of small issuers) in the *POST* period. We also hypothesize that smaller CRAs will be more susceptible to such catering in compensation for their relatively lower reputation and in order to attract more issuers. We thus predict more inflated ratings on the part of smaller CRAs compared to ratings issued by larger CRAs in the *POST* period. Hence, our second hypothesis is-

H2 – The overall quality of credit ratings will decline after the enhanced disclosure requirement for ratings (i) given to larger issuing firms, and (ii) given by smaller CRAs.

4. Research design and data

4.1. Research design

We begin our empirical analysis by running a specification test to examine whether indeed the incidence of ratings shopping declines after the enhanced rating disclosure requirements come into effect. Following prior literature (e.g., Benmelech and Dlugosz, 2010; Griffin et al., 2013; He et al., 2016) we consider a firm to have engaged in ratings shopping if it obtains a rating from only one CRA rather than multiple CRAs. Specifically, we create an indicator variable *SINGLE RATER* that equals one if a firm obtains ratings from only one CRA, and zero otherwise. The intuition behind this way of capturing ratings shopping is that a firm presumably would have obtained a rating from several CRAs, and would strategically report the most favorable rating while hiding the unfavorable ratings. We use the following OLS estimation specification:

$$\boldsymbol{SINGLE\ RATER_{i,t} = \alpha + \beta . POST + \delta . X_{i,t} + \alpha_i + \varepsilon_{i,t}} \qquad (1)$$

Where *i* denotes issuing firm, and *t* the year. The dependent variable *SINGLE RATER* captures the firms' likelihood of getting a rating from a single CRA in a particular year. Our main variable of interest is *POST*, which equals one for years following the implementation of enhanced ratings disclosure requirements, and zero otherwise. We control for macro factors to alleviate concerns related to time trend variations and systematic shifts. These controls include: (1) *GDP GROWTH* to account for overall expansion or contraction of the economy over time; (2) Treasury Bill Yield (*TBILL YIELD*), i.e., the yield on the 10-year maturity of treasury bill, to control for risk; and (3) Aggregate defaults (*AGG DEFAULTS)* to control for the overall health of the debt market. When the overall economy is not doing well as proxied by lower GDP growth, higher level of defaults, and higher treasury yields, we expect a negative impact on the firm performance as well. In such a situation we expect firms to rely more on ratings shopping to obtain favorable ratings despite less favorable performance. Finally, we include firm fixed effects to control for time-invariant firm-specific factors. Following Puri et al. (2011), we use a linear probability model rather than a logit or a probit model to avoid the well-documented incidental parameter problem arising due to the inclusion of fixed effects in nonlinear models.

Since the issuing firms' objective in ratings shopping is to obtain favorable, and inflated ratings, in our next set of analyses we examine whether such ratings inflation declines after enhanced ratings disclosure requirements come into effect. We use three measures of ratings inflation. First, we consider the level of ratings. In the presence of ratings shopping the level of ratings is likely to be higher than what is warranted by the issuing firm fundamental characteristics. CRAs provide ratings on the following alphanumeric scale: AAA (highest creditworthiness), AA, A, BBB, BB, B, C, D (default). Scales from "AA" to "C" are further modified with "+" and "−" to indicate the relative strength within the rating categories concerned. Following Baghai and Becker (2018) we convert these ratings into an ordinal scale variable, *RATING LEVEL,* that takes a value of 19 for the highest rating possible, i.e., AAA, and a value of 1 for the lowest rating possible, i.e., - C. Second, we measure the likelihood of a firm getting an investment grade rating. Issuing firms are most likely to benefit from ratings inflation if their pre-inflated rating is close to certain thresholds, such as investment grade rating. At margin, firms that barely manage to obtain an investment grade rating are likely to have a lower borrowing cost than firms that just miss getting such investment grade ratings. Hence, ratings inflation is likely to increase the chances of a firm at such a threshold receiving an investment grade rating. We create an indicator variable, *INVESTMENT GRADE,* that equals one if the *RATING LEVEL* is more than 11, and zero otherwise. Finally, we consider the incidence of Type 1 error as a proxy for ratings inflation. We create an indicator variable *TYPE 1 ERROR* that equals one if the firm receives an investment grade rating in the year *t* and there is a default (no default) in year *t+1*, and zero otherwise.[19] These errors represent instances where the rating agencies assign and/or maintain favorable ratings to defaulting issuers and hence fail to forewarn investors about an impending default. Such failures often lead to increases in regulatory pressure and investor criticism. On the continuum of inflated ratings, these three measures represent the increasing severity of ratings inflation, with *RATING LEVEL* being the most benign and *TYPE 1 ERROR* being the most egregious.

[19] Following Baghai and Becker (2018), we define default at the firm-year level. Specifically, if there is a default by a firm in any debt instrument category, irrespective of which rating agency rates the instrument, we consider the default to have taken place for all debt instruments.

We estimate the following OLS specification to capture the impact of enhanced disclosure requirements on ratings inflation:

$$\boldsymbol{RATING\ QUALITY_{i,j,t} = \alpha + \beta.POST + \delta.X_{i,t} + \alpha_i + \alpha_j + \varepsilon_{i,t}} \qquad (2)$$

Where *i* denotes issuing firm, *j* denotes the rating agency and *t* the year. The dependent variable *RATING QUALITY* is the measure of inflation in ratings issued by CRA *j* for firm *i* in the year *t*, captured in three different ways: ratings level, propensity of getting investment grade rating, and propensity of Type 1 error. We include all other variables in the model which were also included in equation (1). In addition, we also include rating agency fixed effects to capture differences in rating quality that arise due to unobservable CRA specific factors such as expertise and relationships with issuing firms.

4.2. Data

The sample period for this study spans 2014-2019. Since our objective is to examine the impact of enhanced ratings disclosure regulation implemented on November 1, 2016, our sample period covers three years before and after the regulation entered into effect. We obtained all data on credit ratings, financial performance, and industry classification from the Prowess database managed by the Center for Monitoring Indian Economy (CMIE). This database has been extensively used in prior literature (e.g., Khanna and Palepu, 2000; Bertrand et al., 2002; Gopalan et al., 2007; Manchiraju and Rajgopal, 2017; Aghamolla and Li, 2018; Baghai and Becker, 2018) due to its comprehensive coverage and high data quality.

