Reputation at Risk: How Bond Defaults Improve Credit Ratings Quality

Haoyu Gao, Yuting Huang, Xiaoming Li, Ruochen Wang*

June 30, 2025

Abstract

Credit rating agencies (CRAs) are often criticized for inflating ratings, largely due to weak market-based discipline. This paper examines whether bond defaults—by increasing reputational costs—can mitigate this issue. Exploiting the post-2014 emergence of bond defaults in China's corporate bond market, where credit derivatives are absent, we develop a theoretical framework and provide empirical evidence that defaults significantly reduce ratings inflation. The effect operates through increased reputational damage from rating failures and is especially pronounced for high-risk issuers, lower-reputation CRAs, and in more concentrated rating markets. Furthermore, defaults enhance the informational efficacy of ratings: post-default, ratings demonstrate greater explanatory power for yield spreads and improved predictive accuracy for future defaults. Our study reveals how credit events, despite potential short-term disruptions, can discipline financial intermediaries and catalyze credit market development. These findings offer important implications for regulatory design in the formative stage of the credit market.

Keywords: ratings quality, default, reputation, credit rating agency
JEL Codes: G24, G14

---

* Haoyu Gao: Renmin University of China (email: gaohaoyu@ruc.edu.cn); Yuting Huang: Capital University of Economics and Business (email: huangyuting0@gmail.com); Xiaoming Li: University of International Business and Economics (email: xiaomingli@uibe.edu.cn); Ruochen Wang: Capital University of Economics and Business (email: wangruochen814@gmail.com). We appreciate the valuable comments from Hui Bu, Yuejiao Duan, Zhao Jin, Wanfa Lin, Dong Lu, Xiaoran Ni, Joel Shapiro, Zhan Shi, Stephan Siegel, Guochao Yang, Jinfan Zhang, and Zilong Zhang, as well as seminar and conference participants at the Capital University of Economics and Business (CUEB), Central University of Finance and Economics (CUFE), Renmin University of China (RUC), University of International Business and Economics (UIBE), the Banking and Financial Intermediation Conference, the China Economic Annual Conference, the China Financial Research Network (CFRN) Conference, the China International Forum on Finance and Policy (CIFFP), the China Banking & Corporate Finance Conference (CBCF), the China Finance Frontier Forum and the Spring Finance Forum of the CUFE, Dishui Lake International Conference in Finance.

1 Introduction

Credit ratings are essential for mitigating information asymmetry between issuers and investors, providing a standardized assessment of credit risk that facilitates access to financial markets and supports informed decision-making.[1] However, the "experience good" nature of credit ratings, where their true quality becomes observable only after default events (Bonsall IV et al., 2023), creates opportunities for credit rating agencies (CRAs) to inflate ratings to meet issuers' preferences. This practice raises concerns about misaligned incentives, sparking ongoing debates on mechanisms to ensure the provision of accurate and credible ratings.

A growing body of literature highlights the reputation as the key asset that disciplines CRAs to maintain rating accuracy (Mathis et al., 2009; Baghai and Becker, 2020; Piccolo and Shapiro, 2022). Accurate ratings improve investor trust, build reputational capital, and strengthen CRAs' market credibility to secure future business opportunities. Conversely, inaccurate ratings erode reputation, reducing competitive advantages. In developing markets such as China, financial systems lack instruments such as credit default swaps (CDS) and transparent secondary bond markets to improve risk disclosure and impose market discipline on CRAs (Badoer and Demiroglu, 2019; Bonsall IV et al., 2022). Additionally, these markets are in an early stage, with corporate bond defaults only recently emerging. In the absence of defaults, CRAs face weaker reputational constraints, allowing opportunistic practices and ratings inflation. Defaults, however, expose inaccuracies and impose reputational costs, compelling CRAs to prioritize long-term credibility over short-term gains.[2] This study hypothesizes that defaults act as a vital market discipline mechanism, heightening CRAs' reputational concerns, discouraging opportunistic behavior, and promoting more accurate ratings.

To better frame our paper, we first build a simple two-period model to illustrate our

[1] Apart from the informational role of credit ratings (e.g., Gredil et al., 2022; Bernstein et al., 2025; Li, 2025), a large body of literature has extensively explored the economic roles of credit ratings in shaping issuers' real behavior (e.g., Badoer et al., 2019; Sethuraman, 2019; Goldstein and Huang, 2020; Bongaerts and Schlingemann, 2024), influencing investors' trading decisions (e.g., Cornaggia et al., 2018; deHaan et al., 2023; Baghai et al., 2024), and serving as a regulatory tool for measuring and mitigating risks (e.g., White, 2010; Behr et al., 2018).

[2] For example, following the onset of defaults in China, domestic rating agencies sharply increased downgrades—cutting a record 88 issuer ratings in the first half of 2016—indicating rising reputational concerns and a shift toward more conservative rating practices; see *Bloomberg News*, "Default Pain Turns Into Gain for China's Debt Rating Companies," July 21, 2016.

reputation-based mechanism. The model highlights the optimal ratings inflation strategy of CRAs, balancing its current income from issuer's agency fee against the future income loss due to potential reputational damage. On the one hand, a more aggressive ratings inflation strategy would enable the CRA to issue more high ratings that can be purchased by the issuer in period 1, thus raising its current income. On the other hand, the CRA's ratings inflation is disciplined by reputational concerns, as less precise ratings would undermine the CRA's reputation, and shrink its income in period 2. We study the impact of a reputation cost shock that significantly raises the CRA's reputational concerns. Our model yields the following testable propositions for empirical analysis. First, an increase in reputation costs is expected to reduce the CRA's ratings inflation, leading to more accurate credit ratings. Second, the reduction in ratings inflation is more pronounced (i) for ratings assigned to riskier issuers, (ii) for lower-quality CRAs, and (iii) for CRAs operating in a more concentrated market.

We test these predictions using data from the Chinese corporate bond market, where defaults—emerging only since 2014—serve as quasi-random shocks to the reputational costs faced by CRAs. Because rating agencies typically assign analysts along industry lines, defaults of intra-industry bonds are especially salient to other CRAs rating bonds within the same sector.[3] Even without direct involvement, these affected CRAs may reassess the reputational consequences of being associated with future defaults, thereby increasing the perceived reputational costs of issuing inflated ratings. Such heightened concerns, in turn, incentivize more conservative and accurate assessments. Therefore, the staggered and highly visible nature of these intra-industry defaults provides a unique setting to examine how bond defaults influence CRAs' rating outcomes through reputational channels.

Our study investigates the initial ratings assigned to newly issued bonds, which are critical due to their significant impact and effectiveness in shaping market perceptions and investor decisions (Bonsall et al., 2015). To evaluate ratings quality, we compare issuer-paid CRA ratings at the time of bond issuance with the first available ChinaBond market-implied ratings. The latter provides an immediate, post-issuance market-based assessment of credit risk, derived by mapping observed bond yield spreads to domestic credit rating

[3]Our paper does not focus on CRAs directly involved in defaults, as they face two opposing forces: heightened reputational costs and the incentive to regain market share by issuing optimistic ratings after experiencing reputational damage, as discussed by Baghai and Becker (2020). Our results in Appendix Table D3 also indicate that inter-industry defaults provide little additional explanatory power in improving ratings quality, further supporting the validity of the intra-industry empirical specification.

categories. This market-implied rating reflects an objective credit evaluation, effectively capturing the market's assessment, akin to investors "voting with their feet." After validating our measure of ratings quality,[4] we investigate whether credit ratings improve within six months following intra-industry bond defaults. Consistent with our hypothesis, we find that newly issued bonds in industries with recent defaults exhibit significantly better ratings quality than those unaffected by such events. The effect is stronger for unexpected defaults or those involving industry-leading firms, further highlighting the role of defaults in reshaping CRAs' behavior. A key assumption in our reputation-based explanation is that CRAs face reputational damage when involved in defaults, which in turn influences other CRAs' rating behavior. Supporting this, we find that CRAs implicated in defaults are less likely to issue new ratings within the same industry, with their market share declining by 3% (from a mean value of 12.5%) in the year following such events. This underscores the reputational consequences of defaults for CRAs.

To further support our reputation-based interpretation, we conduct a series of heterogeneity tests, yielding results consistent with our theoretical predictions. First, we examine whether the improvement in ratings quality following defaults varies across issuer characteristics. We find that the effect is more pronounced among riskier, poorer-performing issuers—those that pose a greater threat to CRA reputation if ratings are inflated and subsequently fail. Second, we show that defaults have a stronger disciplining effect on lower-quality CRAs, such as those with smaller market shares or lower rankings. These agencies face more severe reputational damage from rating failures and are less able to derive benefits from inflating ratings, leading to a sharper reduction in ratings inflation. Third, we find that the disciplining effect of defaults is stronger in more concentrated markets, as measured by a higher Herfindahl-Hirschman Index (HHI). In such settings, reputational costs are less likely to be diffused across multiple CRAs, prompting more cautious behavior and greater improvements in ratings quality. These findings align with those of Becker and Milbourn (2011), which argue that CRAs in concentrated markets are more likely to take a long-term view, avoiding ratings inflation to protect their reputation and market position, particularly when faced with increased reputational costs.

We further examine how credit rating agencies enhance their ratings quality. First, we find that issuer-paid ratings exhibit greater explanatory power over issuance spreads and a

[4]See Section 3 for more details.

stronger predictive effect on ex post default risks. Notably, the increased informativeness primarily stems from the component of ratings tied to issuers' fundamentals, suggesting that a more cautious incorporation of fundamental information strengthens ratings quality. Additionally, we analyze changes in issuer-paid and market-implied ratings following recent intra-industry defaults. Empirical evidence shows that issuer-paid ratings tend to decline, while market-implied ratings tend to rise, indicating a convergence between the two. These findings suggest that both the screening and classification capacities of CRAs improve in response to defaults.

We rule out several alternative explanations for the observed improvements in ratings inflation. One possibility is that changes in industry conditions might coincide with defaults, potentially confounding the observed improvements in ratings quality. To mitigate this, we incorporate dynamic industry-level controls, an industry stock index, and interacted industry-cycle fixed effects, with our results remaining robust.We also address concerns that defaults of industry peers could prompt issuers to enhance self-disclosure, reducing information asymmetry. However, after incorporating self-disclosure quality measures, we find no significant change in the explanatory role of our default indicator, nor does the interaction term between the default indicator and self-disclosure quality suggest that the improvements in ratings quality are driven by changes in the issuer's information environment. Another potential explanation is that increased media attention and investor scrutiny following defaults might improve the public information environment for issuers. To test this, we construct a news coverage index for issuers within a one-year window around bond issuance dates, but find no significant changes. Similarly, an analysis of listed issuers reveals no significant changes in analyst coverage. Furthermore, we find no significant differences between SOE (or *Chengtou*) and non-SOE (or *non-Chengtou*) bonds,[5] suggesting that our results are not solely driven by the weakening of implicit government guarantees (Jin et al., 2023).

Another limitation is that samples exposed to intra-industry defaults may differ from those without such exposure. To address such potential selection bias, we apply propensity score matching (PSM) and include issuer-level fixed effects. Additionally, we implement an instrumental variable approach using the average stock price crash risk of A-share listed

[5] *Chengtou* bonds, also known as municipal corporate bonds (MCBs), are issued by Local Government Financing Vehicles (LGFVs) specializing in urban development. Given that *Chengtou* bonds are corporate bonds predominantly owned by local governments (Chen et al., 2020), *Chengtou* issuers have easier access to local guarantee resources.

companies in the same industry as an instrument for bond defaults. This instrument meets the exogeneity assumption, as it captures unpredictable market performance due to negative news without directly providing bond-level information, while also reflecting the relationship between industry-level stock market crash risk and credit risk. Our baseline findings remain consistent across all additional tests. For further robustness, we use alternative definitions of the default indicator, such as restricting the control group to bonds unaffected by any intra-industry defaults, focusing on the first default event within industries, or applying more detailed industry classifications. We also employ different event windows, ranging from six to 18 months, and find long-lasting improvements in ratings quality following defaults.

This paper contributes to the ongoing debate on the effectiveness of reputation in improving ratings quality. To our knowledge, it is the first study to examine the role of bond defaults in a relatively less developed market that lacks advanced credit instruments, providing intra-industry evidence that rating improvements are driven by increased reputational costs from peer CRAs' failures. Most prior research has focused on external forces disciplining CRAs, such as competition from investor-paid rating agencies (Xia, 2014), CRA failures in financial instruments (DeHaan, 2017), business press coverage on issuers (Bonsall IV et al., 2018), mandated public dissemination of over-the-counter transactions via the TRACE system (Badoer and Demiroglu, 2019), issuers' credit default swap (CDS) trading initiation (Bonsall IV et al., 2022), and stock analyst coverage (Fong et al., 2022). Our findings illustrate how bond defaults and CRA rating failures themselves can act as a market disciplinary mechanism, alerting peer CRAs within the same industry to reduce ratings inflation—particularly for those CRAs dealing with riskier issuers, lower reputational capital, and more concentrated markets. These results provide valuable insights for regulators, showing how bond defaults can prompt CRAs to update their beliefs and strengthen reputational concerns, thereby leading to industry-wide improvements in ratings accuracy.

