What Happens when Ratings Shopping is Visible? Evidence from Unaccepted Ratings Disclosure in India

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Abstract:

It has been argued that the inherent conflict of interest from the issuer-pay model in the credit rating agencies (CRA) leads to rating shopping behavior, and ratings inflation. But the extent of rating shopping by debt issuers, and the CRAs ability to cater is unobservable and therefore difficult to empirically examine. In this paper, we exploit a unique setting in India that enhanced disclosure requirements for CRAs to disclose rating shopping from issuer; and ask whether these increased disclosures have an effect on ratings shopping and ratings inflation. We find that the disclosure requirements result in a decline in explicit rating shopping. We also find that in the post-regulation period, issuers are more likely to approach a smaller CRA, and this bargaining leads to an unintended increase in implicit rating shopping. We document an increase in the incidence of an issuing instrument receiving an investment grade, with the results being stronger to the subsample of larger issuing firms, and smaller CRAs suggesting that the potential for future business induces CRA to issue favorable ratings to larger issuers. These results are consistent with the view that the enhanced disclosure requirements had an unintended effect, and that it did not achieve its objective in reducing shopping and reducing.

"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, on several instances CRAs have failed to sufficiently forewarn about the impending defaults (e.g., financial crisis of 2008-09), thereby raising questions on the quality of these credit ratings.[2] Prior research on credit rating (e.g., Sangiorgi et al., 2009; Skreta and Veldkamp, 2009; Bolton et al., 2012; Sangiorgi and Spatt, 2017) identifies *rating shopping* as an important factor that adversely affects the ability of CRAs to provide reliable credit ratings. Rating shopping refers to the phenomenon where the issuer receives preliminary opinions from multiple CRAs but purchases and reports only the most favorable rating(s).[3] Due to this selection bias induced by rating shopping, observed ratings are often likely to be inflated on average. This ability of issuers to shop for inflated ratings can also create pressure on CRAs to cater to such demands as they do not want to miss out on business opportunity.

Given the importance of quality and the accuracy of ratings, regulators have long recognized these concerns, specifically in designing the regulation of CRAs. For example, in response to the financial crisis, the US Congress passed the Dodd-Frank Wall Street Reform and Consumer Protection Act (2010) in July 2010. The act proposed several measures to improve the functioning of CRAs, including to increase transparency, increase liability provisions, and regulatory penalties. However, in empirically studying the impact of Dodd-

[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 subprime mortgage business, eventually leading to the financial crisis of 2008–2009. [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."*

Frank act on credit ratings, Dimitrov et al. (2015) find no evidence that the act disciplines CRAs, and improves the quality of ratings. Instead, the authors find that after Dodd-Frank, CRAs issue lower ratings, and give more false warnings, which Dimitrov et al. attribute to the weak nature of reforms in the Dodd-Frank act. In November 2016, in an attempt to limit conflicts of interest in CRAs in India, the Securities Exchange Board of India (SEBI), the regulatory body that oversees the functioning of capital markets in India, passed a more radical reform that requires CRAs to provide details of ratings that were provided by them but rejected and hence not disclosed by the issuers.[4] These details include the name of the issuer, name/type of instrument, size of the issue, rating and outlook assigned, etc., and are available on the website of CRAs. In this paper, we examine whether such enhanced disclosure requirements about rejected ratings (enhanced ratings disclosure, hereafter) by issuers can limit rating shopping and thereby reduce rating inflation.

We argue that after CRAs start disclosing the rejected ratings of issuers, market participants can compare the presumably unbiased credit ratings that were rejected by the issuer with the new rating that the issuer obtained after "shopping", thereby making shopping a futile exercise. Hence it is likely that the extent of rating shopping will go down after the enhanced ratings disclosure became effective, compared to the period before the introduction of enhanced rating disclosure (hereafter, we refer to these periods as the *PRE* and *POST* periods). Further, the disclosure of rejected ratings will relieve the pressure on CRAs to cater. Hence under this *disciplining* hypothesis, we expect lower incidence of rating shopping and reduced rating inflation in the *POST* compared to the *PRE* period.

While the disciplining role of enhanced disclosures is very intuitive, it is possible that the new disclosure requirement might change the behaviour of the firms issuing debt instruments

[4] The regulation can be referred to at https://www.sebi.gov.in/sebi_data/attachdocs/1477999985100.pdf

that seek ratings. Issuers must trade off the benefits associated with obtaining a rating from a reputed rating agency versus the cost of getting an unfavourable rating from them. Since the new disclosure requirement increases the cost in terms of publicly disclosing the unfavourable rating, without necessarily increasing the benefit, issuing firms might want to obtain rating from smaller but less reputable rating agencies and thereby shift to a new equilibrium at lower benefit (in terms of reputation) and to less cost (in terms of unfavourable rating). Thus, while enhanced ratings disclosure can keep *explicit shopping* (i.e., issuers getting rated and then deciding whether to accept it or not) under check, the *implicit shopping* (i.e., issuers relying on informal channels and their experience to choose the CRAs that will give it a better rating), would still go on.

Furthermore, anticipating this change in behaviour by firms seeking credit ratings, more reputed rating agencies might also lower their rating quality due to the pressure of generating revenue. Hence, under the *competitive pressure* hypothesis, we expect an increase in both implicit shopping and CRA competition to gain market share, that leads to higher rating inflation in the *POST* period compared to the *PRE* period. We also expect that the change in ratings inflation in the *POST* period will vary depending on the relative bargaining power of the CRA vis-a-vis the issuer. We expect that CRAs are more likely to cater when they are rating instruments of bigger issuers as it will help them foster business relationship with the issuer and potentially generate more revenue in the future. Hence, we predict that the ratings will be more inflated for instruments of big issuers (compared to instruments of small issuers) in the *POST* period. Similarly, smaller CRAs will be more susceptible to catering issuers in order to attract more issuers and due to their relatively lower reputation. Hence, we predict that the ratings will be more inflated for ratings issued by smaller CRAs (compared to ratings issued by larger CRAs) in the *POST* period.