We followed the procedure outlined in Baghai and Becker (2018) to construct our sample. The credit rating data on the Prowess database includes all ratings issued by the seven CRAs operating in the Indian capital market: CRISIL, ICRA, CARE, BRICKWORK, IND-RA, ACUITE, and IVR. We removed observations for ratings assigned by rating agency IVR as this is a small credit rating agency with very few observations in the post-regulation period and no observations in the pre-regulation period. Second, we removed observations with rating statuses of default, withdrawn, or not applicable. Third, we removed duplicate observations. The ratings data on the Prowess database do not have a unique identifier for a firm's debt security. Hence, we consider a rating observation as duplicate if entries in the following fields are the same: *issuer, instrument name, issue amount, rating date*, *rating agency*, *status*, and *rating*. Fourth, we retained only the ten most common instrument categories. These include: long term loans, cash credit, term loans, short term loans, letter of credit, bank guarantee, fund-based financial facilities, non-fund based financial facilities, non-convertible debentures, non-government debt, and commercial paper. The Prowess database has 65 different instrument categories; the ten instrument types we include in our sample comprise about 76% of all rating observations in the database.[20] The above data filters result in 187,243 unique rating observations. This data is further aggregated at an issuer-year level to construct ratings shopping measures. Our sample comprises 48,256 unique issuer-year observations relating to 12,094 unique issuing firms. We also aggregate the unique rating observations at an issuer-agency-year to construct measures of rating quality. We take the median of ratings over all the instruments for each issuing firm provided by a particular rating agency in a given year.[21] This process results in 57,478 unique issuer-agency-year ratings in our sample.

5. Results

5.1. Descriptive statistics

We provide summary statistics for the analysis of ratings shopping and quality of ratings in Table 1. In panel A, we show the yearly distribution of unique firms receiving credit ratings and the number of ratings assigned by CRAs. Herein, the distribution is reasonably stable across time. Across the years, the number of unique firms rated ranges between 7,801

[20] We include only the top 10 instruments in the sample to make our sample construction comparable with Baghai and Becker (2018). The results are qualitatively similar when we retain the full sample for our analyses.
[21] Our results do not change significantly if we take mean, maximum, or most recent rating for each issuing firm, rating agency, and year, across all instrument categories.

and 8,380, while the number of unique rating observations ranges between and 8,808 and 10,139. In panel B, we present the distribution of the number of CRAs engaged by a firm in a given year. Over our sample period, 83% of firms obtain ratings from just one CRA. This is surprising, given that in a year a typical firm has on average 18 different debt instruments. A very small minority of firms (about 2%) engage more than 2 CRAs to rate their debt instruments. Interestingly, the number of firms engaging only one CRA to rate their various debt securities drops from 85% to 81% between the pre- and the post-regulation period, and we observe a corresponding increase in the number of firms engaging more than one CRA. We document the frequency of ratings provided by various CRAs in panel C. The “big three” CRAs—CRISIL, ICRA, and CARE—provide 80% of all ratings in our sample period. However, their market share drops from 85% to 76% from the pre- to the post-regulation period. In panel D, we show the distribution of ratings by level. On average there are very few AAA ratings and these increase in the post-regulation period. The frequency of securities with AAA, AA, or A rating also increases from 27% to 35% from the pre- to the post-regulation period. Lastly, in panel E we show the incidence of default by a firm in the year $t+1$, conditioned on the rating of the debt security in the year t. As expected, firms receiving lower ratings in the year t are more likely to default in the year $t+1$. There are, however, a non-trivial number of instances where firms received an investment grade rating in the year t but defaulted in the year $t+1$. This tendency of CRAs to maintain a high rating in the year prior to default increased in the post-regulation period. The percentage of firms who received AAA, AA, or A rating in the year t, but that defaulted in the year $t+1$, is 2.03% in the pre-regulation period but 6.11% in the post-regulation period, signifying a three-fold increase in CRAs badly missing potential defaults.

In Table 2, we provide the summary statistics of key variables used in the regression analysis. In panel A, we document that on average, nearly 83.3% of firm-year observations in our sample engaged one CRA for all their rating requirements (*SINGLE RATER*). Moreover, on average, 22.2% of firm-year observations are represented by smaller CRAs i.e. BRICKWORK, IND-RA, ACUITE, (*SMALL RATER*). The average rating level is 10.32 (*RATING LEVEL*), 37.5% of firm-year rating observations are of investment-grade (*INVESTMENT GRADE*), and the Type 1 error is 0.5%. Panel B presents the difference in the mean of these variables from the pre- to post-regulation periods. There is a statistically significant decrease in *SINGLE RATER,* and a significant increase in *SMALL RATER*, *RATING LEVEL*, *INVESTMENT GRADE,* and *TYPE 1 ERROR* in the post-regulation period.

5.2. Disclosure of unaccepted ratings and incidence of ratings shopping

First, we examine the impact of regulation on ratings shopping. We estimate equation (1) and show the results in Table 3. The dependent variable is *SINGLE RATER*. In column 1, we report results from a specification that includes industry fixed effects. The coefficient of the *POST* variable, i.e., β_1, is significantly negative (coefficient= -0.0508, p-value<1%).[22] In column 2, we show results from estimating a different specification of equation (1) that includes firm fixed effects. The coefficient on the variable *POST* remains significantly negative (coefficient= -0.0496, p-value<1%). The coefficients on controls are generally consistent with the expectations. The economic significance of this result (column 1) is that there is a 5.1% decline in the average tendency of firms to employ just a single CRA in the post-enhanced disclosure regime. This suggests a reduction in the ratings shopping behavior of firms in the post- regulation period.

5.3. Disclosure of unaccepted ratings and ratings inflation

In this section, we examine the impact of enhanced ratings disclosure requirements on the extent of ratings inflation. To the extent that the enhanced ratings disclosure requirement

[22] We test the sensitivity of this result by estimating equation (1) using a logit regression model. The coefficient of *POST* variable, i.e., β_1, is significantly negative (-0.436, p-value<1%) and the odds ratio is 0.646.

acts as a check on ratings shopping, this is likely to relieve the pressure on CRAs to cater to the demand for inflated ratings by issuing firms, eventually leading to more unbiased ratings in the post-regulation period. However, if in response to the regulation, firms adjust their choice of CRA and prefer CRAs that are more likely to cater to their demands, then ratings inflation is likely to go up in the post-regulation period. We test these hypotheses by estimating model (2) and present the results in Table 4. Columns (1) – (3) show results with *RATING LEVEL, INVESTMENT GRADE,* and *TYPE1 ERROR* as dependent variables, respectively. In all of these specifications, we employ a within-rating-agency fixed effect model to control for inherent differences among the various CRAs. In addition, we also include firm fixed effects to account for time-invariant unobservable firm characteristics.