Our results also contribute to the literature on the costs and benefits of credit events. While prior studies have primarily focused on the negative externalities of credit events, such as contagion effects among industry peers (Hertzel and Officer, 2012), suppliers (Hertzel et al., 2008), strategic alliance partners (Boone and Ivanov, 2012), and local peers (Benmelech et al., 2019), this paper instead highlights how credit events can enhance the information quality provided by financial intermediaries. In this regard, we expand the growing literature on the Chinese bond market, particularly regarding the unintended consequences of bond

defaults. Jin et al. (2023) shows that state-owned enterprises (SOEs) reduce investment relative to non-SOEs after the first SOE default in China's onshore bond market, especially those with significant agency issues. Geng and Pan (2024) finds that the absence of government bailouts improves price discovery and increases the gap between SOEs and non-SOEs. Our work complements this earlier research by demonstrating that the explicit reduction or removal of implicit government guarantees not only improves credit allocation efficiency but also facilitates a more effective allocation of rating resources.

Lastly, our paper contributes to the broader literature on market forces versus regulatory power. We align with studies that highlight market self-regulation, rather than government intervention, as a mechanism to correct inefficiencies and improve market functionality (Flannery and Bliss, 2019). While markets are not immune to imperfections and can sometimes spiral into crises—triggering liquidity issues, bank failures, and severe economic consequences (Gorton, 2009; Duffie, 2019)—they are often adaptive and resilient, capable of adjusting to evolving financial landscapes. For instance, the bankruptcy and exit of noncompetitive firms reallocates resources to more efficient firms, fostering healthier dynamics within the remaining firms (Lang and Stulz, 1992; Jorion and Zhang, 2007; Grieser and Liu, 2019). Echoing Adam Smith's concept of the market's invisible hand, our work examines the rise of bond defaults in China's corporate bond markets since 2014, illustrating how market-driven corrective forces encourage credit rating agencies to enhance accuracy and uphold credibility, thus promoting a more transparent and mature credit market.

2 A Theoretical Framework

We present a simple two-period model to illustrate the reputation-based mechanism, in which the CRA's optimal ratings inflation varies with reputation costs. Our model builds on the framework established by Bolton et al. (2012) and Piccolo (2021). We focus on comparative statics analysis derived from the model that can guide our empirical investigation.

2.1 Model setup

Consider a simple two-period economy which consists of a representative issuer (the firm), CRAs, and competitive investors. We assume that all agents are risk-neutral and perfectly

rational.

The issuer. In each period $t = 1, 2$, the issuer has a project, and the quality θ_t is unknown to all the agents including the issuer itself. The project could be a good project, denoted as G with probability p_G, and otherwise, to be bad denoted as B with probability $p_B = 1 - p_G$. Specifically, the project's payoff at the end of each period is $y_t \in \{y_H, y_L\}$. For a good project, its payoff is y_H with probability f, and pays off y_L with probability $1 - f$. For a bad project, the payoff is always y_L. So conditional on a project's realized payoff y_L, the probability of the project to be a good one is

$$Pr\left(\theta_t = G | y_t = y_L\right) = \frac{p_G\left(1 - f\right)}{p_B + p_G\left(1 - f\right)}.$$

Each project requires initial investment I.

Assumption 1 *The good project has positive NPV, $V_G = f y_H + (1 - f) y_L > I$, while the bad project has negative NPV, $V_B = y_L < I$. Moreover, the ex-ante NPV for a project θ_t is also negative, that is, $p_G V_G + p_B V_B - I < 0$.*

According to Assumption 1, without prior knowledge on the project quality, the issuer obtains no financing from investors. However, the CRA has private information, and can improve welfare by screening projects for investors.

The CRA. The CRA can receive signals of the project type, and disclose its rating on the issuer's project. For simplicity, we assume that the CRA i always receives the precise signal of the project type in period t, $\theta_t \in \{H, L\}$, but chooses to disclose the rating r_{it} truthfully or not. Specifically, there are two types of CRAs, the committed CRA, denoted as $\mathcal{C}$, and the opportunistic CRA, denoted as $\mathcal{O}$, respectively. The committed CRA always truthfully reveals the project signal. While for the opportunistic CRA, it could inflate or deflate the rating to maximize its own expected payoff. Specifically, in period t, the opportunistic CRA i will optimally choose to inflate the rating and assign a high credit rating H for a bad project with probability $\epsilon_{i,t}$, or, $Pr\left(r_{it} = H | \theta_t = B\right) = \epsilon_{it}$. Obviously, the CRA never deflates the rating and assigns a bad rating for a good project.

We denote q_0 as the ex-ante probability of the CRA to be a committed one. At the end of each period, the payoff of the project realizes, and investors will update their beliefs on the CRA's private type accordingly. We interpret the probability of the CRA to be a committed

one in period t, q_t, as its *reputation*. Since the economy ends at the end of the second period, the opportunistic CRA always chooses to inflate the rating in period 2, or, $\epsilon_{i2} = 1$.

In our baseline model, we analyze the monopolistic CRA case, where only one CRA rates the issuer. The CRA assigns a high credit rating H, either when the project is good, or the CRA is opportunistic. If the CRA assigns a low credit rating L, the issuer would never purchases the rating, and remain unrated, $r_{it} = \varnothing$. Specifically, the issuer's rating in period t by the CRA i, is $r_{it} \in \{H, \varnothing\}$.

In period 1, if a monopolistic CRA decides to assigns the credit rating, it will optimally set the agency fee to extract all the surplus. Thereby, given the investor's belief on the CRA's type q_0 and the opportunistic CRA's rating strategy $\hat{\epsilon}_{i1}$, the CRA's expected payoff is $\psi\left(q_0, \hat{\epsilon}_{i1}\right) = p_H V_G + \left(1 - p_H\right) V_B - I$, where p_H is the probability of the project to be a good one *conditional* on the CRA's high credit rating, or,

$$p_H = Pr\left(\theta_1 = G | r_{i1} = H\right) = \frac{p_G}{p_G + p_B\left(1 - q_0\right)\hat{\epsilon}_{i1}}.$$

At the end of period 1, the project payoff realizes, and investors would update their beliefs on the CRA's type. Specifically, we denote $q_{H,y_1} = Pr\left(\mathcal{C} | r_{i1} = H, y_1\right)$ as the investor's posterior belief on the CRA's type *conditional* on the CRA's high rating in period 1 and the realized project payoff $y_1 \in \{H, L\}$, and $q_{\varnothing} = Pr\left(\mathcal{C} | r_{i1} = \varnothing, y_1\right)$ as the investor's posterior belief on the CRA's type conditional on the CRA's no rating in period 1.

Among the group of CRAs that assigned high ratings, some may truthfully disclose high ratings based on good signals, while others—the opportunistic CRAs—may inflated ratings despite receiving bad signals. This inflating behavior lowers the overall quality of the group, with more aggressive inflating strategies by opportunistic CRAs resulting in a more severe erosion of average quality. Conversely, in the group of CRAs assigning low ratings, some opportunistic CRAs have been screened out, and thus the average quality is expected to be higher than the prior belief q_0. We formally derive the posterior beliefs and summarize the result in Lemma 1.

Lemma 1 *For any realized project payoff $y_1 \in \{y_H, y_L\}$, the posterior beliefs on the CRA's quality, given CRA rating, satisfies that $q_{H,y_1} \leq q_0 \leq q_{\varnothing}$. For a more aggressive inflating strategy by the opportunistic CRA, the screening effect is more pronounced, that is, $\frac{\partial q_{H,y_1}}{\partial \hat{\epsilon}_1} < 0$, and $\frac{\partial q_{\varnothing}}{\partial \hat{\epsilon}_1} > 0$.*

Proof. See the Appendix B. ■

In period 2, the opportunistic CRA will always choose inflate the issuer's rating. Define γ as the payoff weighting that the CRA assigns to the second-period income. The weighting γ could be potentially greater than one, as future payoffs may arrive over a long time horizon (Bolton et al., 2012). We interpret γ as the CRA's *reputation cost*, representing the relative importance of future income compared to current income. For given the investor's belief, $\{q_0, \hat{\epsilon}_1\}$, the opportunistic CRA i's optimal inflating strategy for a bad project, ϵ_{i1}, is to maximize its expected payoff,

$$\pi\left(\epsilon_{i1}; q_0, \hat{\epsilon}_1\right) = \epsilon_{i1}\left[\psi\left(q_0, \hat{\epsilon}_1\right) + \gamma \int_{y_1} \psi\left(q_{H,y_1}, 1\right) f_B\left(y_1\right) dy_1\right] + \left(1 - \epsilon_{i1}\right)\gamma\psi\left(q_{\varnothing}, 1\right),$$

where $\psi\left(q_{H,y_1}, 1\right)$ and $\psi\left(q_{\varnothing}, 1\right)$ are the opportunistic CRA's expected payoff in period 2, conditional on its inflating the bad project in period 1 or not, respectively. $f_B\left(y_1\right)$ is the probability density function for the realized payoff of a bad project. Since the payoff of a bad project is always y_L, we have $f_B\left(y_L\right) = 1$.

Notably, the opportunistic CRA's inflating strategy in period 1, ϵ_{i1}, is determined by balancing the trade-off between its profits in period 1 and period 2. On the one hand, a more aggressive inflating strategy would enable the CRA to issue more high ratings that are purchased by the issuer in period 1, and thus raising its current income. On the other hand, however, the inflating strategy would undermine the CRA's reputation, and shrink its income in period 2.

The equilibrium. We consider a symmetric equilibrium such that, (i) given $\{q_0, \hat{\epsilon}_t\}$, the opportunistic CRA choose its optimal inflating strategy for a bad project, $\epsilon_{it} = \epsilon^*\left(\hat{\epsilon}_t\right) = \hat{\epsilon}_t$; (ii) given the precise signal θ_t, each type of the CRA assigns its credit rating, $r_{it} \in \{H, L\}$, and sets the agency fee ψ; (iii) given the CRA's rating, the issuer decides to purchase the rating, or decline the rating and remain unrated $r_{it} = \varnothing$. (iv) given beliefs on the CRA's type at each period and the issuer's rating, the investor chooses to purchase the issuer's securities or not.

The model solution. In equilibrium, the committed CRA always assigns a truthful rating for the project. The opportunistic CRA, however, will truthfully rate a good project, but will inflate the rating for a bad project with probability $\hat{\epsilon}_t$. Obviously, in period 2, the CRA always inflates the rating, so $\hat{\epsilon}_2 = 1$. To solve the problem, it suffices to determine the

opportunistic CRA's inflating strategy in period 1, $\hat{\epsilon}_1$. Specifically, when the reputation cost γ is sufficiently low, the CRA places little value on future income, and will always inflate the rating in period 1, so $\hat{\epsilon}_1 = 1$. Consequently, reputational concerns fail to impose any discipline on the opportunistic CRA. As the reputation cost γ rises, reputational concerns become more important, and the CRA inflates with a probability of less than one. We summarize the model's solution in Proposition 1.