We test these differing hypotheses on a sample of 58,400 unique ratings relating to 12,119 Indian firms from 2014-2019. We evaluate how rating shopping and rating inflation change due to the introduction of enhanced ratings disclosure requirements under SEBI Circular 2016/119. As the enhanced ratings disclosures became effective towards the end of the year 2016, our sample period covers three years before and after these additional disclosure requirements were in effect. 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 the aggregate defaults. Finally, in certain specifications 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 explicit rating shopping declines in the post SEBI Circular 2016/119 disclosure regime that makes rating shopping visible. 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 rating shopping if its debt instrument is rated by only one CRA rather than by multiple CRAs. This construct measures explicit rating shopping and assumes that the ratings for debt instruments with one rating are more likely to reflect selection bias arising due to ratings shopping as issuers would disclose only the best rating they receive and hide the unfavorable ratings. We find that in the *PRE* period, 85% of all instruments were rated by only one CRA. However, in the *POST* period 80% of all instruments were rated by single CRA. These statistics show that explicit rating shopping is an extremely widespread phenomenon, and that enhanced disclosure requirement under SEBI Circular 2016/119 leads to a decline in explicit rating shopping.

We then examine whether the enhanced disclosure norms lead to change in issuing firm's choice of rating agency. Specifically, we examine whether issuing firms are more likely to approach a smaller CRA in the *POST* period compared to the *PRE* 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. Our conjecture is that this 58% increase in the business of smaller CRAs is due to the fact that smaller CRAs (compared to bigger CRAs) are more likely to cater to issuing firms' demands of an inflated rating and hence issuing firms are more likely to gravitate towards them in the *POST* period. Thus, we find that, while the enhanced rating disclosure reduces explicit shopping, it increases the implicit shopping.

Next, we examine the overall level of ratings in the *PRE* versus *POST* period. We find about 6.96% increase in the level of ratings in the *POST* period. The incidence of an instrument receiving an investment grade rating also increases by 25.08% in the *POST* period. While the economic significance of these average results is modest, we find stronger results for subsample of larger issuing firms. This cross-sectional variation suggests that, all else equal, potential for future business induces CRAs to give more favorable rating to bigger issuers.

Since we find that the level of ratings has slightly increased in the *POST* period, we further examine whether such inflated ratings lead to Type 1 prediction errors. Following Cheng and Neamtiu (2009) and Baghai and Becker (2018) we consider that a rating agency has made a Type 1 error if it assigns an investment grade rating to an issuing firm in the year *t* and such firm defaults in the year *t+1*. Examining the changes in incidence of Type 1 error is important because these types of errors attract adverse investor and regulatory attention and are costly for CRAs (Cheng and Neamtiu, 2009). We find that there is an increase in the incidence of Type 1 Error in the *POST* period, and this effect is stronger among larger issuing firms. Furthermore, increase in ratings level, incidence of investment grade ratings, and type 1 errors are higher among ratings issued by smaller CRAs vis-à-vis ratings issued by larger CRAs.

Overall, our results suggest that the enhanced disclosure requirements under SEBI Circular 2016/119, especially the requirement on CRAs to disclose rejected ratings, has not achieved its objective of keeping rating shopping under check and reducing rating inflation.

We find support for the *competitive pressure* hypothesis suggesting that the pressure on CRAs to generate business has a greater impact on the ratings quality compared to the disciplining role of disclosures. We argue that “shopping” can be understood in a narrow sense or a broad sense. What SEBI’s additional disclosure requirement has deterred is shopping in the narrow sense, that of getting rated and then deciding whether to accept it or not. But in the broader sense, issuers can continue to shop by figuring out through informal conversations etc. what rating the CRA will give and choose the ones that give it a better rating.

While issuing firms as well as CRAs might benefit from catering, an obvious question that arises is that why would debtholders accept inflated ratings? We argue that the nature of debt market in India makes our finding extremely plausible. Unlike the United States, public debt market in India is relatively very small. Bank financing is the major source of debt for Indian companies. Not surprisingly, 83% of instruments in our sample relate to bank loans and other types of bank facilities.[5] Compared to investors in public debt, banks are more likely to tolerate (or even prefer) inflated ratings because higher ratings can improve capital adequacy calculations (Gopalan et al., 2019). For instance, banks can assign a lower risk to an asset if it has higher rating and hence manage the risk-weighting rules. Further, higher ratings for their loans will also allow banks to provide lower provision against the expected loan losses. Thus, banks may have incentives to encourage inflated ratings and hence our results are not totally unexpected. In line with this argument, we document a relatively lower increase in rating level, incidence of investment grade ratings, and type 1 error post enhanced disclosure regulation, among non-bank instruments.

This paper contributes to the credit rating literature. First, we contribute to the literature that examines the impact of regulatory changes on the properties of credit ratings (Jorion et al.,

[5] For this reason, we are unable to perform tests examining whether bond markets can see through rating shopping and catering and price the bonds accordingly.

2005; Cheng and Neamtiu, 2009; Goel and Thakor, 2011; Dimitrov et al., 2015). Our results suggest that there can be unintended consequences of regulatory changes and that the quality of credit ratings might in fact decline due to intensified competitive pressure resulting due to the regulation. Second, we contribute to the stream of literature that examines the determinants of credit rating quality. While one group of studies (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) provide evidence that the competitive pressure results in inflated ratings for firms; another stream (e.g., Bonsall IV, 2014; Xia, 2014; Bonsall IV et al., 2017; deHaan, 2017) suggests that reputational concerns keep ratings inflation under check. We contribute to this literature by showing that the incentive of the end-user of the credit ratings is an important variable that is likely to determine which of the two factors – reputation or competitive pressure, has a greater impact on credit rating quality. Finally, this paper is also related to the broader literature on real effects of disclosure regulation (Leuz and Wysocki, 2016). This literature examines situations in which the firms and intermediaries change their behavior in the real economy because of mandated disclosure, more specifically induced around regulatory changes. We add to this literature by exploiting a novel setting from India and document that once CRAs begin to disclose unaccepted ratings, there is change in the competitive landscape for CRAs.