In column 1, where we examine the impact of enhanced ratings disclosure requirements on the level of ratings, we find that the coefficient on *POST* variable is positive and significant (coefficient= 0.6696, p-value<1%). This result indicates that, post the enhanced disclosure regulation, the average rating assigned to firms is approximately 0.66 notches higher. In column (2), we examine the incidence of investment grade ratings post disclosure regulation. If firms at the lower end of the rating spectrum (i.e., non-investment grade) obtain investment grade ratings due to ratings shopping, their investment ability increases. Hence, ratings shopping is most likely to take place around important thresholds such as investment grade ratings. Consistently, we find that the coefficient on *POST* variable is positive and significant (coefficient= 0.0913, p-value<1%). This represents a 9.13% increase in a firm's propensity to obtain an investment grade rating in the post-enhanced ratings disclosure regulation period. In column (3), we examine whether the incidence of Type 1 error – the most severe form of ratings inflation, changes in response to the enhanced ratings disclosure requirements. The Type 1 error captures the instances in which CRAs miss out on predicting default or do not forewarn about impending default by assigning investment grade ratings to issuers that eventually default in the following period. We find that the coefficient on the *POST* variable is insignificant, suggesting that the incidence of Type 1 error does not vary significantly between the pre- and post-regulation period.

Overall, these results indicate an increase in ratings inflation to a certain extent in response to the enhanced ratings disclosure requirements. While there is an increase in the level of ratings and the propensity of a firm to receive an investment grade rating, there is no significant change in the Type 1 errors committed by the ratings agencies.

5.4. Cross-sectional variation of disclosure requirements on ratings inflation

In this section we examine the cross-sectional variation in the impact of enhanced ratings disclosure requirements on ratings inflation. As discussed in prior literature (Griffin et al., 2013; Kronlund, 2020), ratings inflation arises because of both ratings shopping and ratings catering. Ratings shopping, which is carried out by issuers, is a result of a selection bias wherein an issuing firm discloses only its most favorable rating, while hiding unfavorable ratings. Catering, on the other hand, is a practice wherein CRAs intentionally give a debt security a higher rating than what is actually warranted. These two factors are likely to work in tandem, as issuing firms' desire for higher ratings incentivizes the CRAs to cater to such demand. Hence, we consider both issuing firm as well as CRA characteristics to examine the cross-sectional variation in our results.

First, we consider firm size. Larger firms bear more weight in influencing CRA rating decisions and are known to get higher ratings (He et al., 2016). CRAs stand to generate more revenue from larger firms by providing rating as well as non-rating services. To capture the differential impact of regulation on ratings inflation, we expand model (2) to include an indicator variable *LARGE FIRM* that equals one if the firm size (measured by total assets) is above the sample median, and zero otherwise. We also include the interaction term *POST X LARGE FIRM* to measure the differential impact of regulation on large versus small firms.

The results from the analysis are documented in Table 5. In columns (1) – (3), we consider *RATING LEVEL, INVESTMENT GRADE,* and *TYPE1 ERROR* as dependent variables, respectively. The coefficient on *POST X LARGE FIRM* is positive and significant across all three columns. The economic significance of the results is as follows: compared to smaller firms, larger issuers receive higher ratings by approximately 0.11 notches. Larger firms also have a 3.1% greater propensity to receive an investment grade rating in the post-regulation period. Finally, the frequency of Type 1 error in the post-regulation period increases by 1% in the larger firms whereas it decreases by 0.33% in the smaller firms. Overall, these results indicate that larger firms obtain more favorable ratings in the post-regulation period, possibly because CRAs cater to their demands in expectation of future revenues.

Next, we consider the cross-sectional variation in the impact of enhanced ratings disclosure requirements on ratings inflation based on the rating agency characteristics. We argue that compared to larger and more established CRAs, smaller CRAs are under greater pressure to increase their revenues. Hence, they are more likely to cater to issuing firms' demands for favorable ratings. We also posit that larger CRAs are more concerned about preserving their reputation under greater regulatory scrutiny. Hence, compared to smaller CRAs, larger CRAs are less likely to cater. Based on these arguments, we expect greater inflation in the ratings provided by the smaller CRAs in the post-regulation period. To test this prediction, we expand model (2) to include an indicator variable *SMALL RATER* that takes a value of one if the rating is provided by any one of the following three rating agencies: India Rating, Brickwork, and Acuite, and zero otherwise. We also include the interaction term *POST X SMALL RATER* to measure the differential impact of regulation on ratings provided by small versus large CRAs. These results are documented in Table 6. The dependent variable is

RATING LEVEL, INVESTMENT GRADE, and *TYPE 1 ERROR* in columns (1)-(3), respectively. The coefficient on *POST X SMALL RATER* is positive and significant across all columns. The results suggest that ratings provided by smaller CRAs in the post-regulation period are 0.36 notches higher than the ratings provided by larger CRAs. The probability of getting an investment grade rating in the post-regulation period is also higher by 1.7% if such rating is provided by smaller CRAs. The frequency of Type 1 error increases by 0.5% in the post-regulation period for ratings provided by smaller CRAs, while it does not change for the ratings provided by larger CRAs. Overall, these results are consistent with our expectations that smaller CRAs are more likely to cater to the demand for favorable ratings by issuing firms.

Finally, we consider whether the ratings inflation varies in the post-regulation period based on the debt instrument being rated. As discussed in the data section, a firm can issue a variety of debt securities. In our sample we include only the top ten most frequently-issued debt instruments. We further classify these debt instruments as bank financing vs. public debt. Bank financing includes various financing facilities obtained from banks such as term loans, cash credit, and bank guarantees, whereas public debt includes commercial paper, non-convertible debentures and non-government debt, which are typically raised from individual or institutional (non-bank) investors. We argue that investors in public debt are more likely to rely on disclosures to discern ratings inflation and adjust the bond yields accordingly. In contrast, banks are more likely to tolerate (or even encourage) ratings inflation, as higher ratings enable them to classify loans as less risky and thereby improve capital adequacy calculations (Opp et al., 2013; Gopalan et al., 2019). To test this prediction, we expand model (2) to include an indicator variable *NONBANK FIN* that equals to one if the majority of the firm's debt financing comes from non-banking sources such as bonds and commercial paper, and zero otherwise. We also include the interaction term *POST X NONBANK FIN* to measure the differential impact of enhanced ratings disclosure regulation on ratings of debt instruments relating to bank financing vs. public financing.