Proposition 1 *There exists a threshold $\bar{\gamma}$, such that, for $\gamma < \bar{\gamma}$, the opportunistic CRA chooses the corner solution, $\hat{\epsilon}_1 = 1$, and the interior solution $\hat{\epsilon}_1 < 1$ otherwise. Moreover, for $\gamma > \bar{\gamma}$, the CRA is less likely to inflate the rating as γ goes larger, or, $\frac{\partial \hat{\epsilon}_1}{\partial \gamma} < 0$.*

Proof. See the Appendix B. ■

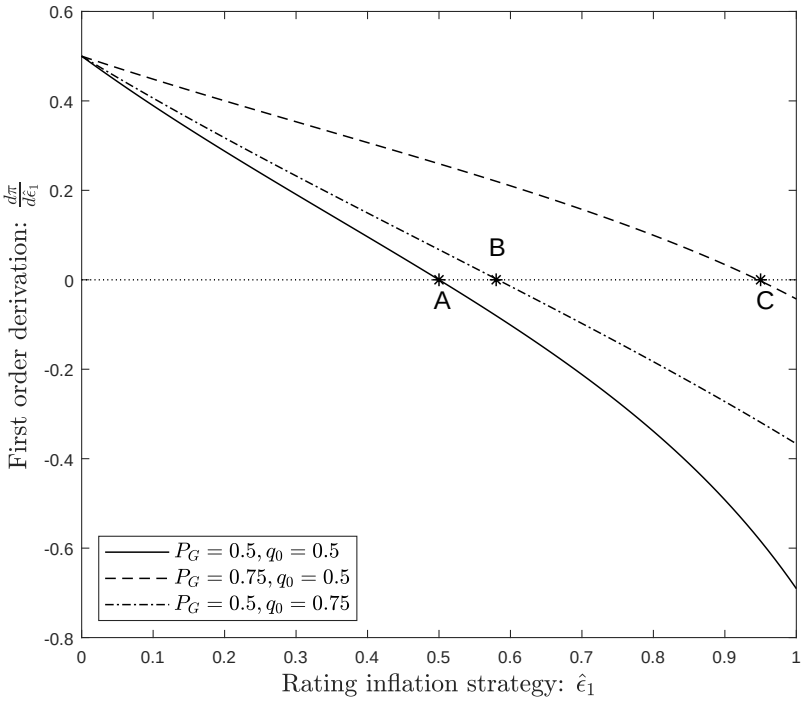
2.2 Comparative statics analysis

Our comparative statics analysis starts from a sufficiently low level of the initial reputation cost γ_0 such that $\gamma_0 < \bar{\gamma}$. A low reputation cost indicates that the CRA considers its current and future income separately, meaning that its current rating strategy is not disciplined by the reputational concerns. Consequently, in equilibrium, the opportunistic CRA will always choose to inflate the rating for a bad project, $\hat{\epsilon}_1 = 1$, resulting in a poor credit rating quality.

We then consider a reputation cost shock that heightens the CRA's reputational concerns, raising the reputation cost from γ_0 to γ_1. We focus on the interesting case where the opportunistic CRA adopts an interior solution after the shock, which implies that $\gamma_1 > \bar{\gamma}$. In our empirical analysis, we leverage bond defaults within the issuer's industry, that do not affect the issuer's own default risk, but raise the CRA's reputational concerns. We make the following assumption to ensure that a high credit rating more likely to be issued by a CRA receiving good signals, rather than inflated by opportunistic CRAs with bad signals.

Assumption 2 *The issuer's riskiness p_G and the CRA's quality q_0 satisfies that $p_G > (1 - q_0)(1 - p_G)$.*

Figure 1. Comparative statics analysis



Notes: This figure plots the first-order derivation of the CRA's expected profits, $\frac{d\pi}{d\hat{\epsilon}_1}$, as functions of the ratings inflation strategy, $\hat{\epsilon}_1$, for different parameter values of p_G and q_0. The black stars A, B, and C denote the equilibrium values of $\hat{\epsilon}_1$ under different parameter values. Other parameter values are $f = I = 0.5, y_H = 2, y_L = 0, \gamma_1 = 2$.

In the following exercise, we explore the heterogeneous effects of the reputation cost shock across multiple dimensions, including the characteristics of the issuer, the CRA, and the industry. We start with the analysis of issuer riskiness, p_G. For riskier issuers (lower p_G), the project is more likely to be a bad one. As a result, the CRA's posterior reputation, q_{H,y_1}, would experience a more severe erosion if it inflates the rating of a bad project in period 1. As illustrated in Figure 1, for a given reputation cost γ_1, when the issuer becomes riskier (p_G drops from 0.75 to 0.5), the opportunistic CRA's marginal revenue shifts downward (from the dashed line to the solid line), leading to a less inflated rating strategy $\hat{\epsilon}_1$ (from point C to point A). We provide a formal analysis in Proposition 2.

Proposition 2 *Following an increase in the reputation cost (i.e. from γ_0 to γ_1), the CRA's*

tendency to inflate the rating would reduce. Furthermore, the reduction in inflation would be more pronounced for ratings assigned to riskier issuers, that is, $\frac{\partial \hat{\epsilon}_1}{\partial p_G}\Big|_{\gamma=\gamma_1} > 0$.

Proof. See the Appendix B. ■

We next examine the role of CRA quality, indicated by the initial quality level, q_0. A high-quality CRA provides more reliable ratings to investors, and can charge higher agency fees if an issuer purchases its ratings. As a result, ratings inflation tends to be more profitable for high-quality CRAs. Moreover, with a higher initial quality q_0, the reputational damage caused by ratings inflation is less severe, resulting in a smaller loss of future income. Therefore, given the same reputation cost γ_1, a high-quality CRA is more inclined to inflate ratings for bad projects, compared to a low-quality CRA. As illustrated in Figure 1, for a given reputation cost γ_1, when the CRA's quality gets worse (q_0 drops from 0.75 to 0.5), the CRA's marginal revenue shifts downward (from the dash-dotted line to the solid line), leading to a less inflated rating strategy $\hat{\epsilon}_1$ (from point B to point A). We summarize heterogeneous effects of CRA quality on ratings inflation in Proposition 3.

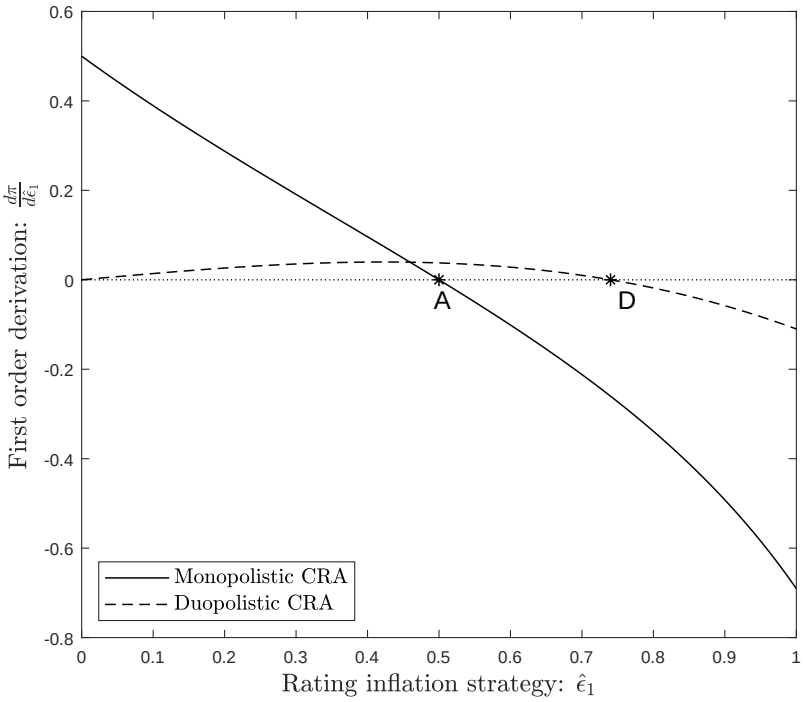
Proposition 3 *Following an increase in the reputation cost (i.e. from* γ_0 *to* γ_1*), the CRA's tendency to inflate the rating would reduce. Furthermore, under the condition that* $q_0 p_G > (1-q_0)$*, the reduction in inflation would be more pronounced for CRAs with lower quality* q_0*, that is,* $\frac{\partial \hat{\epsilon}_1}{\partial q_0}\Big|_{\gamma=\gamma_1} > 0$.

Proof. See the Appendix B. ■

Finally, we investigate the role of CRA competition. The same issuer could be rated by multiple CRAs, rather than a single monopolistic one. We extend our baseline model to introduce competition between duopolistic CRAs. To save space, we leave model details in Appendix A.

To simplify notation, we use the superscript M to denote the monopolistic CRA case, and D to denote the duopolistic CRA case. We assume that the initial reputation cost γ_0 satisfies that $\gamma_0 < \min\left\{\bar{\gamma}^M, \bar{\gamma}^D\right\}$, so that opportunistic CRAs always inflate their ratings in both scenarios, i.e., $\hat{\epsilon}_1^M = \hat{\epsilon}_1^D = 1$. We then consider a reputation cost shock that raises the CRA's reputational concerns, and increases the reputation cost from γ_0 to γ_1, where opportunistic CRAs adopt interior solutions in both cases, i.e., $\gamma_1 > \max\left\{\bar{\gamma}^M, \bar{\gamma}^D\right\}$.

Figure 2. CRA competition



Notes: This figure plots the first-order derivation of the CRA's expected profits, $\frac{d\pi}{d\hat{\epsilon}_1}$, as functions of the ratings inflation strategy, $\hat{\epsilon}_1$, for the case of monopolistic CRA (solid line), and duopolistic CRA (dashed line) respectively. The black stars A and D denote the equilibrium values of $\hat{\epsilon}_1$ under the two scenarios. Parameter values are $p_G = q_0 = f = I = 0.5, y_H = 2, y_L = 0, \gamma_1 = 2$.

In the monopolistic CRA case, a bad project can be certified whenever the opportunistic CRA inflates its rating. However, with duopolistic CRAs, certification can be passed only if both opportunistic CRAs inflate their ratings simultaneously. As a result, the involvement of multiple CRAs can dilute individual reputational concerns by imposing a stricter certification process. Consequently, given the same reputation cost, CRAs in a more competitive industry would adopt a more aggressive ratings inflation strategy. As shown in Figure 2, when the CRA industry becomes more competitive (from monopoly to duopoly), the CRA's marginal revenue gets flatter (from the solid line to the dashed line), leading to a more inflated rating strategy $\hat{\epsilon}_1$ (from point A to point D).

Proposition 4 *Following an increase in the reputation cost (i.e. from γ_0 to γ_1), the CRA's*

tendency to inflate the rating would reduce. Furthermore, the reduction in inflation would be more pronounced for CRAs in a more concentrated industry, that is, $\hat{\epsilon}_1^M(\gamma_1) < \hat{\epsilon}_1^D(\gamma_1)$.

Proof. See the Appendix B. ■

3 Data, Variables and Summary Statistics

We obtained the data from the Wind database, covering all exchange-traded corporate bonds, enterprise bonds, and medium-term notes (MTNs) issued by non-financial firms in China's corporate bond market from 2014 to 2019. This dataset includes 11,701 newly issued corporate bonds and 237 defaulted bonds. Since our research focuses on the responses of CRAs that rate bond issuers in industries with defaults in the past half a year, we consider that CRAs involved in bond defaults may have different incentives compared to those not involved. CRAs implicated in recent defaults may face conflicting pressures: they may be disciplined by default information and thus issue less inflated ratings, but they could also try to attract business by issuing more favorable ratings, as suggested by Baghai and Becker (2020). To address this potential bias, we exclude bond issuances rated by CRAs that experienced bond defaults in the past six months, retaining only those rated by CRAs without recent reputational damage. As a result, the bond sample size narrows to 10,136 for our baseline regression. In the robustness test, the sample size further decreases as the observation window extends, with more CRAs becoming involved in defaults over time.

Dependent Variable (*Ratings Inflation*): The dependent variable, *Ratings Inflation*, is defined as the difference between the issuer-paid credit rating (*Issuer-paid Ratings*) and the first available ChinaBond market-implied rating (*Market-implied Ratings*) for each newly issued bond.[6] The ChinaBond market-implied ratings are produced by the ChinaBond Pricing Center, a subsidiary of the China Central Depository & Clearing Co., Ltd. These ratings offer a market-based assessment of credit risk by mapping observed bond yield

[6]Investor-paid ratings cannot serve as a benchmark because they rarely provide bond-level ratings. Moreover, we focus on bond ratings rather than issuer ratings because investor-paid ratings from China Bond Rating Co., Ltd. cover only 32% of bond issuers during our sample period, as documented in Appendix Table D7. For completeness, we focus on issuer ratings quality in robustness checks and report the results in Section 4.5.3. We also assess the informativeness of credit ratings for credit spreads and default prediction, particularly post-default in Section 4.3.1. These tests consistently demonstrate that ratings quality improves after bond defaults, reinforcing our baseline findings.

spreads to corresponding domestic credit rating categories. Given long-standing concerns over the reliability and comparability of domestic Chinese issuer-paid CRA ratings—which are heavily clustered in high-grade categories such as AA and above—the market-implied rating provides an alternative, timely, and market-driven benchmark for evaluating issuer-paid ratings. This benchmark is particularly valuable in the context of potential conflicts of interest inherent in the issuer-pays business model.[7]

Empirically, we operationalize the comparison by converting letter grades into numerical values using a consistent scale: AAA = 5, AA+ = 4, AA = 3, AA− = 2, and A+ and below (including A, A−, BBB+, BBB, etc.) = 1. A larger numerical difference indicates greater optimism in issuer-paid ratings relative to the market-implied benchmark. Empirically, we find that approximately 45% of bonds exhibit rating discrepancies, with issuer-paid ratings generally more favorable. Among these discrepancies, 70% fall within one notch and 26% within two notches, reflecting a widespread but moderate degree of overrating.[8]

Given that our benchmark is the first data point available, derived from the secondary market. This lag between the pre-issuance issuer-paid rating and the post-issuance initial market-implied rating could introduce noise. However, the data suggest that this concern is limited: the average delay between the bond's listing date and the first market-implied rating is 6.5 days, with a median of just 3 days, and 75% of bonds receive a market-implied rating within two weeks of listing. Given the short interval, during which the underlying credit quality is unlikely to change materially. Moreover, in unreported robustness tests, we exclude bonds with delays exceeding 30 days (approximately 3% of the sample) and find that our main results remain unchanged.