Rest of the paper is organized as follows. In section 2 we present institutional background and describe the regulatory change. Section 3 reviews the related literature. Section 4 describes our research design and data. Section 5 presents our empirical analysis and results. Section 6 concludes.

2. Institutional Background

2.1 Debt Market and Rating Agencies in India

Policy makers in India have identified the development of a vibrant corporate debt market as one of their key ongoing agenda items to sustain capital market growth. The Indian corporate debt market has witnessed reasonable growth in the last decade. The growth in the Indian debt markets has prompted the gain in significance of credit ratings in the last three decades. Credit ratings are important in assuring arm's length investors, and the Indian financial markets, about the credit quality of the issuers. Regulatory norms for large bond market investors limit the extent to which they can invest in bond, specifically by stipulating minimum rating requirements. For example, Employees' Provident Fund Organization (EPFO), India's largest public pension fund is limited to invest in AA or higher rated debt. Mutual funds are primarily only allowed to invest in bonds that are rated BBB- and above, but can only invest up to ten-percent of their portfolio in unrated debt instruments. Insurance companies can invest at most sixty percent of assets in AA, or higher rated corporate bonds.

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. It is important to highlight that a number of Indian CRAs are owned by the American rating agencies and follow industry best practices in the ratings process. For example, Standard and Poor's Global Inc., holds majority shareholdings in CRISIL, Moody's Corporation owns 51.86% stake in ICRA, and Fitch Ratings Inc., holds 100% ownership in IND-RA. The Indian rating agencies also offer non-rating services such as risk management, industry and competitor analytics, research, and information technology services (see Baghai and Becker 2018).

2.2 Regulating Rating Agencies

The Securities and Exchange Board of India (SEBI) was established on 1992 in accordance with the provisions of the Securities and Exchange Board of India Act, 1992. Its objective is to protect investors; develop, and regulate the securities market. SEBI also regulates the credit rating agencies; and 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 on conflicts-of-interest for rating agencies. SEBI has continuously acknowledged the role of credit rating agencies as important gatekeepers in maintaining the trust of investors in bond ratings (SEBI, 2018).

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 disclose to the public information, which will have material bearing on the ratings. For instance, in May 2010, SEBI strengthened regulation through a “Circular CIR/MIRSD/CRA/6/2010” by requiring CRAs disclose the movement of the ratings, the history of credit ratings on all outstanding securities on their website twice a year. These rules also included CRAs to 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).

The CRA Disclosure regulation were further tightened in 2016, when SEBI issued the circular “MIRSD/MIRSD4/CIR/P/2016/119”, with additional disclosure requirements to directly address ratings shopping amongst issuers, which we exploit in the empirical analysis in our paper. These rules 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 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. Each CRA was required to promptly disclose the information on their website. In addition, an important requirement is related to the disclosure of ratings not accepted by the issuer. Each CRA was required to disclose on their website details of all ratings assigned by them, regardless of whether the issuer accepted the rating or not. The CRAs had effectively sixty-days to implement the guidelines from the circular.

In discussing the reasoning for the regulation, a senior SEBI official, Rajeev Kumar suggested that the enhanced disclosure regulation was built on the underlying principle to enhance transparency and accountability of CRAs. Similarly, the then Chairman of SEBI, U K Sinha stated that SEBI was acting against CRAs, after understanding that the CRAs were offering only limited disclosures when ratings were suspended, a process that SEBI would not "tolerate" insisting that investors had the right to know of specific rating actions of CRAs.[6] These enhanced disclosure regulations were welcomed by both the rating agencies and investors. For e.g., Rajesh Patel, then CEO of India Ratings and Research, remarked that "*The guidelines will bring in greater transparency and consistency in ratings process across the industry which will help investors take an informed investment decision*."[7] Consistent with the rating agencies views, Lakshmi Iyer, Chief Investment Officer at the Asset Management firm Kotak suggested that "*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*

[6] Retrieved from https://indianexpress.com/article/business/economy/sebi-to-tighten-norms-for-credit-rating-agencies-2828178/

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

rules on disclosures, withdrawal of ratings have disincentivized rating-shopping; it has a certain suasion."[8]

3. Literature Review

Credit ratings are important in assuring investors about the credit quality – more specifically, the likelihood of default – of debt issuers. They allow uninformed investors to assess the risk characteristics of the security issuances using a widely adopted scale. Credit ratings directly enable corporations and government entities to raise capital; and facilitate investors and fiduciaries to make investments. Beginning in the 1930s in the US, financial regulation has mandated that ratings be the primary measure about 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.[9] Taken together, the quality of ratings is a key factor for the functioning of the debt markets.

Several factors have been attributed to the quality of the ratings provided by the credit rating agencies. A significant factor of discussion is the conflict due to the business model of the credit rating agencies in their issuer pays model, where the entity issuing debt also pays the rating agency to rate the issuance. This feature presents the desire of the rating agency to satisfy the issuer by biasing the rating upward, due to the pressure to generate business and prevent the issuer in seeking ratings from another credit rating agency, which raises questions about the quality of the ratings. However, there are the reputational costs for the rating agencies in issuing low-quality ratings that may create an incentive for them to truthfully reveal the issuer's

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

[9] 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 the jurisdiction for identifying assets that are eligible for investment purposes, for determining capital requirements.

credit quality and future prospects (Smith and Walter, 2002; White, 2010; Becker and Milbourn, 2011). A large stream of research builds on the above trade-off in understanding its influence on ratings quality. On the one hand, several studies document evidence that the conflicts from issuer pays model results in poorer ratings quality (Becker and Milbourn, 2011; Cornaggia and Cornaggia, 2013; Griffin et al., 2013; He et al., 2016; Baghai and Becker, 2018). On the other hand, another stream suggests the long-run reputational concerns of the rating agencies dominate to provide incentives for higher ratings quality (Covitz and Harrison, 2003; Bonsall IV, 2014; Xia, 2014; Bonsall IV et al., 2017; deHaan, 2017). Bolton et al. (2012) theoretically model the conditions when reputational concerns dominate the pressure to generate business, and vice versa. Their model suggests that CRAs are more prone to poor quality ratings when reputation costs are smaller, and the fraction of trusting investors (who take the ratings at face value) are larger. Conversely, the model further suggests that when reputation costs are larger and the fraction of the sophisticated investors are larger, then CRAs are more likely to reveal the credit quality of investors truthfully.[10] Other studies examining the quality of ratings document a temporal trend, and find that credit ratings are conservative over time (Baghai et al., 2014). Baghai and Becker (2018) examine the Indian setting, and provide evidence that rating agencies in India, which also provide non-rating services to its issuers, issue lower quality ratings.