These results are documented in Table 7. The dependent variable is *RATING LEVEL, INVESTMENT GRADE,* and *TYPE1 ERROR* in columns (1)-(3), respectively. The coefficient on *POST X NONBANK FIN* is negative and significant in columns (1) and (2), while the coefficient is positive and significant in column (3). The results suggest that ratings provided for non-bank debt instruments in the post-regulation period are 0.15 notches lower than the ratings provided for bank debt instruments. The probability of getting an investment grade rating for non-bank debt instruments in the post-regulation period is also lower by 2.5%. Further, the frequency of Type 1 error increases by 2.4% in the post-regulation period for ratings relating to non-bank debt instruments.

Overall, these results are consistent with our expectations that enhanced ratings disclosure requirements are going to be useful for investors, as they will be able to see through the shopping efforts of CRAs and can price bonds accordingly. As a result, ratings shopping will be less attractive for issuing firms in such situations. However, when the end user of the ratings is a bank with perverse incentives for preferring inflated ratings, enhanced ratings disclosure requirements are unlikely to keep ratings shopping and ratings inflation in check.

5.5. Disclosure of unaccepted ratings and the strategic choice of CRA

Our results so far indicate that, while the enhanced disclosure requirement for unaccepted ratings leads to a decline in ratings shopping (as proxied by obtaining ratings from a single CRA), it has an unintended consequence of increasing rating inflation. To explain the mechanism behind this unintended consequence, we examine if issuing firms are more likely to engage with smaller CRAs. By doing so, issuing firms are able to achieve their objective of obtaining favorable ratings. At the same time, issuing firms will also be able to avoid the negativity associated by the disclosure of unaccepted rating by the bigger CRA, had the issuing firm gotten an unfavorable rating by the bigger CRA. To test this prediction, we estimate the following equation –

$$\boldsymbol{SMALL\ RATER_{i,t} = \alpha + \beta.POST + \delta.X_{i,t} + \alpha_i + \varepsilon_{i,t}} \quad (3)$$

where the dependent variable *SMALL RATER* is an indicator variable that equals one if the ratings is provided by one of the following CRAs - CRAs i.e. BRICKWORK, IND-RA, ACUITE, and zero otherwise. All other variables are previously defined when explaining equation (1).

We present the results from estimating equation (3) in Table 8. In column 1, we include industry fixed effects. The coefficient of the *POST* variable, i.e., β_1, is significantly positive (coefficient= 0.1105, p-value<1%). In column 2, we include firm fixed effects, and the coefficient of *POST* variable remains significantly positive (coefficient= 0.1061, p-value<1%). Economically, this result (column 1) translates to an 11.1% increase in the average likelihood of a firm obtaining ratings from a smaller CRA in the post-regulation period. This finding indicates an increase in firms strategically selecting smaller CRAs for their possible ratings leniency predicated on the smaller CRA incentive to gain market share.

5.6. Robustness Tests

We assess the robustness of our empirical findings through several tests.[23] First, one concern with our research design is the possibility of firms dropping out of the sample during the post-regulation period. This self-selection can induce bias due to differences in the types of firms in our sample in the *PRE* and *POST* periods. To alleviate this concern, we repeat our analysis for the subsample of firms that receive ratings in both the *PRE* and *POST* periods. The results are consistent with our baseline inferences; and reinforce the findings of a significant

[23] We do not tabulate these results in the paper. However these are available upon request.

increase in the level of ratings assigned and propensity to receive investment-grade ratings in the *POST* period. Second, a potential alternate explanation for our findings of inflated ratings in the *POST* period is that CRAs cater more to their long-term clients in the *POST* period. Under this explanation, CRAs assign inflated ratings to maintain market share and avoid losing "loyal" customers. To mitigate the impact of this relationship-driven rating assignment, we restrict our sample to firms that receive ratings from only one CRA in the pre-period and more than one CRA in the post-period. Therefore, the firms in this subsample do not rely solely on CRAs that rate them in the pre-regulation period for their rating requirements. We find that the baseline results of higher rating level and propensity to receive investment grade ratings are robust to this subsample and alleviate concerns about relationship-driven rating inflation in the post-regulation period.

Third, the baseline argument that firms strategically shift to smaller CRAs post-regulation assumes that they anticipate more favorable ratings from smaller CRAs. To validate this proposition, we retain only those firms in the sample that receive majority of their ratings from larger CRAs in the pre-period, and smaller CRAs in the post-period. The results for this subsample indicate higher ratings level and increased propensity to receive investment grade ratings in the post regulation period. This reinforces the argument that the choice to shift towards smaller CRAs in the post-regulation period benefits firms in the form of receiving inflated ratings. Fourth, we specifically re-examine the impact of the regulation on the propensity to receive an investment-grade rating for the subsample of firms that receive ratings just above or below the cut-off. Since the investment-grade rating level is well-defined, managers can form expectations and manipulate CRAs to receive such ratings. For instance, managers of firms with severely poor financial stability can form reasonable expectations of receiving non-investment grade ratings and engage in egregious financial reporting or alternate routes to ensure investment grade ratings. However, managers of firms whose stability and instrument outlook is at the threshold of investment grade rating can't accurately predict the probability of receiving investment grade ratings. Accordingly, the presence of managers manipulation in receiving investment grade ratings is reasonably low in the narrow thresholds around the cutoff. Consequently, in line with the regression discontinuity models that retain samples in narrow thresholds around cut-offs to alleviate such concerns, we create two subsamples that retain ratings (+2, -2) notches and (+1, -1) notches around the investment-grade rating level cut-off, and repeat the analysis. We find a stronger propensity to receive investment-grade ratings in these subsamples, which are plausibly unaffected by managers' expectations. Finally, it is worth highlighting that the instruments in our sample are not subject to regulatory requirements for a certain number of minimum ratings from the CRAs. This alleviates concerns regarding specific regulatory requirement interference in our analysis.