Market-implied ratings, which may incorporate immediate market reactions, may differ in informational content from issuer-paid ratings, which provide a more stable, long-term assessment. Following Badoer et al. (2019), we conduct tests to validate the comparison of these ratings as a measure of poor ratings quality rather than mere informational differences. In Column (1) of Appendix Table D2, we find that riskier bond issuances, including

[7] A large body of literature has documented the inherent conflicts of interest in issuer-paid credit ratings (Jiang et al., 2012). Explanations include revolving-door employment arrangements (Cornaggia et al., 2016; Jiang et al., 2018; Kempf, 2020), cross-selling of non-rating services (Efing and Hau, 2015; Baghai and Becker, 2018), home bias (Cornaggia et al., 2020), political alignment and partisanship (Kempf and Tsoutsoura, 2021), and informal relationships (Cornaggia et al., 2024).

[8] For further institutional background on the credit rating landscape in the Chinese bond market, see Appendix C.

non-SOEs, high-leverage firms, and those with lower ROE or cash flow to assets ratios, are more likely to receive inflated ratings, suggesting that such ratings more likely reflect conflicts of interest rather than informational content. Given that one of the most important drivers of inflated ratings is the tendency to cater to bond issuers to earn market share, we thus construct a dummy variable *FrequentIssuer* to reflect such incentives, which equals one for those issuers whose annual bond issuance volume exceeds the yearly median, and zero otherwise. Results in Column (2) confirm that frequent issuers are more likely to receive inflated ratings, controlling for other characteristics.

In Columns (3)–(5), we examine the economic implications of ratings inflation. In Column (3), the dependent variable, *Ex-postDefault*, equals 1 if the bond defaults by 2023, and 0 otherwise. Inflated ratings are associated with a significantly higher default probability, indicating compromised ratings quality rather than informational differences. Since credit rating agencies must consider the reputational costs of maintaining overly optimistic ratings, we expect that rating disagreements arising from ratings inflation by agencies will be less persistent. In Columns (4) and (5), the dependent variables are *Uprating* and *Downrating*, respectively, where *Uprating* equals 1 if the first post-issuance issuer-paid rating exceeds the initial rating, and 0 otherwise, and *Downrating* equals 1 if it is lower, and 0 otherwise. Bonds with inflated initial ratings are less likely to be uprated and more likely to be downgraded, reflecting a correction process by CRAs as market-implied ratings become available. This convergence further validates the use of market-implied ratings as a benchmark and suggests that issuer-paid ratings adjust post-issuance under external validation.

Key Independent Variable (*Default6M*): The key independent variable, *Default6M*, is an indicator variable that identifies whether the bond issuance was influenced by recent bond defaults within the issuer's industry. Specifically, if there were bond defaults in the issuer's industry during the six months preceding the bond issuance, this variable is set to one; otherwise, it is set to zero. We define industry classification based on the first-digit industry classification codes provided by the China Securities Regulatory Commission (CSRC) as outlined in the "*Guidelines on Industry Classification of Listed Companies*" published in 2012.

To address potential confounding factors, we also collect comprehensive information on issuer-level and bond-level characteristics to serve as control variables. Detailed specifications for these control variables can be found in the Appendix Table D1.

Table 1 provides summary statistics of the main variables in our analysis. The mean value of *Ratings Inflation* is 0.7, indicating that, on average, the ratings provided by issuer-paid rating agencies in the Chinese corporate bond market are approximately 0.7 levels higher than the initial bond market-implied ratings. The median value of *Ratings Inflation* is 1, suggesting that issuer-paid ratings tend to be one level higher than market-implied ratings in more than half of the samples. These consistent patterns are further confirmed in the distribution of *Issuer-paid Ratings* and *Market-implied Ratings*, providing additional evidence of prevalent ratings inflation among rating agencies in the Chinese corporate bond market. Regarding the key explanatory factor, *Default6M*, the mean value is 0.42, indicating that approximately 40% of the newly issued bonds in the sample had a bond default event in the issuer's industry within six months before issuance.

<Insert Table 1 here>

To capture the nuanced distribution of bond issuances affected by intra-industry defaults, we first calculate the time intervals between each bond issuance date and the most recent within-industry default preceding the issuance. We then categorize the issuance samples into seven subgroups, as shown in Appendix Figure D1. The first group, labeled "*Before Default*," consists of bonds issued before the first industry-level default, unaffected by any intra-industry defaults. The second group, labeled "*0-3M*," comprises bonds issued within three months after an intra-industry default event. The third group, labeled "*3M-6M*," includes bonds issued more than three months but less than six months after the most recent intra-industry default event and so forth.

According to the figure, approximately 4,200 bonds were issued before any industry-level defaults, while nearly 6,000 issuances occurred within six months following recent defaults. Additionally, about 1,000 bond issuances occurred more than six months after the most recent industry default. This categorization allows us to better understand and interpret how the timing of intra-industry bond defaults influences bond issuances.

4 Empirical Tests

4.1 Baseline Results

4.1.1 Bond Defaults and Ratings Inflation

This section examines whether recent intra-industry defaults affect the quality of issuer-paid credit ratings. We focus on defaults within the same industry occurring in the six months prior to bond issuance. Because CRAs typically assign analysts by industry, such intra-industry bond defaults are particularly salient to other CRAs evaluating bonds in the same sector. Even without direct involvement, peer CRAs may reassess the reputational consequences of being linked to future defaults, thereby raising the perceived costs of issuing inflated ratings. These reputational concerns, in turn, create stronger incentives for more conservative and accurate rating practices.

To test these predictions, we exploit the staggered and highly visible nature of intra-industry defaults and estimate the following OLS regression model to examine whether recent defaults lead to less optimistic ratings on new bond issues:

$$RatingsInflation_i = \alpha + \beta_1 \times Default6M_i + \sum \beta \times Controls_i + FEs + \epsilon_i, \qquad (1)$$

where i represents each sample of bond issuance. $RatingsInflation_i$ is the dependent variable that represents the quality of the bond rating, calculated as the difference between the issuer-paid rating assigned by the rating agency and the implemented ratings of the ChinaBond market. A higher value indicates stronger ratings inflation by the agency and lower bond ratings quality. $Default6M_i$ is the key independent variable that indicates whether there was a default of the bond in the issuer's industry within the past six months. $Controls_i$ is a vector of control variables including bond and issuer characteristics. For details, see the Appendix Table D1. To control for unobserved factors, we also include fixed effects at the levels of year, CRA, industry, province, and bond type. Standard errors are clustered at the issuer level.

Table 2 reports the stepwise regression results. Column (1) presents the regression results only with the key explanatory variable, *Default6M*, along with fixed effects at the year, CRA, industry, province, and bond type levels. In Column (2), bond-level control variables are added to the specification in Column (1). The Column (3) then adds the issuer-level control

variables.

<Insert Table 2 here>

Consistent with Proposition 1 proposed in the prior theoretic framework, the coefficients of *Default6M* in all three empirical specifications are significantly negative at the 1% level. This suggests that bond defaults within an industry increase the reputation costs for CRAs, heightening their concern for reputation by prioritizing long-term credibility over short-term gains. This shift results in improved ratings accuracy in the current period. The regression coefficient in Column (3) is both statistically and economically significant: compared to bond issuances unaffected by prior defaults, those issued within six months of an intra-industry default exhibit significantly lower ratings inflation, with an effect magnitude of 8% (calculated as 0.056/0.7) relative to the sample mean.[9]

To further validate our empirical specification, we examine whether bond defaults occurring in other industries can also heighten CRAs' reputational concerns. To explore this, we classify default shocks into three categories: (1) defaults occurring only within the same industry, (2) defaults occurring only in other industries, and (3) defaults occurring both within and across industries. Table D3 in the Appendix presents the results. Column (1) compares the effects of within-industry defaults with those of defaults occurring both within and across industries. We find no significant differences, suggesting that defaults outside the industry do not provide additional disciplinary effects on CRAs. In contrast, Column (2) compares the effects of cross-industry defaults with those of defaults occurring both within and across industries. Here, we find a statistically significant result, indicating that conditional on cross-industry defaults, the presence of within-industry defaults adds further disciplinary pressure on CRAs, reinforcing reputational concerns and improving rating accuracy. Therefore, we find that default shocks are not transmitted across industries, further validating our empirical identification strategy based on intra-industry shocks.

[9]Although the average time lag between the two ratings is 6.5 days, with a median of just 3 days and less than a two-week difference for 75% of the samples, longer delays between the release date of the initial market-implied rating and the bond issuance date could occur. For example, if the delay exceeds a month, the bond's credit quality is more likely to change, potentially affecting the validity of the ratings quality measure used in this study. Therefore, in the unreported robustness analysis, we exclude samples with a time gap that exceeds 30 days, which removes less than 3% of the samples. The main research conclusions remain largely unchanged, with the coefficient for *Default6M* still significantly negative.

4.1.2 Types of Bond Defaults

The observed reduction in ratings inflation proposes that recent industry defaults can act as market disciplinary forces to increase reputational concerns and curb ratings inflation. If this hypothesis holds, we anticipate a more pronounced impact following more salient or unexpected defaults. We perform two sets of cross-sectional analyses based on the market influence of bond defaults. First, we consider the final bond rating prior to default announcements. We posit larger CRAs' reputational damage for default bonds with unexpectedly high ratings that lack effective advance warnings, thus exerting a stronger disciplinary effect on other credit rating agencies. Specifically, we define a bond default as unexpected if the rating remains at the investment grade level, i.e., no lower than AA in China. Secondly, we consider defaults by larger firms to potentially exert a greater market impact. Consequently, we expect stronger rating improvements following defaults by industry-leading firms, defined as those ranked in the top 10 by asset value.

Table 3 reports the estimation results. We categorize affected bond issuances into two subgroups based on whether they have been influenced by at least one unexpected default within the last six months. Columns (1) and (2) show the sub-sample results for bond issuances impacted by unexpected (rated no lower than AA) and expected defaults, respectively, both using the same control sample as in the baseline regression. Consistent with our conjecture that unexpected defaults have a more pronounced impact, the coefficient for *Default6M* is significant only in the cases of unexpected defaults, with a magnitude of -0.09. We further investigate whether defaults from industry-leading firms contribute to the effects, as shown in Columns (3) and (4). As anticipated, significant effects are observed only for bond issuances influenced by defaults involving leading firms, which are likely to induce greater market influence and greater reputational concerns on crowding out inflated ratings.

<Insert Table 3 here>

4.1.3 Reputational Damage after CRAs' Implicated Defaults

One key assumption underlying Proposition 1 is that bond defaults impose severe economic consequences on the rating agencies involved, thereby increasing the reputation costs faced by their peers. To validate this, we construct a CRA-year-industry dataset (covering 8 CRAs, 5 years, and 18 industries) and examine whether the market share of a rating agency

involved in a default decreases in the year following the event, which would signal explicit reputational damage for rating agencies following defaults. The dependent variable, *MarketShare*, represents the proportion of bond issuance rated by a given credit rating agency in a particular industry each year. The key explanatory variable, *CRADefault*, is a binary indicator set to 1 if the credit rating agency experienced a default in the prior year and 0 otherwise. Table 4 presents the results.

<Insert Table 4 here>

To ensure robustness, we employ different model specifications. Column (1) of Table 4 shows the results with fixed effects at the industry, year, and CRA levels. In Column (2), we introduce industry-year fixed effects to control for unobserved factors that vary across industries over time. Column (3) further incorporates an agency-industry fixed effect to account for the potential relationship between a rating agency and a specific industry.

In all three empirical models, the coefficients for *CRADefault* are significantly negative at the 1% level, indicating that when a credit rating agency experiences a default in the previous year, its market share decreases significantly in the following year. Given an average market share of 12.5%, involvement in defaults can lead to a 26.4% decrease in market share (calculated as 3.3%/12.5%). These results suggest that defaults make ratings inflation more visible and reputational damage to rating agencies more tangible. Such detection costs arising from rating failures appear to increase CRAs' reputation costs of being inaccurate and curb their opportunistic incentives (Bolton et al., 2012; Bonsall IV et al., 2023). This finding provides direct evidence supporting our earlier argument that bond defaults substantially increase CRAs' reputational concerns, prompting them to improve rating accuracy and build a reputation for future business.