In addition to the studies on the quality of ratings, a related stream of literature has examined ratings bias, specifically ratings inflation. It is widely discussed that ratings inflation is a result of two factors: ratings shopping and ratings catering. The often-cited view, ratings shopping, refers to the scenario where the issuer solicits preliminary ratings from multiple

[10] 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.

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). Rating catering refers to the phenomena where CRAs, in anticipation of ratings shopping by their clients, relax their credit rating standards to match their more lenient competitors to not miss out on revenues or market share. The intensified competition, therefore, will facilitate catering to the demands of the issuers, with 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 these phenomena are not mutually exclusive.

A significant number of empirical studies that examine ratings inflation provide evidence consistent with ratings shopping.[11] 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). The assumption being that the ratings for securities with 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; He et al. (2016) focus on the Mortgage backed securities (MBS) market, and show that MBSs with one rating have higher losses, with lower prices reflecting the future losses. Griffin et al. (2013) also consider the CDO market, but find that defaults are less common in securities with a single rating, which they argue is inconsistent with pure rating shopping. They also document evidence consistent with ratings catering. Kronlund (2020) presents evidence of rating shopping in the corporate bond market.[12]

[11] 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.

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

Kronlund identifies shopping based on the choice to engage CRAs that issue higher ratings in the prior periods, compared to other agencies; and that published ratings are more likely to represent only the highest from all agencies sought.

The ratings inflation, caused from the issuer's ratings shopping, can influence the distribution and information content of credit ratings revealed to investors (debt-holders) and leads to the possibility of them being systematically misled about the issuer's true credit risk. Several papers both theoretically, and empirically understand the investors response to biased credit ratings. In the model in Skreta and Veldkamp (2009), investors do not fully account for the bias in the ratings, allowing issuers to exploit this winner's curse fallacy, and therefore may have adverse effects in investor demand and pricing. In contrast, Sangiorgi and Spatt (2017) demonstrate that even when investors are rational and discount bond prices, ratings shopping can persist in equilibrium in particular states - such as when investors cannot fully observe when specifically issuers disclose one good rating and withhold one bad rating.[13] Investors may even tolerate (or prefer) inflated ratings because of regulatory distortions; specifically, when prudentially regulated investors such as banks, insurance companies carry bonds with inflated ratings, they can reduce their regulatory capital requirements and 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, understand rating shopping and account for the bias in the pricing (Griffin et al., 2013; He et al., 2016; Kronlund, 2020).

Given the central role played by CRAs in the financial markets in the US, and around the world, they have long been a subject to scrutiny; such as after the Asian crisis in the late 1990s, collapse of Enron and WorldCom in 2000s, and the 2007-2009 financial crisis in the US (Ferri et al., 1999; White, 2010). The widespread criticism on the CRAs during the Asian crisis, and

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

collapse of Enron involved credit ratings' lack of timeliness, and failure to predict the bankruptcies. In the case of financial crisis, the CRAs were partly blamed for overly inflated ratings of mortgage related securities, stemming from conflicts of interest (Brunnermeier, 2009; White, 2010). These have resulted in an increased regulatory oversight of the CRAs with the passage of SOX, and the Dodd-Frank act; in an attempt to increase transparency, limit conflicts of interest, and to increase entry, ultimately to improve the quality of credit ratings. For e.g., Jorion et al. (2005) find that the informational content of credit rating upgrades and downgrades increased after the imposition of Regulation Fair Disclosure (FD) in 2000, which exempted firms from disclosing nonpublic information to the CRAs. Similarly, Cheng and Neamtiu (2009) consider the passage of SOX, and investigate the change in properties of credit ratings following its passage. They find that CRAs improve timeliness of downgrades, increase rating accuracy, and reduce rating volatility. On the other hand, Dimitrov et al. (2015) study the effect of Dodd-Frank act on corporate bond ratings and find no evidence of the disciplining effect on CRAs in improving ratings quality. Dimitrov et al. (2015) find that CRAs, instead, issue lower ratings, issue more false warnings, and issue downgrades that are less informative. They argue that CRAs, following the passage of Dodd-Frank Act, are more protective of their reputation. 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 "two-edged" sword. On one hand, CRAs may exert greater due-diligence, resulting in more informative ratings, but on the other hand may, CRAs may obfuscate their ratings, leading to downward-biased ratings.

4. Research design and data

4.1. Research design

We begin our empirical analysis by examining whether the incidence of rating shopping declines after the enhanced rating disclosure requirements come into effect. Rating shopping as such is unobservable in nature and hence empirically difficult to capture (Bae et al., 2017). Therefore, we take two different approaches to proxy rating shopping. First, 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 rating shopping if it obtains 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 rating shopping is that a firm presumably would have obtained a rating from several CRAs and disclosed the most favorable rating while hiding the unfavorable ratings.