6. Conclusion

Credit rating agencies are important gatekeepers that ensure proper functioning of debt markets. However, CRAs' business model has been a subject of longstanding scrutiny. Much of the concerns arise from the issuer-pay model, whereby CRAs' main revenue in fee income comes from the companies they rate. This conflict-of-interest places pressure on CRAs to provide positively biased ratings in exchange for increased fees while likewise allowing issuers to shop for inflated ratings. But the extent of ratings shopping by issuers, and the CRAs ability to cater is unobservable, and therefore difficult to empirically determine.

In this paper, we exploit a setting in India, in which the regulatory body, SEBI, enhanced disclosure requirements for CRAs to provide details of ratings they issued that were rejected by issuers, and hence not disclosed. We examine whether such disclosure regulations have an effect on ratings quality by limiting ratings shopping and thereby reducing ratings inflation. In our analysis, we build on two hypotheses: 1) the *disciplining* hypothesis, which predicts a decrease in ratings shopping and reduced ratings inflation in the post-regulation period, and 2) the *competitive pressure* hypothesis, which predicts an increase in shopping, leading to higher ratings inflation in the post-regulation period.

We provide evidence that ratings shopping is a widespread phenomenon in the Indian setting, and that the enhanced disclosure requirements lead to a decline in ratings shopping, viewed in its narrow form through the strategic reporting of ratings. We also find that in the post-regulation period, issuing firms are more likely to approach a smaller CRA as opposed to a larger one, with the expectation that smaller CRAs are more likely to cater to the demands of issuing firms for inflated ratings. We interpret this result as an unintended consequence of regulation, shown by an increase in ratings shopping in the broader form, in which in the post-regulation period, firms strategically select CRAs. We also find an increase in the incidence of an issuing instrument receiving an investment grade in the post-regulatory period, with the results being stronger in the subsample of larger issuing firms, which suggests that the potential for future business induces CRAs to issue favorable ratings to larger issuers. We finally consider the predictive ability of ratings and document an increase in the incidence of Type 1 error in the post-regulation period, with the results stronger among larger issuing firms. Together, these results support the *competitive pressure* hypothesis, showing that the enhanced disclosure requirements had unintended effects and did not achieve their intended objective of reducing ratings shopping and ratings inflation.

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Appendix A: Unaccepted ratings disclosure example

Panel A presents the snapshot of unaccepted ratings by CRISIL. Panel B presents the snapshot of unaccepted ratings by CARE. Source: CRISIL and CARE website.

Panel A

Unaccepted Ratings

Assignment relating to products "Advance Rating Services" and "Private Credit Assessment" do not require acceptance or non-acceptance and are published only for regulatory purposes

Updated on December 20, 2021

Company Name | Instrument | Rating

S. No	Name of the Issuer	Sector	Instrument Type	Issue Size (Rs.Crore)	Date of Non-acceptance	Listing Status	Rating Assigned
1	Chemi Enterprises LLP	Traders	BLR - New	30	December 20, 2021	Unlisted	CRISIL BB+/Stable/CRISIL A4+
2	D D Medical & Educational Trust	Health Care - Hospital	CCR - New	0	December 20, 2021	Unlisted	CCR BB+/Stable
3	Lakshmi Ganapathi Rice Mill	Agriculture - Others	BLR - New	30	December 20, 2021	Unlisted	CRISIL BB+/Stable
4	Magic Landbase Private Limited	Hotels & Resorts	BLR - New	23	December 20, 2021	Unlisted	CRISIL B/Stable

Panel B

Search Company Here

Search

List of Unaccepted Ratings (As on 19-December-2021)

Name of issuer	Sector	Name/type of instrument	Size (Rs. Million)	Date of Non-acceptance	Listing Status	Rating and outlook	Provisional Step And Document
Diwakar Tracom Private Limited	NBFI	Bank Facilities	100.00	18 Dec 2021	Unlisted	CARE B-; Stable	
K.V. Tex Firm	Wholesale and retail trade	Bank Facilities	230.00	18 Dec 2021	Unlisted	CARE B+; Stable / CARE A4	
Panchamrut Orgochem Private Limited	Chemicals and chemical products	Bank Facilities	480.00	18 Dec 2021	Unlisted	CARE B+; Stable / CARE A4	
ACC India Private Limited	Construction	Bank Facilities	550.00	17 Dec 2021	Unlisted	CARE BB-; Stable / CARE A4	
Adhunik Metaliks Limited	Iron and Steel	Bank Facilities	2500.00	16 Dec 2021	Listed	CARE BB; Stable / CARE A4	
ACG Associated Capsules Private Limited	Pharmaceuticals	Bank Facilities	380.00	10 Dec 2021	Unlisted	CARE AA; Positive	
Khazana Jewellery Private Limited	Other manufacturing	Commercial Paper (Carved out)	500.00	10 Dec 2021	Unlisted	CARE A1	
Eminent Solar Power Private Limited	Electricity - Generation	Bank Facilities	560.70	02 Dec 2021	Unlisted	CARE BBB+; Stable	

Table 1 Sample distribution

Panel A reports a frequency distribution of firm-years and firm-agency-years over the sample period 2014–2019. Panel B tabulates the incidence of firms with multiple ratings in our sample, reported separately for pre (2014-2016) and post (2017-2019) regulation of disclosure of rejected ratings. Panel C tabulates the ratings observations provided by rating agencies, reported separately for pre and post disclosure requirement. Panel D reports the distribution of ratings categories, reported separately for pre and post disclosure requirement. Panel E reports the number of defaults by rating category, reported separately for pre and post rejected rating disclosure requirement. Default in year *t + 1* is defined at the firm-year level and takes the value of one in year *t* if a given company has a debt instrument on which the company defaults in year *t + 1* (irrespective of which agency rates that instrument); the variable takes a value of zero otherwise.