Taken together, the findings above support the hypothesis in Proposition 1, demonstrating that within-industry bond defaults compel CRAs to update their beliefs about market conditions, making them more aware of the risk of losing future business due to low-quality ratings. In turn, these market dynamics intensify CRAs' reputational concerns, acting as a self-regulatory mechanism that disciplines rating agencies and mitigates ratings inflation.

4.2 CRAs' Reputational Concerns: Heterogeneity Tests

In this section, we examine various scenarios in which CRA reputational concerns can change following the default-driven shock on reputation costs. Specifically, we examine how bond defaults interact with characteristics of the issuer and the CRA to influence CRAs' propensity to inflate ratings.

4.2.1 The Quality of Bond Issuers

Building on the previous model prediction in Proposition 2, we hypothesize that when the quality of the issuer weakens, default shocks will further compel CRAs to improve rating accuracy. This is because low-quality issuers are more likely to default and CRAs would face a greater likelihood of erosion if they inflate ratings for these issuers. This hypothesis is consistent with the findings of Bonsall IV et al. (2023), which demonstrate that CRAs adopt more cautious behavior when rating riskier issuers.

To validate our expectation, we examine whether issuer-paid credit ratings improvements after defaults are more pronounced for issuers with higher expected default risk. Specifically, we focus on high-risk or low-performance issuers, who pose a greater threat to the reputation of CRAs compared to their counterparts. Columns (1) and (2) of Table 5 report the heterogeneity results by examining the low-rated (below AA +) and high-rated (AA + or AAA) bond issuers separately. Columns (3) and (4) show sub-sample results for bond issuers with high or low ROA volatility, calculated using a three-year window before bond issuance, following the methodology described by Faccio et al. (2011). Higher ROA volatility indicates a greater inclination towards risk-taking behavior. Consistent with Proposition 2, we observe a significant decline in ratings inflation only for Columns (1) and (3), representing high-risk bond issuers, but no significance for relatively safer bond issuers. The economic magnitudes of the risky subgroups are also much larger than those of their counterparts.

<Insert Table 5 here>

In Columns (5) through (8), we extend the analysis performed in Columns (1) through (4) by employing ROA and Cash flow/Assets as indicators of issuer profitability and financial health. The results show that *Default6M* remains significant only in Columns (6) and (8), which relate to issuers with poorer financial profiles. This finding suggests that following intra-industry defaults, ratings inflation decreases notably for new bonds issued by these

riskier or underperforming entities compared to their counterparts. This reduction in ratings inflation is likely due to the CRAs facing higher reputational concerns when rating weaker issuers, and are more motivated to provide more accurate initial ratings for their issued bonds.

4.2.2 The Quality of CRAs

Furthermore, according to Proposition 3, given the same intra-industry shock to CRAs' reputational costs, the incentives to inflate ratings diverge based on CRAs' quality. Low-quality CRAs derive limited benefits from ratings inflation due to the lack of trust from investors. In contrast, as suggested by the confidence cycle theory of Mathis et al. (2009), reputable CRAs can command higher revenues from inflated ratings. Under such circumstances, profit-driven motives may overweigh reputation-building incentives, potentially leading reputable CRAs to cash in their established reputation by relaxing rating standards. Moreover, the reputational damage associated with defaults is likely more severe for CRAs with insufficient reputational capital. Consequently, we expect that the reduction in ratings inflation following intra-industry defaults will be more pronounced for low-quality CRAs. Heightened reputational concerns force these CRAs to implement stricter standards to mitigate reputational risks and improve their credibility.

To test this hypothesis, we use two indicator variables to capture the reputational capital of a given CRA in a certain year. The first proxy we consider is the market share, which is an overall proxy for market power to the extent that global CRAs' ability to raise fees is higher when the CRAs have a larger client base (Hung et al., 2022). An indicator variable is constructed to identify whether a credit rating agency's market share falls within the bottom 50% of all agencies in a given year; the variable takes the value of 1 if the agency's market share is below the median and 0 otherwise. The second indicator captures the relative regulatory evaluation of rating agencies: it equals 1 if the agency is ranked among the bottom two in the annual assessment published by the National Development and Reform Commission and 0 if it is ranked among the top two. These indicators help us analyze how agencies with different reputational capital respond to intra-industry defaults in terms of their ratings quality improvements.

The Columns (1)-(2) and (3)-(4) of Table 6 present the sub-sample regression results based on differences in market shares and CRA ranking, respectively. The coefficients for

Default6M are significant only in Columns (1) and (3), corresponding to low-quality CRAs, while no significant effects are observed for high-quality CRAs in Columns (2) and (4). These findings are in align with Proposition 3 which suggests that intra-industry bond defaults reduce the short-term gain incentives of less reputable CRAs, instead encouraging them to adopt stricter rating standards to build their long-term reputation. [10]

<Insert Table 6 here>

4.2.3 The Role of CRAs' Industry Concentration

We further explore the role of CRA market competition. As suggested by Proposition 4, when there are many competing CRAs, the potential loss of market share or customer trust spreads across the entire industry, diluting the reputational cost of inflating ratings. In contrast, in more concentrated industries, the impact of reputational damage is concentrated on individual CRAs, leading to greater concerns about rating inaccuracies that could cause such damage.

To test this, we construct annualized CRA-by-Industry and CRA-Industry-Province Herfindahl-Hirschman Indices (HHI) and present regression results in Table 7. We divide the sample into high-HHI and low-HHI subgroups, where higher HHIs indicate a more concentrated CRA market. The negative and significant coefficients for *Default6M* in Columns (1) and (3) suggest that in more concentrated markets, ratings become less inflated following bond defaults. In contrast, the insignificant coefficients for *Default6M* in Columns (2) and (4) show no improvement in ratings inflation in more competitive markets with low HHIs. These heterogeneous effects suggest that bond defaults lead to reductions in ratings inflation only in more concentrated markets. In such markets, the lack of dilution effects and stronger reputational concerns among CRAs enable defaults to function as effective market forces, promoting more accurate ratings. This finding is consistent with Becker and Milbourn (2011), who argue that CRAs in concentrated markets are more likely to adopt a long-term

[10] Furthermore, if the observed improvement in ratings were solely attributable to methodological refinements spurred by the emergence of defaults—that is, defaults enhancing the informational basis of the rating model—one would anticipate more reputable CRAs to be better equipped to adapt to and benefit from such information. Consequently, a stronger effect would be expected for these high-quality CRAs. Instead, our findings reveal the opposite: significant effects are exclusively observed for lower-reputation CRAs. This outcome underscores that the primary mechanism at play is driven by reputational incentives rather than merely improved information processing.

perspective, avoiding inflated ratings to preserve their reputational capital. It also reinforces the theoretical prediction of Atkeson et al. (2015), highlighting the role of entry regulation in shaping reputational incentives and sustaining rating quality.

<Insert Table 7 here>

In summary, our findings empirically validate the hypothesis that defaults heighten CRA reputational concerns. These results highlight the critical role of market forces in compelling CRAs to adopt stricter standards, especially when rating riskier issuers or for lower-quality CRAs. Our analysis also demonstrates how a concentrated CRA market structure amplifies reputational concerns, further reinforcing discipline within the industry.

4.3 Further Discussions

4.3.1 Improvements on Rating Informativeness

As noted by Dimitrov et al. (2015), lower ratings do not necessarily imply greater informativeness. To evaluate whether credit rating informativeness improves following intra-industry bond defaults, we conduct two additional empirical tests, presented in Table 8, examining the explanatory power of ratings in issuance spreads and their ability to predict bond default rates.

<Insert Table 8 here>

We begin by examining the relationship between credit ratings and yield spreads at issuance. Yield spreads reflect the market value of bonds, and a stronger correlation between credit ratings and yield spreads suggests that ratings provide more informative insights into bond value (Becker and Milbourn, 2011). The Column (1) in Panel A presents the regression results, where the dependent variable is the issuance yield spreads relative to China Development Bank (CDB) bonds with the closest maturity. Explanatory variables include the issuer-paid credit rating (*Issuer-paid Ratings*), the industry default event shock (*Default6M*), and their interaction term, along with fixed effects for issuers, years, rating agencies, and bond types. The coefficient for *Issuer-paid Ratings* is significantly negative, indicating that higher bond ratings are associated with lower credit risk for the issuers and lower bond issuance costs. More importantly, the interaction term *Issuer-paid Ratings*Default6M* is also significantly negative, which implies that the negative relationship between bond ratings and credit spreads strengthens following defaults in the same industry in the last six

months. This result suggests an increase in the information content of the ratings for the industry with recent defaults.

To further analyze changes in the informational content of ratings, we decompose ratings into two components: one attributable to issuer fundamentals and a residual component unexplained by fundamental information.[11] The results in Columns (2)–(4) reveal that while both components exhibit a significantly negative correlation with credit spreads, only the component driven by the fundamentals of the issuer becomes more informative after bond defaults. This indicates that additional fundamental information contained in ratings plays an important role in improving the informativeness of ratings, when defaults act as market forces to intensify CRA reputational concerns.

Secondly, in Panel B of Table 8, we analyze the dynamics of rating informativeness by evaluating its ability to predict future defaults, recognizing that one of the key advantages of ratings over market-based measures is their long-term predictive power (Gredil et al., 2022). The analysis incorporates *Default6M*, *Issuer-paid Ratings*, and their interaction term as key independent variables, with *Ex-post Default Probability* serving as the dependent variable. The latter is equal to one if the issued bond has defaulted by the end of 2023. The logit model regression results are reported in Column (1) in Panel B of Table 8. As expected, *Default6M* positively correlates with ex-post default probabilities, reflecting the increased likelihood of defaults in industries experiencing recent shocks. Meanwhile, *Issuer-paid Ratings* exhibits a negative relationship with default probabilities, confirming that higher bond ratings are associated with a reduced risk of default. In particular, the interaction term between *Default6M* and *Issuer-paid Ratings* is also significantly negative, suggesting an improved predictive ability of issuer-paid ratings to assess default risks following intra-industry default events.

To explore these dynamics further, we decompose credit ratings into two components: the portion explained by the issuer's fundamentals and the residual unexplained component. The results, reported in Columns (2)–(4) in Panel B, reveal that the interaction between *Default6M* and *Rating(Fundamental)* demonstrates significant predictive power, while no such effect is observed for the residual component. These findings emphasize that the funda-

[11] The fundamentals we consider include bond issuance amount, maturity, presence of a guarantee, bond type, and issuer characteristics such as state ownership, listing status, asset size, leverage, return on equity, and the cash flow-to-asset ratio.

mentally driven portion of credit ratings becomes more effective in predicting default risks when defaults act as market-driven forces, increasing the incentives for CRAs to prioritize accuracy and credibility.

Therefore, the enhanced explanatory power of issuer-paid ratings for issuance spreads, along with their improved ability to predict defaults, underscores the increased informativeness of these ratings due to heightened reputational concerns among CRAs. These findings also align with and complement our earlier baseline results, which demonstrate a decline in ratings inflation after default events.

4.3.2 Decompose Ratings Inflation

To better understand drivers behind the decline in ratings inflation following intra-industry bond defaults, we decompose *Ratings Inflation* into *Issuer-paid Ratings* and *Market-implied Ratings* and examine their respective responses. Table 9 presents the empirical results.

<Insert Table 9 here>

In Column (1), we find a negative coefficient for issuer-paid ratings, though it is not statistically significant ($p \approx 0.2$), suggesting a tendency toward more conservative ratings post-defaults. In contrast, market-implied ratings in Column (2) exhibit a weakly significant positive coefficient, indicating an upward adjustment. These findings imply that the observed reduction in ratings inflation results from both a decline in issuer-paid ratings and an increase in market-implied ratings. Heightened reputational concerns prompt CRAs to tighten their rating standards—lowering assigned ratings while simultaneously refraining from inflating ratings for weaker issuers. This stricter approach raises the average market-implied rating for the remaining issuers, as lower-quality firms are effectively screened out. In this way, intra-industry defaults reinforce CRAs' role as gatekeepers of the bond market and enhance the allocative efficacy of rating resource.

4.4 Rule out Alternative Explanations

In this section, we consider alternative mechanisms that could drive the improvement of ratings quality.