The variable *SINGLE RATER* captures rating shopping in a narrow sense where an issuing firm gets rated and then decides whether to accept it or not. But in a broader sense, issuers can also shop by figuring out what rating the CRA will give through informal conversations, past experience, experience of peer firms, etc. and then choose the CRA that gives it a better rating without even getting ratings from a stricter CRA. Consistent with this line of reasoning, Kronlund (2020) identifies rating shopping based on the choice to engage a particular CRA that issued higher ratings to issuances in the prior periods, compared to other agencies; and that published ratings are more likely to represent only the highest from all agencies sought. Based on this logic, we consider a firm to have engaged in rating shopping if it obtains rating from smaller rating agencies as opposed to larger and more reputed rating agencies. Our assumption is that - in a tradeoff between the need to generate revenues against reputation, smaller CRAs (as opposed to larger CRAs) are more likely to pick revenue growth and appease issuing firms' demands of favorable ratings. Hence, we create an indicator variable *SMALL RATER* that equals one if the issuing firm obtains rating from smaller CRAs, i.e., BRICKWORK, IND-RA, and ACUITE, and zero otherwise. As discussed in the background section, the three largest CRAs in India, namely CRISIL, ICRA, and CARE together account for around 80% of all ratings issued since 2014. In contrast, BRICKWORK, IND-RA, and ACUITE, are relatively new CRAs and have much lower market share.

To examine the impact of enhanced ratings disclosure requirements on the incidence of rating shopping, we use the following OLS estimation specification:

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

Where *i* denotes issuing firm, and *t* the year. As described above, the dependent variables *SINGLE RATER* and *SMALL RATER* capture firms that are likely to have engaged in explicit and implicit rating shopping in a particular year, respectively. Our main variable of interest is *POST* that equals one for years after the enhanced ratings disclosure requirements came into effect, 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 it to have a negative impact on the firm performance as well. In such a situation we expect firms to rely more on rating shopping to get 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 the probit model to avoid the well-documented incidental parameter problem arising due to inclusion of fixed effects in nonlinear models.

Since the objective of issuing firms to shop for ratings is to obtain favorable and inflated ratings, in our next set of analyses we examine whether such rating inflation declines after enhanced ratings disclosure requirements come into effect. We use three measures of rating inflation. First, we consider the level of ratings. In the presence of rating shopping the level of ratings is likely to be higher than what is warranted by the issuing firm fundamental characteristics. CRAs provide ratings on alphanumeric scale: AAA (highest creditworthiness), AA, A, BBB, BB, B, C, D (default). These scales from "AA" to "C" are further modified as "+" and "−" to indicate the relative strength within the rating categories concerned. Following Baghai and Becker (2018) we convert these ratings in 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 investment grade rating. Issuing firms are most likely to benefit from rating inflation if their pre-inflated ratings is close to certain thresholds such as investment grade rating. At margin, firms that manage to just get investment grade rating are likely to have lower cost of borrowing than firms that just missed getting investment grade ratings. Hence, rating inflation is likely to increase the chances of a firm getting 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 investment grade rating in the year *t* and there is a default (no default) in year *t+1* and zero otherwise.[14] These errors represent instances where the rating agencies assign/maintain favorable ratings to defaulting issuers and hence fail to forewarn investors about an impending default. These failures often lead to increase in regulatory pressure and investor criticism. On the continuum of inflated ratings, these three measures represent the increasing severity of inflation with ratings level being the most benign and type 1 error being the most egregious.

[14] 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-

$$\boldsymbol{RATING\ LEVEL_{i,j,t}\ or\ INVESTMENT\ GRADE_{i,j,t}\ or\ TYPE\ 1\ ERROR_{i,j,t}}$$

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

Where *i* denotes issuing firm, *j* denotes the rating agency and *t* the year. The dependent variable 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, relationship with issuing firms, etc.

4.2. Data

The sample period for this study spans from 2014-2019. Since our objective is to examine the impact of enhanced ratings disclosure regulation implemented on November 1st, 2016, our sample period covers three years before and after the regulation. We obtain 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 follow the procedure outlined in Baghai and Becker (2018) to construct our sample.[15] The credit rating data on Prowess database includes all ratings issued by the seven CRAs operating in the Indian capital market – CRISIL, ICRA, CARE, BRICKWORK, IND-

[15] Our results are not sensitive to choices we make to construct our sample.

RA, ACUITE, and IVR. We drop 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 drop observations with rating status as either default, withdrawn, or not applicable. Third, we drop duplicate observations. The ratings data on the Prowess database does not have a unique identifier for a firm's debt security. Hence, we consider a rating observation as duplicate if entries in the fields - *issuer, instrument name*, *issue amount*, *rating date*, *rating agency*, *status*, and *rating* are same. Fourth, we retain 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. Prowess database has 66 different instrument categories and the top ten instrument types we include in our sample comprise about 80% of all rating observations in the database. Another important institutional detail that emerges from the data is that about 83% of all financing in our sample is from banks and the remaining 17% is public debt. The above data filters result in 208.795 unique rating observations. This data is further aggregated at a firm year level to construct rating shopping measures. Our sample comprises of 48,475 unique firm-year observations relating to 12,119 unique firms. To construct the rating quality measures, we take the median of ratings over all the instruments for each issuing firm, rating agency, and year.[16] This gives us issuer rating from a given agency in a given year. There are 58,400 unique issuer firm-agency-year ratings in our sample.

[16] 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.