Panel A – Sample distribution over time

	Firms		**Ratings**	
Year	Frequency	Percent	Frequency	Percent
2014	7,809	16.18%	8,808	15.32%
2015	8,089	16.76%	9,392	16.34%
2016	8,380	17.37%	10,095	17.56%
2017	7,928	16.43%	9,441	16.43%
2018	8,249	17.09%	10,139	17.64%
2019	7,801	16.17%	9,603	16.71%
Total	**48,256**	**100%**	**57,478**	**100%**

Panel B - Frequency of rating agencies per firm-year

	Full sample		**Pre**		**Post**	
Number of rating agencies	Frequency	Percent	Frequency	Percent	Frequency	Percent
1	40,180	83.26	20,669	85.13%	19,511	81.37%
2	7,087	14.69	3,250	13.39%	3,837	16%
3	854	1.77	320	1.32%	534	2.23%
4	124	0.26	37	0.15%	87	0.36%
5 and above	11	0%	2	0.01%	9	0.04%
Total	**48,256**	**100%**	**24,278**	**100%**	**23,978**	**100%**

Panel C – Distribution by rating agency

	Full sample		**Pre**		**Post**	
Rating agency	Frequency	Percent	Frequency	Percent	Frequency	Percent
CRISIL	18,405	32.02	9,640	34.07%	8,765	30.03%
CARE	15,885	27.64	7,899	27.92%	7,986	27.37%
ICRA	12,023	20.92	6,472	22.87%	5,551	19.02%
BRICKWORK	4,706	8.19	1,805	6.38%	2,901	9.94%
IND-RA	4,354	7.58	1,901	6.72%	2,453	8.41%
ACUITE	2,105	3.66	578	2.04%	1,527	5.23%
Total	**57,478**	**100%**	**28,295**	**100%**	**29,183**	**100%**

Panel D – Distribution by rating category

Rating category	Full sample		Pre		Post	
	Frequency	Percent	Frequency	Percent	Frequency	Percent
AAA	1,191	2.13%	410	1.49%	781	2.74%
AA	6,924	12.36%	2,964	10.76%	3,960	13.91%
A	9,230	16.48%	4,145	15.05%	5,085	17.87%
BBB	13,875	24.77%	6,994	25.39%	6,881	24.18%
BB	14,002	25.00%	7,396	26.85%	6,606	23.21%
B	9,041	16.14%	4,790	17.39%	4,251	14.94%
C	1,742	3.11%	843	3.06%	899	3.16%
Total	**56,005**	**100.00%**	**27,542**	**100.00%**	**28,463**	**100.00%**

Panel E – Distribution of defaults by rating category

	AAA	AA	A	BBB	BB	B	C	Total
Full sample								
Default in t+1 = 0	895	5,570	7,428	11,363	11,249	6,936	1,220	44,661
Default in t+1 = 1	18	42	100	303	606	696	206	1,971
% Default in t+1 = 1	**2.01%**	**0.75%**	**1.35%**	**2.67%**	**5.39%**	**10.03%**	**16.89%**	**4.41%**
Pre								
Default in t+1 = 0	407	2,959	4,099	6,842	7,069	4,408	731	26,515
Default in t+1 = 1	3	5	46	152	327	382	112	1,027
% Default in t+1 = 1	**0.74%**	**0.17%**	**1.12%**	**2.22%**	**4.63%**	**8.67%**	**15.32%**	**3.87%**
Post								
Default in t+1 = 0	488	2,611	3,329	4,521	4,180	2,528	489	18,146
Default in t+1 = 1	15	37	54	151	279	314	94	944
% Default in t+1 = 1	**3.07%**	**1.42%**	**1.62%**	**3.34%**	**6.67%**	**12.42%**	**19.22%**	**5.2%**

Table 2 Summary statistics

Panel A of this table reports the number of observations, mean, standard deviation, median, 25th percentile and 75th percentile of dependent variables used in subsequent regression analysis over the sample period 2014–2019. *SINGLE RATER* is an indicator variable that equals one if a firm employs just one rating agency to rate its instruments, and zero otherwise. *SMALL RATER* is an indicator variable that equals one if a firm employs any one of the following three rating agencies – India Rating, Brickwork, and Acuite, and zero otherwise. *RATING LEVEL* is the median of all the ratings a firm receives from a given rating agency in a given year for all its instruments, with a value of 19 denoting the highest credit rating "AAA" and the value 1 denoting "-C". *INVESTMENT GRADE* is an indicator variable that equals one if the *RATING LEVEL* is more than 11 and zero otherwise. *TYPE I ERROR* is an indicator variable that equals one if a firm receives an investment grade rating in the year t and there is a default in the year $t+1$. Panel B presents the difference in mean and median values of these variables for the pre (2014-2016) and the post (2017-2019) regulation of disclosure of unaccepted ratings. The significance of differences in means and medians are evaluated based on the t-test and Wilcoxon test, respectively (p-values for the t-statistics and Z-statistics are two-tailed). ***, **, and * correspond to 1%, 5%, and 10% significance levels, respectively.

Panel A – Summary statics for full sample

	N	Mean	SD	P25	P50	P75
SINGLE RATER	48,256	0.833	0.373	1	1	1
SMALL RATER	48,256	0.222	0.416	0	0	0
RATING LEVEL	57,478	10.319	4.121	7	10	13
INVESTMENT GRADE	57,478	0.375	0.484	0	0	1
TYPE I ERROR	47,875	0.005	0.07	0	0	0

Panel B – Difference in mean

	PRE			*POST*			Difference in mean
	N	Mean	Median	N	Mean	Median	
SINGLE RATER	24,278	.851	1	23,978	.814	1	-0.037***
SMALL RATER	24,278	.173	0	23,978	.273	0	0.1000***
RATING LEVEL	28,295	10.002	10	29,183	10.627	10	0.6250***
INVESTMENT GRADE	28,295	.336	0	29,183	.414	0	0.0780***
TYPE I ERROR	28,295	.003	0	19,580	.008	0	0.0050***

Table 3 Impact of Enhanced Ratings Disclosure on Ratings shopping

This table reports the coefficients for linear regression models estimating the impact of enhanced ratings disclosure requirements on ratings shopping through strategic reporting of ratings. *SINGLE RATER* is the measure of ratings shopping and is an indicator variable that equals one if a firm employs a single rating agency to rate its instruments, and zero otherwise. *POST* is an indicator variable that equals one if the observation belongs to years 2017-2019 when the disclosure of rejected ratings was required. *GDP GROWTH* is the yearly change in GDP. *TBILL YIELD* is the yield on the 10-year maturity T-Bill. *AGG DEFAULTS* is number of firms defaulting in any of its debt securities in a year divided by total number of firms in the sample in a year. The sample period is 2014–2019. Each observation corresponds to a firm-year. The *t*-statistics is reported in the parentheses below the coefficient estimate and is based on heteroskedasticity-robust standard errors, clustered by firm. ***, **, and * denotes estimates that are significantly different from zero at the 1% level, at the 5% level, and at the 1% level, respectively.