4.4.1 Changes within the Affected Industry

One potential concern is that changes in industry conditions might coincide with default events, raising the possibility that observed improvements in ratings quality are not driven exclusively by changes in CRA reputational concerns. To address this issue, we incorporate dynamic industry-level controls into our empirical model, with the results presented in Table 10. In Column (1), we include industry-level averages for issuer asset values, leverage, ROE, and the cash flow to assets ratio as additional controls. Column (2) extends the baseline analysis by incorporating the industry-level stock index to capture broader market fluctuations within the affected industry. In Column (3), we refine the model by identifying booms and recessions in each industry cycle and replacing industry-fixed effects with industry-cycle interacted fixed effects to control for dynamic unobservables. In all three specifications, the coefficient for *Default6M* remains statistically and economically significant in reducing ratings inflation. These findings help mitigate concerns that changes in the underlying industry conditions are responsible for the observed improvements in ratings quality.

<Insert Table 10 here>

4.4.2 Improved Information Environments

Improvements in ratings quality may also reflect enhancements in issuers' information environments (e.g., Badoer and Demiroglu, 2019; Brockman et al., 2024), particularly if investors demand greater disclosure when credit ratings lose credibility (Sethuraman, 2019). In this context, industry peer defaults could prompt issuers to improve the quality of voluntary disclosures to reduce information asymmetry. As a result, the observed improvement in rating accuracy may be driven not by stronger reputational incentives for CRAs, but by enhanced issuer transparency following defaults.

To examine this possibility, we follow Bhattacharya et al. (2003) and Francis et al. (2004) by using earnings aggressiveness (EA) and earnings smoothness (ES) as proxies for accounting information transparency to measure issuer self-disclosure quality. The results, presented in Columns (1) through (4) of Table 11, evaluate whether changes in self-disclosure quality affect ratings accuracy. In Columns (1) and (3), we include EA and ES as additional controls in our baseline regression. The coefficients for *Default6M* remain significantly negative in

both cases, indicating that the improvements in ratings quality are not driven by changes in the information environments of the issuers. To further investigate whether our earlier findings are influenced by the information environment, we introduce interaction terms between *EA* and *Default6M* in Column (2), and between *ES* and *Default6M* in Column (4). However, the interaction terms do not exhibit significant coefficients in either specification. This lack of significant interaction effects suggests that the observed improvements in ratings quality after defaults are not dependent on the underlying information environment of the issuers, excluding the improved self-disclosure quality as an alternative explanation.

<Insert Table 11 here>

Next, we consider the possibility that defaults improve the public information environment for issuers due to increased investor attention and media coverage. To test this, we analyze the number of news articles and stock analyst reports covering the bond issuer within the one-year window of new bond issuance. The results, shown in Columns (5) and (6) of Table 11, use *ln(News)* and *Analyst Coverage* as the dependent variables, respectively.[12] However, the analysis finds no significant changes in the public information environment after defaults, suggesting that the observed improvements in rating informativeness are not driven by increased public information availability.

4.4.3 Role of Implicit Government Guarantee

An alternative explanation is that the improvement in ratings quality results from the government's explicit reduction or removal of implicit guarantees on LGFVs and SOEs following the emergence of defaults (Jin et al., 2023). To test this hypothesis, we interact *Default6M* with the *LGFV* and *SOE* dummies, where *LGFV* identifies bonds issued by Local Government Financing Vehicles (*Chengtou* bonds), and *SOE* represents state-owned enterprise bonds. The results, reported in Table 12, help evaluate whether the observed effects are driven by the weakening of implicit government guarantees.

If ratings quality improvements were solely due to the weakening of IGG, we would expect significant differences in the interaction terms, *LGFV*Default6M* and *SOE*Default6M*. However, our findings show no significant effects, suggesting that the results are not merely a direct consequence of IGG changes. Instead, they likely reflect broader market forces, in-

[12]Only listed issuers have analyst coverage, which is why our sample size drops to 1,827 in Column (6).

cluding adjustments in investors' expectations and CRAs' reputational concerns, as defaults serve as a signal that prompts belief updating about credit risk and rating credibility.

<Insert Table 12 here>

4.4.4 Selection Bias

Another potential limitation of the analysis is the possibility that samples exposed to intra-industry bond defaults may differ from those without such exposure. Specifically, only high-quality firms may be able to successfully issue bonds following defaults within the industry. To address this concern and rule out the possibility that improvements in the credit quality of subsequent bond issuers within the same industry are driving the reduction in ratings inflation after bond defaults, we introduce issuer-level fixed effects in Column (1) of Table 13. This fixed effect controls for unobservable issuer-level heterogeneity, and the baseline results remain robust, which suggests that the decline in ratings inflation is not solely attributable to issuer-level selection.

<Insert Table 13 here>

Additionally, we apply the propensity score matching (PSM) method to ensure robustness by mitigating the potential for biased estimates arising from sample selection based on observables.[13] The coefficient for *Default6M* remains significantly negative in the matched sample, as shown in Column (2), consistent with the findings of the baseline regression.

4.4.5 Instrumental Variable (IV) Analyses

To further strengthen our research findings and address potential endogeneity problems, we also employ instrumental variable methodology. Given that our key explanatory variable is whether there has been a credit default risk in the bond issuer's industry over a certain period, we select the average stock price crash risk of A-share listed companies in the same industry as the instrumental variable for intra-industry bond defaults. Following Kim et al. (2011), we use three indicators reflecting stock market crash risk: *NCSKEW*, which measures the negative skewness of stock returns after market adjustment; *DUVOL*, which captures the difference in volatility between the rising and falling phases of stock prices;

[13] We employ the same set of variables as in the baseline specification.

and *CRASH*, a dummy variable that represents whether the weekly return of the stock after market adjustment is less than -3.2 standard deviations below the annual average.

The rationale for using stock market crash risk in the same industry as an instrumental variable for bond defaults is twofold. Firstly, this variable meets the exogeneity assumption of instrumental variables. The stock market crash risk indicator directly characterizes the distribution of stock returns and typically reflects market price performance due to the excessive accumulation of negative news by the management of listed companies (Kim et al., 2011). Therefore, the occurrence of stock price crashes is unpredictable, particularly as an industry-level indicator, and does not provide information at the bond level, thus exogenously affecting the dependent variable of interest (*Ratings Inflation*) in our study. [14] Secondly, this variable is correlated with the key independent variable (*Default6M*), indicating a positive correlation between stock market crash risk in listed companies and credit risk in the bond market within the same industry. Table 14 reports the regression results for the instrumental variable approach. Columns (1) to (6) present the two-stage regression results for the three indicators respectively: negative skewness of stock returns after market adjustment (*NCSKEW*), the difference in volatility between rising and falling phases of stock prices (*DUVOL*), and a dummy variable for stock price crashes (*CRASH*).

<Insert Table 14 here>

Columns (1), (3), and (5) present the first-stage regression results using the three instruments, showing a consistently positive correlation between industry-average stock market crash risk and bond default occurrences. This confirms the relevance of the chosen instruments. Additionally, the F-statistics exceed 10, rejecting the weak instrument assumption at the 1% significance level. Columns (2), (4), and (6) report the second-stage regression results, where the coefficient for the key independent variable, *Default6M*, remains significantly negative. Moreover, both its magnitude and significance increase, suggesting that endogeneity issues in the baseline regression may have weakened the estimated impact on ratings inflation.

[14] To ensure the exogeneity of the instrumental variables, we also exclude bonds issued by listed companies, which represent 18% of the sample. The results remain robust to this exclusion.

4.5 Robustness

4.5.1 Alternative Definitions of Default Indicator

Appendix Table D4 presents the regression results using different definitions of *Default6M*. In Column (1), we exclude samples with time intervals between the most recent default and bond issuance date exceeding 182 days, ensuring that the unaffected sample consists only of those issued before the first occurrence of a bond default within each industry. In Column (2), we focus on the effects of the first default within each industry. Finally, in Column (3), we use a more detailed industry classification based on the first two digits of the CSRC industry codes. These adjustments consistently show that the coefficients for *Default6M* remain significant across all specifications.

4.5.2 Alternative Window Horizons

To further explore the dynamics of credit ratings inflation following industry-specific defaults and reinforce the robustness of our baseline results, we use various event windows of -6, 9, 12, and 18 months, as shown in Appendix Table D5. Our findings consistently reveal significant negative coefficients across all specifications. In particular, the coefficients reach their most pronounced negative magnitude of -0.081 within the nine-month observation window, gradually reverting to -0.07 after a one-year interval. These long-lasting effects following defaults suggest a relatively permanent increase in the scrutiny and caution exercised by credit rating agencies.

4.5.3 Issuer Ratings Quality

Our primary analysis focuses on bond ratings quality due to its broader sample coverage and greater representativeness. As a robustness check, we examine issuer ratings by constructing a firm-by-year-quarter panel dataset and measuring issuer rating inflation as the difference between issuer-paid ratings and ChinaBond ratings, which are issued by China Bond Rating Co., Ltd., a government-backed, investor-paid rating agency. Similar to our baseline model, our key variable of interest, *Default6M*, captures whether any bond defaults occurred within the issuer's industry in the past six months. The empirical results, reported in Appendix Table D6, remain consistent across specifications. Column (1) includes issuer, CRA, and

year-quarter fixed effects. Column (2) replaces year-quarter fixed effects with province∗year-quarter fixed effects to account for time-varying unobservables within each province. Column (3) instead incorporates issuer-paid ratings∗year-quarter fixed effects to control for potential dynamic unobservables within each rating level. Across all models, the consistently negative coefficients on *Default6M* indicate that recent intra-industry defaults significantly reduce issuer rating inflation. However, due to the limited coverage of ChinaBond ratings on firms—averaging 32% as reported in Appendix Table D7—and their minimal coverage of bonds, we use them solely for robustness checks and instead rely on the first-recorded ChinaBond market-implied ratings as the benchmark.

5 Conclusion

Credit ratings are experience goods, with quality discernible only ex post. In markets without bond defaults, investors feel that it is difficult to verify ratings quality, providing little incentive for CRAs to build reputational capital. However, bond defaults expose inaccuracies, making reputational damage tangible and reshaping CRAs' incentives toward long-term credibility over short-term gains. This paper tests whether the emergence of defaults in the Chinese corporate bond market since 2014 improved ratings quality, focusing on CRAs' reputational concerns.

We develop a simple two-period model that illustrates the trade-off between immediate rating fees and future income loss from potential reputation damage. The model predicts that heightened reputational costs can increase CRAs' reputational concerns and reduce ratings inflation, particularly for riskier issuers, lower-quality CRAs, and those in concentrated markets. Empirical evidence supports these predictions. Defaults significantly reduce ratings inflation, with newly issued bonds in affected industries exhibiting better ratings quality. These effects are more pronounced for unexpected defaults or those involving leading firms, underscoring the role of defaults in shaping CRA behavior. This improvement reflects that CRAs prioritize credibility over short-term gains due to potential reputational damage, as further supported by our finding that CRAs implicated in defaults experience market share declines.

Further analysis reveals that reductions in ratings inflation are concentrated among high-risk issuers, those with lower credit ratings or weaker financial performance, highlighting the

increased caution of CRAs towards issuers with a higher probability of default. Low-quality CRAs experience the most significant reductions in inflation, as reputational damage disproportionately affects their market position. Additionally, defaults in concentrated markets drive greater improvements in ratings quality than in competitive markets, aligning with the hypothesis that reputation costs are diluted in less concentrated settings. More importantly, we find that the informativeness of the ratings improves significantly, as evidenced by a stronger value relevance and a greater accuracy in predicting defaults.

Robustness checks support our main findings, ruling out alternative explanations such as changes in industry conditions, issuer disclosure practices, media coverage, or implicit government guarantees. The results hold under propensity score matching, issuer fixed effects, instrumental variable estimation, alternative default definitions, varying event windows, and when focusing on issuers' ratings quality. Overall, our study demonstrates that intra-industry defaults function as a market discipline mechanism to compel CRAs to adopt more cautious and accurate rating practices, thereby enhancing the overall credibility of the credit rating system.

These findings have important implications. While the short-term consequences of defaults—such as layoffs, supply chain disruptions, and creditor losses—are well-known, the long-term benefits of allowing a manageable number of defaults far outweigh these costs. As China's onshore corporate credit market grows and defaults become more common, investors are increasingly demanding ratings that better reflect ownership risks. This growing demand highlights the value of accurate credit ratings and information, creating new opportunities for rating agencies. In this evolving market, only those agencies that demonstrate prudence and reliability will thrive. The discipline imposed on credit rating agencies and the resulting improvements in ratings quality mark a significant milestone in the maturation of the bond market. These changes will improve risk pricing and capital allocation efficiency, reduce issuers' moral hazard, and empower investors to make better-informed decisions in a more transparent and efficient environment—contributing to the stability and sustainable growth of the capital market.