5. Results

5.1. Descriptive statistics

We provide summary statistics for the analysis of rating shopping and quality of ratings in Table 1. In panel A, we show the yearly distribution of the of unique firms receiving credit ratings and the number of ratings assigned by CRAs. Herein, the distribution is reasonably stable across time. Every year there are about 7,800-8,400 unique firms that get rated and 8,800-10,400 unique rating observations. In panel B, we present the distribution of the number of CRAs engaged by a firm in a given year. Over our sample period, 82% 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 instrument. Interestingly, the number of firms engaging only one CRA to rate its various debt securities drops from 85% to 80% from pre- to post-regulation period, and a corresponding increase in the number of firms engaging more than one CRA is observed. We document the frequency of ratings provided by various CRAs in panel C. The big-3 CRAs - CRISIL, ICRA, and CARE provide 80% of all ratings in our sample period. However, their market share drops from 85% to 76% from pre- to post-regulation period. In panel D, we show the distribution of rating by the level of ratings. On average there are very few AAA ratings and they have increased in the post-regulation period. The frequency of securities with AAA, AA, or A rating also increases from 28.04% to 36.03% from pre- to post-regulation period. Lastly, in panel E we show the incidence of a default by a firm in the year *t+1*, conditioned on the rating its debt securities got in the year *t*. As expected, firms getting lower ratings in the year *t* are more likely to default in the year *t+1*. There are however non-trivial number of instances where the firm got investment grade rating in the year *t*, but there was still a default in the year *t+1*. This tendency of CRAs to maintain high rating in the year before default has increased in the post-regulation period. The percentage of firms who get AAA, AA, or A rating in the year *t*, but default in the year *t+1 is* 2.19% in the pre-regulation period and of all firms getting a high rating 6.69% 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 82.38% of firm-year observations in our sample engages one CRA for all their rating requirements (*SINGLE RATER*). Moreover, on average, 22.5% of firm-year observations are represented by smaller CRAs (*SMALL RATER*). The average rating level is 10.42 (*RATING LEVEL*), 38.49% of firm-year rating observations are of investment-grade (*INVESTMENT GRADE*), and the type 1 error is 0.5%. The difference in the mean of these variables from the pre- to post-regulation period is presented in the panel B. There is a statistically significant decrease in *SINGLE RATER* and 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 rating shopping

While the *disciplining* hypothesis predicts a decrease in rating shopping in the post-regulation period, the *competitive pressure* hypothesis predicts the opposite. In this section, we discuss our empirical analysis that tests these competing hypotheses.

First, we examine the impact of regulation on explicit rating shopping. We estimate equation (1) with *SINGLE RATER* as the dependent variable and show the results in table 3. 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= -0.0625, p-value<1%). 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* continues to remain significantly negative and significant (coefficient= -0.0630, 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 6.2% decline in the average tendency of firms to employ just a single CRA in the post enhanced disclosure regime. This suggests a slight reduction in the *explicit* rating shopping behavior of firms in the post- regulation period.

We next examine the impact of regulation on implicit rating shopping. We estimate a specification of equation (1) with *SMALL RATER* as the dependent variable and show the results in table 4. In column 1, we include industry fixed effects. The coefficient of the *POST* variable, i.e., β_1, is significantly positive (coefficient= 0.1137, p-value<1%). In column 2, we include firm fixed effects, and the coefficient of *POST* variable continues to remain significantly positive (coefficient= 0.1103, p-value<1%). Economically, this result (column 1) translates to 11.3% increase in the average likelihood of a firm to get ratings from a smaller CRA in the post-regulation period. This finding indicates an increase in implicit rating shopping, as firms are switching to smaller CRAs for their possible leniency in credit rating standards and incentive to gain market share.

Overall, we find that while the enhanced disclosure requirement for unaccepted ratings leads to a decline in explicit rating shopping (as proxied by getting ratings from a single CRA), it leads to an increase in implicit rating shopping (proxied by a firm getting ratings from a smaller CRA). These results suggest that by engaging more with smaller CRAs, issuing firms are able comply with the new disclosure requirements, and yet achieve their objective of obtaining favorable ratings.

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 acts as a check on rating shopping, it is likely to relieve the pressure on CRAs to cater the demand of 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 who are more likely to cater to their demands, then rating 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 5. Columns (1) - (3) show results with *RATING LEVEL, INVESTMENT GRADE,* and *TYPE1 ERROR* as dependent variables, respectively. In all 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= 0.6654, p-value<1%). This result indicates that, post disclosure regulation, the average ratings 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 rating due to rating shopping, their investment ability increases. Hence, rating 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= 0.0902, p-value<1%). This represents a 9.02% increase in propensity of a firm to get 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 rating inflation, changes in response to the enhanced ratings disclosure requirements. The type 1 error captures the instances where 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 pre and post regulation period.

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

5.4. Cross-sectional variation

In this section we examine the cross-sectional variation in the impact of enhanced ratings disclosure requirements on rating inflation. As discussed in prior literature (Griffin et al., 2013; Kronlund, 2020), rating inflation arises because of both rating inflation as well as catering. Rating shopping is done by issuers and is a result of a selection bias where issuing firm picks and discloses only the most favorable rating it obtains, while hiding the unfavorable ratings. On the other hand, catering is done by the CRAs where they intentionally give a debt security a higher rating than what is actually warranted. These two factors are also likely to work in tandem as issuing firms must be shopping hard for higher ratings for 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. We argue that larger firms are under more scrutiny of investors and regulators. Hence, they are less likely to engage in rating shopping and attract negative publicity right after the regulation that specifically focuses on curbing rating shopping. Yet, these are the firms who have the ability to influence CRAs 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 rating 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 for large versus small firms. These results are documented in table 6. 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 results is as follows – compared to smaller firm, larger issuers receive higher ratings by approximately 0.08 notches. Larger firms also have 2.7% greater propensity to get an investment grade rating in the post-regulation period. Finally, frequency of type 1 error after the regulation increases by 1.01% in the larger firms whereas it decreases by 0.33% in the smaller firms. Overall, these results indicate that larger firms get more favorable ratings in the post regulation period possibly because of CRAs catering such demands in expectation of future revenues

Next, we consider the cross-sectional variation in the impact of enhanced ratings disclosure requirements on rating 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 have greater need to preserve 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 equals 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 *SMALL RATER* to measure the differential impact of regulation on ratings provided by small versus large CRAs. 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 SMALL RATER* is positive and significant across all columns. The results suggest that ratings provided by smaller CRAs in the post regulation period are 0.35 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 CRA. The frequency of type 1 error increases by 0.4% 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 of favorable ratings by issuing firms.