Dependent variable = ***SINGLE RATER***	**(1)**	**(2)**
POST	**-0.0508*** **	**-0.0496*** **
	[-7.3242]	**[-6.6629]**
GDP GROWTH	-3.6659***	-3.5455***
	[-4.3751]	[-3.9622]
TBILL YIELD	0.9760	1.1130*
	[1.5876]	[1.7221]
AGG DEFAULTS	-2.0399***	-2.0522***
	[-4.3815]	[-4.1619]
Firm FE	No	Yes
Industry FE	Yes	No
Observations	48,254	46,913
Adjusted R-square	0.041	0.297

Table 4 Impact of Enhanced Ratings Disclosure on Ratings Inflation

This table reports coefficients for linear regression models estimating the impact of enhanced ratings disclosure requirements on ratings inflation. Ratings inflation is measured as *RATING LEVEL, INVESTMENT GRADE,* and *TYPE I ERROR* in columns (1)-(3), respectively. *RATING LEVEL* is the median of all the ratings a firm receives from a given rating agency in a given year for all its instruments, with a value of 19 denoting the highest credit rating "AAA" and the value 1 denoting "-C". *INVESTMENT GRADE* is an indicator variable that equals one if the *RATING LEVEL* is more than 11 and zero otherwise. *TYPE I ERROR* is an indicator variable that equals one if a firm receives an investment grade rating in the year *t* and there is a default in the year *t+1*. *POST* is an indicator variable that equals one if the observation belongs to years 2017-2019 when the disclosure of rejected ratings was required. *GDP GROWTH* is the yearly change in GDP. *TBILL YIELD* is the yield on the 10-year maturity T-Bill. *AGG DEFAULTS* is number of firms defaulting in any of its debt securities in a year divided by total number of firms in the sample in a year. The sample period is 2014–2019. Each observation corresponds to a firm-rating agency-year. The *t*-statistics is reported in the parentheses below the coefficient estimate and is based on heteroskedasticity-robust standard errors, clustered by firm. ***, **, and * denotes estimates that are significantly different from zero at the 1% level, at the 5% level, and at the 1% level, respectively.

Dependent variable →	**(1)** ***RATING LEVEL***	**(2)** ***INVESTMENT GRADE***	**(3)** ***TYPE 1 ERROR***
POST	**0.6696***** **[21.2061]**	**0.0913***** **[17.1417]**	**0.0006** **[0.3731]**
GDP GROWTH	45.1394*** [14.2248]	5.4155*** [10.0178]	0.1229 [0.7721]
TBILL YIELD	8.0109*** [4.0413]	0.7196** [2.2274]	-0.0608 [-0.4806]
AGG DEFAULTS	21.8715*** [12.7359]	2.6884*** [9.4838]	0.5605*** [4.7539]
Firm FE	Yes	Yes	Yes
Rating agency FE	Yes	Yes	Yes
Observations	56,181	56,181	46,371
Adjusted R-square	0.885	0.792	0.146

Table 5 Impact of Enhanced Ratings Disclosure on Ratings Inflation- variation based on Issuer size

This table reports coefficients for linear regression models estimating the impact of enhanced ratings disclosure requirements on ratings inflation conditioned on firm size. Ratings inflation is measured as *RATING LEVEL, INVESTMENT GRADE,* and *TYPE I ERROR* in columns (1)-(3), respectively. *RATING LEVEL* is the median of all the ratings a firm receives from a given rating agency in a given year for all its instruments, with a value of 19 denoting the highest credit rating "AAA" and the value 1 denoting "-C". *INVESTMENT GRADE* is an indicator variable that equals one if the *RATING LEVEL* is more than 11 and zero otherwise. *TYPE I ERROR* is an indicator variable that equals one if a firm receives an investment grade rating in the year *t* and there is a default in the year *t+1*. *POST* is an indicator variable that equals one if the observation belongs to years 2017-2019 when the disclosure of rejected ratings was required. *LARGE FIRM* is an indicator variable that equals one if the firm size (measured by total assets) is above the sample median, and zero otherwise. *GDP GROWTH* is the yearly change in GDP. *TBILL YIELD* is the yield on the 10-year maturity T-Bill. *AGG DEFAULTS* is number of firms defaulting in any of its debt securities in a year divided by total number of firms in the sample in a year. The sample period is 2014–2019. Each observation corresponds to a firm-rating agency-year. The *t*-statistics is reported in the parentheses below the coefficient estimate and is based on heteroskedasticity-robust standard errors, clustered by firm. ***, **, and * denotes estimates that are significantly different from zero at the 1% level, at the 5% level, and at the 1% level, respectively.

Dependent variable →	**(1) *RATING LEVEL***	**(2) *INVESTMENT GRADE***	**(3) *TYPE 1 ERROR***
POST	**0.6143*** **	**0.0790*** **	**-0.0032* **
	[16.4602]	**[12.6491]**	**[-1.7996]**
POST X LARGE FIRM	**0.1053*** **	**0.0308*** **	**0.0094*** **
	[2.8358]	**[5.1257]**	**[4.3013]**
GDP GROWTH	44.0873***	5.5294***	0.1776
	[13.0552]	[9.3475]	[1.0048]
TBILL YIELD	7.4981***	0.7444**	-0.0056
	[3.5767]	[2.1229]	[-0.0410]
AGG DEFAULTS	23.4531***	2.8031***	0.5975***
	[12.8439]	[9.0360]	[4.5417]
Firm FE	Yes	Yes	Yes
Rating agency FE	Yes	Yes	Yes
Observations	48,781	48,781	40,775
Adjusted R-square	0.888	0.793	0.144

Table 6 Impact of Enhanced Ratings Disclosure on Ratings Inflation- variation based on CRA size

This table reports coefficients for linear regression models estimating the impact of enhanced ratings disclosure requirements on ratings inflation conditioned on credit rating agency. Ratings inflation is measured as *RATING LEVEL, INVESTMENT GRADE,* and *TYPE I ERROR* in columns (1)-(3), respectively. *RATING LEVEL* is the median of all the ratings a firm receives from a given rating agency in a given year for all its instruments, with a value of 19 denoting the highest credit rating "AAA" and the value 1 denoting "-C". *INVESTMENT GRADE* is an indicator variable that equals one if the *RATING LEVEL* is more than 11 and zero otherwise. *TYPE I ERROR* is an indicator variable that equals one if a firm receives an investment grade rating in the year *t* and there is a default in the year *t+1*. *POST* is an indicator variable that equals one if the observation belongs to years 2017-2019 when the disclosure of rejected ratings was required. *SMALL RATER* is an indicator variable that equals one if a firm employs any one of the following three rating agencies – India Rating, Brickwork, and Acuite, and zero otherwise. *GDP GROWTH* is the yearly change in GDP. *TBILL YIELD* is the yield on the 10-year maturity T-Bill. *AGG DEFAULTS* is number of firms defaulting in any of its debt securities in a year divided by total number of firms in the sample in a year. The sample period is 2014–2019. Each observation corresponds to a firm-rating agency-year. The *t*-statistics is reported in the parentheses below the coefficient estimate and is based on heteroskedasticity-robust standard errors, clustered by firm. ***, **, and * denotes estimates that are significantly different from zero at the 1% level, at the 5% level, and at the 1% level, respectively.