References

Amstad, M. and He, Z. (2020). Chinese Bond Markets and Interbank Market. In *The Handbook of China's Financial System*, pages 105–148. Princeton University Press.

Atkeson, A., Hellwig, C., and Ordoñez, G. (2015). Optimal regulation in the presence of reputation concerns. *The Quarterly Journal of Economics*, 130(1):415–464.

Badoer, D. C. and Demiroglu, C. (2019). The relevance of credit ratings in transparent bond markets. *The Review of Financial Studies*, 32(1):42–74.

Badoer, D. C., Demiroglu, C., and James, C. M. (2019). Ratings quality and borrowing choice. *The Journal of Finance*, 74(5):2619–2665.

Baghai, R. P. and Becker, B. (2018). Non-rating revenue and conflicts of interest. *Journal of Financial Economics*, 127(1):94–112.

Baghai, R. P. and Becker, B. (2020). Reputations and credit ratings: Evidence from commercial mortgage-backed securities. *Journal of Financial Economics*, 135(2):425–444.

Baghai, R. P., Becker, B., and Pitschner, S. (2024). The use of credit ratings in the delegated management of fixed income assets. *Management Science*, 70(5):3059–3079.

Becker, B. and Milbourn, T. (2011). How did increased competition affect credit ratings? *Journal of Financial Economics*, 101(3):493–514.

Behr, P., Kisgen, D. J., and Taillard, J. P. (2018). Did government regulations lead to inflated credit ratings? *Management Science*, 64(3):1034–1054.

Benmelech, E., Bergman, N., Milanez, A., and Mukharlyamov, V. (2019). The agglomeration of bankruptcy. *The Review of Financial Studies*, 32(7):2541–2586.

Bernstein, A., Frydman, C., and Hilt, E. (2025). The value of ratings: Evidence from their introduction in securities markets. *Journal of Political Economy, forthcoming*.

Bhattacharya, U., Daouk, H., and Welker, M. (2003). The world price of earnings opacity. *The Accounting Review*, 78(3):641–678.

Bolton, P., Freixas, X., and Shapiro, J. (2012). The credit ratings game. *The Journal of Finance*, 67(1):85–111.

Bongaerts, D. and Schlingemann, F. (2024). The real effects of ratings actions: Evidence from corporate asset sales. *Management Science*, 70(3):1505–1528.

Bonsall, S., Koharki, K., and Neamtiu, M. (2015). The effectiveness of credit rating agency monitoring: Evidence from asset securitizations. *The Accounting Review*, 90(5):1779–1810.

Bonsall IV, S. B., Green, J. R., and Muller III, K. A. (2018). Are credit ratings more rigorous for widely covered firms? *The Accounting Review*, 93(6):61–94.

Bonsall IV, S. B., Koharki, K., Kraft, P., Muller III, K. A., and Sikochi, A. (2023). Do rating agencies behave defensively for higher risk issuers? *Management Science*, 69(8):4864–4887.

Bonsall IV, S. B., Koharki, K., and Neamtiu, M. (2022). The disciplining effect of credit default swap trading on the quality of credit rating agencies. *Contemporary Accounting Research*, 39(2):1297–1333.

Boone, A. L. and Ivanov, V. I. (2012). Bankruptcy spillover effects on strategic alliance partners. *Journal of Financial Economics*, 103(3):551–569.

Brockman, P., Subasi, M., Wang, J., and Zhang, E. (2024). Do credit rating agencies learn from the options market? *Management Science*, 70(11):7851–7867.

Chen, Z., He, Z., and Liu, C. (2020). The financing of local government in China: Stimulus loan wanes and shadow banking waxes. *Journal of Financial Economics*, 137(1):42–71.

Cornaggia, J., Cornaggia, K. J., and Israelsen, R. D. (2018). Credit ratings and the cost of municipal financing. *The Review of Financial Studies*, 31(6):2038–2079.

Cornaggia, J., Cornaggia, K. J., and Xia, H. (2016). Revolving doors on Wall Street. *Journal of Financial Economics*, 120(2):400–419.

Cornaggia, J., Jiang, F., Li, J. Y., Shan, C., and Tang, D. Y. (2024). Informal relationships and credit ratings. *Available at SSRN 3858235*.

Cornaggia, J. N., Cornaggia, K. J., and Israelsen, R. D. (2020). Where the heart is: Information production and the home bias. *Management Science*, 66(12):5532–5557.

DeHaan, E. (2017). The financial crisis and corporate credit ratings. *The Accounting Review*, 92(4):161–189.

deHaan, E., Li, J., and Watts, E. M. (2023). Retail bond investors and credit ratings. *Journal of Accounting and Economics*, 76(1):101587.

Dimitrov, V., Palia, D., and Tang, L. (2015). Impact of the Dodd-Frank act on credit ratings. *Journal of Financial Economics*, 115(3):505–520.

Dong, Y., Hou, Q., and Ni, C. (2021). Implicit government guarantees and credit ratings. *Journal of Corporate Finance*, 69:102046.

Duffie, D. (2019). Prone to fail: The pre-crisis financial system. *Journal of Economic Perspectives*, 33(1):81–106.

Efing, M. and Hau, H. (2015). Structured debt ratings: Evidence on conflicts of interest. *Journal of Financial Economics*, 116(1):46–60.

Faccio, M., Marchica, M.-T., and Mura, R. (2011). Large shareholder diversification and corporate risk-taking. *The Review of Financial Studies*, 24(11):3601–3641.

Flannery, M. J. and Bliss, R. R. (2019). Market discipline in regulation: Pre-and post-crisis. *Oxford Handbook of Banking, forthcoming*.

Fong, K., Hong, H., Kacperczyk, M., and Kubik, J. D. (2022). Do security analysts discipline credit rating agencies? *The Review of Corporate Finance Studies*, 11(4):815–848.

Francis, J., LaFond, R., Olsson, P. M., and Schipper, K. (2004). Costs of equity and earnings attributes. *The Accounting Review*, 79(4):967–1010.

Geng, Z. and Pan, J. (2024). The SOE premium and government support in China's credit market. *The Journal of Finance*.

Goldstein, I. and Huang, C. (2020). Credit rating inflation and firms' investments. *The Journal of Finance*, 75(6):2929–2972.

Gorton, G. B. (2009). Slapped in the face by the invisible hand: Banking and the panic of 2007. *Available at SSRN 1401882*.

Gredil, O. R., Kapadia, N., and Lee, J. H. (2022). On the information content of credit ratings and market-based measures of default risk. *Journal of Financial Economics*, 146(1):172–204.

Grieser, W. and Liu, Z. (2019). Corporate investment and innovation in the presence of competitor constraints. *The Review of Financial Studies*, 32(11):4271–4303.

Hertzel, M. G., Li, Z., Officer, M. S., and Rodgers, K. J. (2008). Inter-firm linkages and the wealth effects of financial distress along the supply chain. *Journal of Financial Economics*, 87(2):374–387.

Hertzel, M. G. and Officer, M. S. (2012). Industry contagion in loan spreads. *Journal of Financial Economics*, 103(3):493–506.

Hu, X., Huang, H., Pan, Z., and Shi, J. (2019). Information asymmetry and credit rating: A quasi-natural experiment from China. *Journal of Banking and Finance*, 106:132–152.

Hu, X., Shi, J., Wang, L., and Yu, J. (2020). Foreign ownership in Chinese credit ratings industry: Information revelation or certification? *Journal of Banking and Finance*, 118:105891.

Hung, M., Kraft, P., Wang, S., and Yu, G. (2022). Market power and credit rating standards: Global evidence. *Journal of Accounting and Economics*, 73(2-3):101474.

Jiang, J., Wang, I. Y., and Wang, K. P. (2018). Revolving rating analysts and ratings of mortgage-backed and asset-backed securities: Evidence from linkedin. *Management Science*, 64(12):5832–5854.

Jiang, J. X., Stanford, M. H., and Xie, Y. (2012). Does it matter who pays for bond ratings? Historical evidence. *Journal of Financial Economics*, 105(3):607–621.

Jiang, X. and Packer, F. (2019). Credit ratings of Chinese firms by domestic and global agencies: Assessing the determinants and impact. *Journal of Banking and Finance*, 105:178–193.

Jin, S., Wang, W., and Zhang, Z. (2023). The real effects of implicit government guarantee: Evidence from Chinese SOE defaults. *Management Science*.

Jorion, P. and Zhang, G. (2007). Good and bad credit contagion: Evidence from credit default swaps. *Journal of Financial Economics*, 84(3):860–883.

Kempf, E. (2020). The job rating game: Revolving doors and analyst incentives. *Journal of Financial Economics*, 135(1):41–67.

Kempf, E. and Tsoutsoura, M. (2021). Partisan professionals: Evidence from credit rating analysts. *The Journal of Finance*, 76(6):2805–2856.

Kim, J.-B., Li, Y., and Zhang, L. (2011). CFOs versus CEOs: Equity incentives and crashes. *Journal of Financial Economics*, 101(3):713–730.

Lang, L. H. and Stulz, R. (1992). Contagion and competitive intra-industry effects of bankruptcy announcements: An empirical analysis. *Journal of Financial Economics*, 32(1):45–60.

Li, W. (2025). Investor-paid credit ratings and managerial information disclosure. *Management Science*, 71(3):2142–2169.

Livingston, M., Poon, W. P., and Zhou, L. (2018). Are Chinese credit ratings relevant? A study of the Chinese bond market and credit rating industry. *Journal of Banking and Finance*, 87:216–232.

Mathis, J., McAndrews, J., and Rochet, J.-C. (2009). Rating the raters: Are reputation concerns powerful enough to discipline rating agencies? *Journal of Monetary Economics*, 56(5):657–674.

Piccolo, A. (2021). Credit ratings and competition. *Available at SSRN 3233964*.

Piccolo, A. and Shapiro, J. (2022). Credit ratings and market information. *The Review of Financial Studies*, 35(10):4425–4473.

Sethuraman, M. (2019). The effect of reputation shocks to rating agencies on corporate disclosures. *The Accounting Review*, 94(1):299–326.

White, L. J. (2010). Markets: The credit rating agencies. *Journal of Economic Perspectives*, 24(2):211–226.

Xia, H. (2014). Can investor-paid credit rating agencies improve the information quality of issuer-paid rating agencies? *Journal of Financial Economics*, 111(2):450–468.

Zhang, L. and Wu, Y. (2019). Credit bonds. *The Future of China's Bond Market*, pages 99–122.

Table 1. Summary Statistics

VARIABLES	N	Mean	SD	P25	P50	P75
Default6M	10,136	0.420	0.494	0	0	1
Issuer-paid Ratings	10,136	4.035	0.870	3	4	5
Market-implied Ratings	10,136	3.335	1.061	3	3	4
Ratings Inflation	10,136	0.700	0.777	0	1	1
Amount (billion)	10,136	1.228	1.217	0.500	1.000	1.500
Maturity	10,136	4.778	1.905	3	5	5
Cross-listed	10,136	0.164	0.370	0	0	0
Guaranteed	10,136	0.140	0.347	0	0	0
SOE	10,136	0.810	0.392	1	1	1
Listed	10,136	0.180	0.384	0	0	0
Assets (billion)	10,136	128.045	248.036	15.679	38.356	116.303
Leverage	10,136	59.721	16.499	49.688	62.548	71.522
ROE	10,136	5.879	6.561	1.634	3.778	8.996
Cash flow/Assets	10,136	0.012	0.062	-0.014	0.015	0.046

Notes: This table reports the summary statistics of the key variables used in this study. The sample consists of 10,136 newly issued corporate bonds issued between 2014 and 2019. Table D1 describes the detailed definitions of the variables.