Finally, we consider whether the rating 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, bank guarantee, etc. Whereas public debt includes commercial paper, non-convertible debentures and non-government debt, which are typically raised from individual or institutional (other than banks) investors. Prior research (Griffin et al., 2013; He et al., 2016) suggests that investors have ability to see through rating inflation and adjust the bond yields accordingly. In contrast, banks are more likely to tolerate (or even encourage) ratings inflation as higher ratings enables them to classify the loan 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 one if majority of the debt financing of the firm comes from non-banking sources such as bonds and commercial paper, and zero otherwise. We also include the interaction term *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 8. 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 across all three columns. The results suggest that ratings provided for non-bank debt instruments in the post regulation period are 0.21 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 3.8%. Further, the frequency of type 1 error decreases by 2.2% in the post regulation period for ratings relating to non-bank debt instruments, whereas it increases for 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 can see through the shopping efforts of CRAs and can price the bonds accordingly. As a result, rating shopping is less attractive for issuing firms in such situations. However, when the end user of the ratings is a bank who has perverse incentives to prefer inflated ratings, enhanced ratings disclosure requirements are unlikely to keep rating shopping and rating inflation under check.

6. Conclusion

Credit rating agencies are important gatekeepers that ensure proper functioning of the debt markets. However, the CRAs business model has been subject of longstanding scrutiny. Much of the concerns are from that the issuer-pay model, where the CRA main revenue in fee income is from the companies that they rate. This conflict creates pressure on the CRAs to provide biased ratings for increased fees, and allows issuers to shop for inflated ratings. But the extent of rating 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, where the regulatory body, SEBI, enhanced disclosure requirements for CRAs to provide details of ratings that were issued by them, but were rejected by issuers, and hence not disclosed by the issuers. We examine whether that such disclosure regulation has an effect on ratings quality, by limiting ratings shopping and thereby reducing ratings inflation. In our analysis, we build on two hypotheses: 1) disciplining hypothesis, which predicts a decrease in rating shopping and reduced rating inflation in the post-regulation period, and 2) competitive pressure hypothesis, which predicts an increase in shopping, leading to higher rating inflation in the post-regulation period.

We provide evidence that explicit rating shopping is a widespread phenomenon in the Indian setting, and that the enhanced disclosure requirements leads to a decline in the explicit rating shopping. We also find that in the post-regulation period, issuing firms are more likely to approach a smaller CRA as against a larger CRA; with the intention that smaller CRAs are more likely to cater to the demands of the issuing firms demands for an inflated rating. We interpret this result as an increase in implicit rating shopping in the post-regulation period. We also find an increase in the incidence of an issuing instrument receiving an investment grade, with the results being stronger to 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, and that the enhanced disclosure requirements had an unintended effect; and did not achieve its intended objective in reducing ratings shopping and ratings inflation.

The Dodd-Frank Act proposed a provision of disclosing rejected ratings, however, this disclosure requirement has long been under consideration. In this context, this paper comes at a critical juncture when policy makers across the globe are considering regulations such as enhanced disclosures to avoid another financial crisis. Consequently, our results should be of interest to academics, regulators, and market participants. Overall, we document that a legislation demanding enhanced disclosures may not be the panacea to resolve conflict of interest issues in CRAs.

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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	7,843	16%	8,881	15%
2015	8,117	17%	9,480	16%
2016	8,409	17%	10,190	17%
2017	7,971	16%	9,659	17%
2018	8,291	17%	10,378	18%
2019	7,844	16%	9,812	17%
Total	**48,475**	**100%**	**58,400**	**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	39,932	82%	20,633	85%	19,299	80%
2	7,355	15%	3,344	14%	4,011	17%
3	1,018	2%	348	1%	670	3%
4	158	0%	42	0%	116	0%
5 and above	12	0%	2	0%	10	0%
Total	**48,475**	**100%**	**24,369**	**100%**	**24,106**	**100%**

Panel C – Distribution by rating agency

	Full sample		**Pre**		**Post**	
Rating agency	Frequency	Percent	Frequency	Percent	Frequency	Percent
CRISIL	18,664	32%	9,719	34%	8,945	30%
CARE	16,053	27%	7,943	28%	8,110	27%
ICRA	12,330	21%	6,556	23%	5,774	19%
BRICKWORK	4,730	8%	1,809	6%	2,921	10%
IND-RA	4,505	8%	1,945	7%	2,560	9%
ACUITE	2,118	4%	579	2%	1,539	5%
Total	**58,400**	**100%**	**28,551**	**100%**	**29,849**	**100%**

Panel D – Distribution by rating category

	Full sample		Pre		Post	
Rating category	Frequency	Percent	Frequency	Percent	Frequency	Percent
AAA	983	1.73%	354	1.27%	629	2.16%
AA	8,136	14.29%	3,302	11.88%	4,834	16.59%
A	9,155	16.08%	4,122	14.83%	5,033	17.28%
BBB	13,863	24.35%	6,985	25.12%	6,878	23.61%
BB	14,012	24.61%	7,403	26.63%	6,609	22.68%
B	9,042	15.88%	4,790	17.23%	4,252	14.59%
C	1,744	3.06%	845	3.04%	899	3.09%
Total	**56,935**	**97.49%**	**27,801**	**100.00%**	**29,134**	**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	742	6,496	7,365	11,354	11,257	6,936	1,222	45,372
Default in t+1 = 1	17	56	98	300	606	698	206	1,981
% Default in t+1 = 1	**2.29%**	**0.86%**	**1.33%**	**2.64%**	**5.38%**	**10.06%**	**16.86%**	**4.37%**
Pre								
Default in t+1 = 0	351	3,295	4,076	6,835	7,075	4,408	733	26,773
Default in t+1 = 1	3	7	46	150	328	382	112	1,028
% Default in t+1 = 1	**0.85%**	**0.21%**	**1.13%**	**2.19%**	**4.64%**	**8.67%**	**15.28%**	**3.84%**
Post								
Default in t+1 = 0	391	3,201	3,289	4,519	4,182	2,528	489	18,599
Default in t+1 = 1	14	49	52	150	278	316	94	953
% Default in t+1 = 1	**3.58%**	**1.53%**	**1.58%**	**3.32%**	**6.65%**	**12.50%**	**19.22%**	**5.12%**