Dependent variable →	**(1)** ***RATING LEVEL***	**(2)** ***INVESTMENT GRADE***	**(3)** ***TYPE 1 ERROR***
POST	**0.6385*** **	**0.0894*** **	**-0.0002**
	[19.9839]	**[16.4687]**	**[-0.1062]**
POST X SMALL RATER	**0.3584*** **	**0.0173*** **	**0.0046*** **
	[9.6643]	**[3.2859]**	**[2.6859]**
GDP GROWTH	47.1989***	5.4842***	0.1284
	[14.8585]	[10.1715]	[0.8094]
TBILL YIELD	7.7516***	0.6897**	-0.0649
	[3.8904]	[2.1314]	[-0.5131]
AGG DEFAULTS	22.7219***	2.7160***	0.5576***
	[13.2194]	[9.6035]	[4.7352]
Firm FE	Yes	Yes	Yes
Observations	56,181	56,181	46,371
Adjusted R-square	0.884	0.792	0.146

Table 7 Impact of Enhanced Ratings Disclosure on Ratings Inflation- variation based on bank versus nonbank financing

This table reports coefficients for linear regression models estimating the impact of enhanced ratings disclosure requirements on ratings inflation conditioned on debt being bank finance versus public debt. Ratings inflation is measured as *RATING LEVEL, INVESTMENT GRADE,* and *TYPE I ERROR* in columns (1)-(3), respectively. *RATING LEVEL* is the median of all the ratings a firm receives from a given rating agency in a given year for all its instruments, with a value of 19 denoting the highest credit rating "AAA" and the value 1 denoting "-C". *INVESTMENT GRADE* is an indicator variable that equals one if the *RATING LEVEL* is more than 11 and zero otherwise. *TYPE I ERROR* is an indicator variable that equals one if a firm receives an investment grade rating in the year *t* and there is a default in the year *t+1. POST* is an indicator variable that equals one if the observation belongs to years 2017-2019 when the disclosure of rejected ratings was required. *NONBANK FIN* is an indicator variable that equals one if majority of the debt financing of the firm comes from nonbanking sources such as bonds and commercial paper, and zero otherwise. *GDP GROWTH* is the yearly change in GDP. *TBILL YIELD* is the yield on the 10-year maturity T-Bill. *AGG DEFAULTS* is number of firms defaulting in any of its debt securities in a year divided by total number of firms in the sample in a year. The sample period is 2014–2019. Each observation corresponds to a firm-rating agency-year. The *t*-statistics is reported in the parentheses below the coefficient estimate and is based on heteroskedasticity-robust standard errors, clustered by firm. ***, **, and * denotes estimates that are significantly different from zero at the 1% level, at the 5% level, and at the 1% level, respectively.

Dependent variable →	**(1)** ***RATING LEVEL***	**(2)** ***INVESTMENT GRADE***	**(3)** ***TYPE 1 ERROR***
POST	**0.6800*** **	**0.0930*** **	**-0.0011**
	[21.4834]	**[17.3871]**	**[-0.6727]**
POST X NONBANK FIN	**-0.1521** **	**-0.0254*** **	**0.0237*** **
	[-2.3376]	**[-3.0015]**	**[3.0477]**
GDP GROWTH	45.0059***	5.3933***	0.1413
	[14.1777]	[9.9745]	[0.8885]
TBILL YIELD	8.0392***	0.7243**	-0.0652
	[4.0569]	[2.2423]	[-0.5155]
AGG DEFAULTS	21.8879***	2.6912***	0.5631***
	[12.7500]	[9.4945]	[4.7765]
Firm FE	Yes	Yes	Yes
Rating agency FE	Yes	Yes	Yes
Observations	56,181	56,181	46,371
Adjusted R-square	0.885	0.792	0.148

Table 8 Impact of Enhanced Ratings Disclosure on Incidence of ratings by small CRAs

This table reports the coefficients for linear regression models estimating the impact of enhanced ratings disclosure requirements on ratings shopping through strategically selecting the CRA. *SMALL RATER* is the measure of ratings shopping and is defined as an indicator variable that equals one if a firm employs any one of the following three rating agencies – India Rating, Brickwork, and Acuite, and zero otherwise. *POST* is an indicator variable that equals one if the observation belongs to years 2017-2019 when the disclosure of rejected ratings was required. *GDP GROWTH* is the yearly change in GDP. *TBILL YIELD* is the yield on the 10-year maturity T-Bill. *AGG DEFAULTS* is number of firms defaulting in any of its debt securities in a year divided by total number of firms in the sample in a year. The sample period is 2014–2019. Each observation corresponds to a firm-year. The *t*-statistics is reported in the parentheses below the coefficient estimate and is based on heteroskedasticity-robust standard errors, clustered by firm. ***, **, and * denotes estimates that are significantly different from zero at the 1% level, at the 5% level, and at the 1% level, respectively.

Dependent variable = *SMALL RATER*	**(1)**	**(2)**
POST	**0.1105*** **	**0.1061*** **
	[16.5326]	**[17.7175]**
GDP GROWTH	4.9023***	4.6630***
	[6.4224]	[7.0356]
TBILL YIELD	-1.1747**	-1.1410**
	[-2.1227]	[-2.4888]
AGG DEFAULTS	3.0457***	2.8262***
	[7.1444]	[7.7781]
Firm FE	No	Yes
Industry FE	Yes	No
Observations	48,254	46,913
Adjusted R-square	0.039	0.639