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	48,475	0.8238	0.3810	1.0000	1.0000	1.0000
SMALL RATER	48,475	0.2250	0.4176	0.0000	0.0000	0.0000
RATING LEVEL	58,400	10.4232	4.1689	7.0000	10.0000	13.0000
INVESTMENT GRADE	58,400	0.3849	0.4866	0.0000	0.0000	1.0000
TYPE I ERROR	48,588	0.0050	0.0708	0.0000	0.0000	0.0000

Panel B – Difference in mean and median

	PRE			*POST*			Difference in mean	Difference in median
	N	Mean	Median	N	Mean	Median		
SINGLE RATER	24,369	0.8467	1.0000	24,106	0.8006	1.0000	-0.0461***	0.0000***
SMALL RATER	24,369	0.1742	0.0000	24,106	0.2764	0.0000	0.1022***	0.0000****
RATING LEVEL	28,551	10.0650	10.0000	29,849	10.7657	10.5000	0.7007***	0.5000***
INVESTMENT GRADE	28,551	0.3412	0.0000	29,849	0.4267	0.0000	0.0856***	0.0000****
TYPE I ERROR	28,551	0.0032	0.0000	20,037	0.0077	0.0000	0.0046***	0.0000****

Table 3 Impact of Enhanced Ratings Disclosure on Rating shopping

This table reports the coefficients for linear regression models estimating the impact of enhanced ratings disclosure requirements on explicit rating shopping. *SINGLE RATER* is the measure of explicit rating shopping and is an indicator variable that equals one if a firm employs just one 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	**-0.0625*** [-8.9207]**	**-0.0630*** [-8.3876]**
GDP GROWTH	-3.9881*** [-4.7467]	-4.0847*** [-4.5606]
TBILL YIELD	0.8525 [1.3841]	0.8787 [1.3597]
AGG DEFAULTS	-2.1470*** [-4.5988]	-2.2746*** [-4.6070]
Firm FE	No	Yes
Industry FE	Yes	No
Observations	48,473	47,139
Adjusted R-square	0.044	0.313

Table 4 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 implicit rating shopping. *SMALL RATER* is the measure of implicit rating 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	0.1137***	0.1103***
	[16.9528]	[18.2991]
GDP GROWTH	5.0211***	4.8487***
	[6.5614]	[7.2962]
TBILL YIELD	-1.1265**	-1.0883**
	[-2.0351]	[-2.3728]
AGG DEFAULTS	3.1115***	2.9431***
	[7.2796]	[8.0772]
Firm FE	No	Yes
Industry FE	Yes	No
Observations	48,473	47,139
Adjusted R-square	0.039	0.635

Table 5 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	**0.6654*** **[21.0515]**	**0.0902*** **[17.1087]**	**0.0007** **[0.4091]**
GDP GROWTH	45.1235*** [14.2247]	5.3962*** [10.0797]	0.1563 [0.9777]
TBILL YIELD	8.0846*** [4.0707]	0.7615** [2.3822]	-0.0334 [-0.2623]
AGG DEFAULTS	21.7820*** [12.6724]	2.6890*** [9.5890]	0.6097*** [5.0316]
Firm FE	Yes	Yes	Yes
Rating agency FE	Yes	Yes	Yes
Observations	57,112	57,112	47,089
Adjusted R-square	0.888	0.797	0.143

Table 6 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	**0.6234***** **[16.7711]**	**0.0800***** **[12.8647]**	**-0.0033*** **[-1.7659]**
POST X LARGE FIRM	**0.0835**** **[2.2564]**	**0.0270***** **[4.5115]**	**0.0101***** **[4.5329]**
GDP GROWTH	44.0727*** [13.0699]	5.5103*** [9.4179]	0.2115 [1.1914]
TBILL YIELD	7.5851*** [3.6090]	0.7899** [2.2787]	0.0211 [0.1535]
AGG DEFAULTS	23.2353*** [12.7095]	2.7965*** [9.1223]	0.6408*** [4.7265]
Firm FE	Yes	Yes	Yes
Rating agency FE	Yes	Yes	Yes
Observations	49,676	49,676	41,471
Adjusted R-square	0.890	0.798	0.142

Table 7 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	**0.6352*** **	**0.0884*** **	**-0.0000**
	[19.9219]	**[16.4645]**	**[-0.0204]**
POST X SMALL RATER	**0.3514*** **	**0.0169*** **	**0.0040** **
	[9.6392]	**[3.2880]**	**[2.3984]**
GDP GROWTH	47.1890***	5.4646***	0.1577
	[14.8557]	[10.2325]	[0.9904]
TBILL YIELD	7.8399***	0.7317**	-0.0374
	[3.9276]	[2.2857]	[-0.2937]
AGG DEFAULTS	22.6414***	2.7164***	0.6044***
	[13.1590]	[9.7076]	[4.9946]
Firm FE	Yes	Yes	Yes
Observations	57,112	57,112	47,089
Adjusted R-square	0.887	0.797	0.143

Table 8 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	**0.6857*** **	**0.0938*** **	**0.0030* **
	[21.5535]	**[17.6247]**	**[1.6756]**
POST X NONBANK FIN	**-0.2138*** **	**-0.0383*** **	**-0.0226*** **
	[-3.6128]	**[-5.0825]**	**[-6.5674]**
GDP GROWTH	44.9936***	5.3729***	0.1430
	[14.1816]	[10.0346]	[0.8933]
TBILL YIELD	8.1458***	0.7725**	-0.0282
	[4.1036]	[2.4172]	[-0.2216]
AGG DEFAULTS	21.8405***	2.6995***	0.6054***
	[12.7188]	[9.6297]	[5.0266]
Firm FE	Yes	Yes	Yes
Rating agency FE	Yes	Yes	Yes
Observations	57,112	57,112	47,089
Adjusted R-square	0.888	0.798	0.146