Table 2. Baseline Results: Bond Defaults and Ratings Inflation

Dep.Var.:	Ratings Inflation		
	(1)	(2)	(3)
Default6M	-0.066***	-0.062***	-0.056**
	(-2.672)	(-2.589)	(-2.428)
Log(Amount)		0.008	0.021
		(0.521)	(1.413)
Maturity		-0.040***	-0.025***
		(-6.350)	(-4.228)
Cross-listed		-0.132**	-0.071
		(-1.965)	(-1.006)
Guaranteed		0.792***	0.798***
		(24.402)	(23.023)
SOE			-0.559***
			(-12.493)
Listed			-0.050
			(-1.368)
Log(Assets)			0.002
			(0.123)
Leverage			0.005***
			(5.189)
ROE			-0.008***
			(-3.382)
Cash flow/Assets			-0.542***
			(-2.940)
Fixed Effects	Year, CRA, Industry, Province, Bond Type		
Observations	10136	10136	10136
R-squared	0.225	0.335	0.392

Notes: This table reports OLS regression results examining how bond defaults affect ratings inflation. The key independent variable of interest is *Default6M*, an indicator variable that represents whether there are defaults in the same industry within six months prior to the bond issuance. The dependent variable *Ratings Inflation* measures the difference between the ratings assigned by rating agencies and the ChinaBond market-implied ratings, serving as a proxy for credit ratings quality. Fixed effects for year, CRA, industry of the issuer, province of the issuer, and bond type are included. Robust standard errors are clustered at the issuer level. T-statistics of the coefficient estimates are reported in parentheses. Symbols of ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 3. Types of Bond Defaults

Dep.Var.:	Ratings Inflation			
	Unexpected Defaults		Leading-firm Defaults	
	Yes	No	Yes	No
	(1)	(2)	(3)	(4)
Default6M	-0.090**	-0.036	-0.168***	-0.024
	(-2.444)	(-1.462)	(-3.525)	(-0.926)
Controls	YES			
Fixed Effects	Year, CRA, Industry, Province, Bond Type			
Observations	7680	8354	6555	9479
R-squared	0.388	0.403	0.409	0.389

Notes: This table reports OLS regression results examining the differential effects of default types in reducing ratings inflation following bond defaults. The dependent variable, *Ratings Inflation*, measures the absolute difference between the ratings assigned by credit rating agencies and the ChinaBond market-implied ratings, serving as a proxy for credit ratings quality. Columns (1) and (2) report the empirical results for unexpected defaults and expected defaults, respectively. Columns (3) and (4) report the results for leading-firm defaults and non-leading-firm defaults, respectively. Control variables are identical to those in Table 2. Fixed effects for year, CRA, industry of the issuer, province of the issuer, and bond type are included. Robust standard errors are clustered at the issuer level. T-statistics of the coefficient estimates are reported in parentheses. Symbols ***, **, * indicate statistical significance at the levels 1%, 5%, and 10%, respectively.

Table 4. CRAs' Reputational Damage Following Defaults

Dep.Var.:	Market Share		
	(1)	(2)	(3)
CRADefault	-0.018**	-0.023***	-0.033***
	(-2.548)	(-2.726)	(-2.937)
Year FE	YES	NO	YES
CRA FE	YES	YES	NO
Industry FE	YES	NO	NO
Industry*Year FE	NO	YES	YES
CRA*Industry FE	NO	NO	YES
Observations	720	720	720
R-squared	0.626	0.627	0.629

Notes: This table reports OLS regression results examining the reputational consequences for CRAs' involvement in defaults. The dependent variable *Market Share*, measures the market share of rating agencies. The key independent variable of interest is *CRADefault*, which reflects whether the rating agency had defaulted in the previous year. The fixed effects of the year, CRA, industry of the issuer are included in Column (1). Columns (2) and (3) use industry-year fixed effect and CRA-industry interacted fixed effect, respectively. Control variables are identical to those in Table 2. Robust standard errors are clustered at the issuer level. T-statistics of the coefficient estimates are reported in parentheses. Symbols ***, **, * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 5. Heterogeneity Across Bond Issuers

	Riskiness				Performance			
Dep.Var.:	Ratings Inflation							
Bond Issuers:	Issuer Rating		ROA Volatility		ROA		Cash Flow	
	belowAA+	aboveAA+	High	Low	High	Low	High	Low
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Default6M	-0.058*	-0.032	-0.095***	-0.012	-0.037	-0.063**	-0.044	-0.048*
	(-1.905)	(-1.241)	(-2.582)	(-0.449)	(-1.153)	(-2.121)	(-1.286)	(-1.772)
Controls	YES							
Fixed Effects	Year, CRA, Industry, Province, Bond Type							
Observations	4263	5873	5121	5015	5113	5023	5102	5034
R-squared	0.511	0.441	0.409	0.412	0.429	0.390	0.414	0.422
Chow Test (Coef.Diff)	90.87***		6.64***		5.90***		15.97***	

Notes: This table reports the OLS regression results examining the role of issuers' quality in the relationship between bond defaults and credit ratings quality. Columns (1) and (2) report the sub-sample results for low-rated (below AA+) and high-rated (above AA+) bond issuers, respectively. Columns (3) and (4) report sub-sample results for bond issuers with high ROA volatility and low ROA volatility, respectively. Columns (5) and (6) report the findings for bond issuers with high and low ROAs, while Columns (7) and (8) report the results for bond issuers with high and low cash flows. Control variables are identical to those in Table 2. Fixed effects for year, CRA, industry of the issuer, province of the issuer, and bond type are included. Robust standard errors are clustered at the issuer level. T-statistics of the coefficient estimates are reported in parentheses. Symbols ***, **, * indicate statistical significance at the levels 1%, 5%, and 10%, respectively.

Table 6. Heterogeneity across CRAs' Reputational Capital

Dep.Var.:	Ratings Inflation			
CRAs:	Market Share		Ranking	
	Low	High	Low	High
	(1)	(2)	(3)	(4)
Default6M	-0.099**	-0.023	-0.085**	-0.019
	(-2.364)	(-0.903)	(-2.317)	(-0.552)
Controls	YES			
Fixed Effects	Year, CRA, Industry, Province, Bond Type			
Observations	3053	7083	2721	2625
R-squared	0.457	0.376	0.446	0.409
Chow Test (Coef.Diff)	19.20***		6.27***	

Notes: This table reports the OLS regression results examining the role of CRA's quality in the relationship between bond defaults and credit ratings quality. Columns (1) and (2) show the differentiated impact of ratings quality improvement after default for rating agencies with low and high market shares, respectively. Columns (3) and (4) report the findings for rating agencies with low and high rankings. Control variables are identical to those in Table 2. Fixed effects for year, CRA, industry of the issuer, province of the issuer, and bond type are included. Robust standard errors are clustered at the issuer level. T-statistics of the coefficient estimates are reported in parentheses. Symbols ***, **, * indicate statistical significance at the levels 1%, 5%, and 10%, respectively.

Table 7. CRAs' Industry Concentration

Dep.Var.:	Ratings Inflation			
CRAs:	Industry HHI		Industry-Province HHI	
	High	Low	High	Low
	(1)	(2)	(3)	(4)
Default6M	-0.051**	-0.007	-0.059**	-0.012
	(-2.004)	(-0.183)	(-2.027)	(-0.374)
Controls	YES			
Fixed Effects	Year, CRA, Industry, Province, Bond Type			
Observations	5794	4342	6775	3361
R-squared	0.424	0.365	0.409	0.413
Chow Test (Coef.Diff)	19.52***		26.96***	

Notes: This table reports the OLS regression results examining the role of CRAs' industry concentration in the relationship between bond defaults and credit ratings quality. Columns (1) and (2) show the differentiated impact of ratings quality improvement after default for concentrated industries and concentrated industry-province cohorts using industry HHI as the classification standard, while Columns (3) and (4) use the industry-province HHI as the criteria. Control variables are identical to those in Table 2. Fixed effects for year, CRA, industry of the issuer, province of the issuer, and bond type are included. Robust standard errors are clustered at the issuer level. T-statistics of the coefficient estimates are reported in parentheses. Symbols ***, **, * indicate statistical significance at the levels 1%, 5%, and 10%, respectively.

Table 8. Bond Defaults and Ratings Informativeness

Panel A. Credit Spreads				
	(1)	(2)	(3)	(4)
Default6M	0.296***	0.346**	0.044*	0.339**
	(2.739)	(2.399)	(1.760)	(2.553)
Issuer-paidRating	-0.632***			
	(-26.389)			
Issuer-paidRating*Default6M	-0.061**			
	(-2.425)			
Rating(Fundamental)		-1.184***		-1.456***
		(-4.300)		(-6.266)
Rating(Fundamental)*Default6M		-0.070**		-0.071**
		(-2.065)		(-2.247)
Rating(Residual)			-0.639***	-0.638***
			(-24.392)	(-24.334)
Rating(Residual)*Default6M			-0.045	-0.047
			(-1.227)	(-1.293)
Controls	Yes			
Fixed Effects	Year, CRA, Industry, Province, Bond Type			
Observations	10131	10131	10131	10131
R-squared	0.600	0.519	0.600	0.600

(Continued)

Table 8—*Continued*

Panel B. Ex-post Default Probability				
	(1)	(2)	(3)	(4)
Default6M	1.179***	2.319***	0.113	2.341***
	(2.713)	(3.096)	(0.549)	(3.091)
Issuer-paidRating	-0.590***			
	(-2.715)			
Issuer-paidRating*Default6M	-0.280***			
	(-2.620)			
Rating(Fundamental)		6.567		5.057
		(1.181)		(0.814)
Rating(Fundamental)*Default6M		-0.562***		-0.564***
		(-2.972)		(-3.029)
Rating(Residual)			-0.713***	-0.719***
			(-3.392)	(-3.369)
Rating(Residual)*Default6M			0.064	0.069
			(0.418)	(0.472)
Controls	Yes			
Fixed Effects	Year, CRA, Industry, Province, Bond Type			
Observations	10136	10136	10136	10136
R-squared	0.512	0.505	0.511	0.513

Notes: This table reports regression results examining how bond defaults affect the informativeness of credit ratings. Panel A shows OLS regressions on credit spreads. The key variable is the interaction term *Issuer-paidRating*Default6M*. Column (1) tests whether the link between issuer-paid ratings and spreads changes post-default. Columns (2)–(3) decompose ratings into components explained by fundamentals (*Rating(Fundamental)*) and unexplained residuals (*Rating(Residual)*). Column (4) includes both components. Panel B presents logit regressions on ex-post default probability. Column (1) assesses changes in the predictive power of issuer-paid ratings. Columns (2)–(4) analyze the separate effects of *Rating(Fundamental)* and *Rating(Residual)*, with both included in Column (4). Control variables are identical to those in Table 2. Fixed effects for year, CRA, industry of the issuer, province of the issuer, and bond type are included. Robust standard errors are clustered at the issuer level. T-statistics or z-statistics of the coefficient estimates are reported in parentheses. Symbols ***, **, * indicate statistical significance at the levels 1%, 5%, and 10%, respectively.

Table 9. Decompose Ratings Inflation

Dep.Var.:	Issuer-paid Ratings	Market-implied Ratings
	(1)	(2)
Default6M	-0.019	0.037*
	(-1.154)	(1.707)
Controls	YES	
Fixed Effects	Year, CRA, Industry, Province, Bond Type	
Observations	10136	10136
R-squared	0.646	0.633

Notes: This table reports the OLS regression results examining the effect of bond defaults on issuer-paid ratings and market-implied ratings, respectively. The control variables remain consistent with those in Table 2. Fixed effects for year, CRA, industry of the issuer, province of the issuer, and bond type are included. Robust standard errors are clustered at the issuer level. T-statistics of the coefficient estimates are reported in parentheses. Symbols ***, **, * indicate statistical significance at the levels 1%, 5%, and 10%, respectively.

Table 10. Control Changes within the Industry

Dep.Var.:	Ratings Inflation		
	(1)	(2)	(3)
Default6M	-0.057**	-0.053**	-0.067***
	(-2.536)	(-2.317)	(-2.969)
Log(IndustryAvg.Assets)	-0.028		
	(-0.577)		
IndustryAvg.Leverage	0.006*		
	(1.674)		
IndustryAvg.ROE	0.007		
	(0.741)		
Log(IndustryAvg.Cash flow/Assets)	-2.625**		
	(-2.549)		
Log(IndustryStockIndex)		0.189***	
		(3.238)	
Bond Controls	YES	YES	YES
Firm Controls	YES	YES	YES
Fixed Effects	Year, CRA, Industry, Province, Bond Type		
Industry*Cycle FE			YES
Observations	10136	10103	10064
R-squared	0.393	0.392	0.394

Notes: This table reports OLS regression results examining the potential confounding effects from changes in industry conditions. Columns (1) and (2) introduce two types of industry-level time-varying control variables: the mean of firm-level control variables within the industry and the natural logarithm of the industry-level stock index variable. Column (3) adds industry*cycle fixed effect. Control variables are identical to those in Table 2. Robust standard errors are clustered at the issuer level. T-statistics of the coefficient estimates are reported in parentheses. Symbols ***, **, * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 11. Rule Out Information Environment Effects

Dep.Var.:	Self-Disclosure Ratings Inflation				Public Disclosure ln(News)	Public Disclosure Analyst Coverage
	(1)	(2)	(3)	(4)	(5)	(6)
Default6M	-0.057**	-0.055**	-0.051**	-0.052**	-0.113	-1.816
	(-2.315)	(-2.240)	(-2.247)	(-2.245)	(-1.325)	(-0.668)
EA	-0.013	0.031				
	(-0.211)	(0.453)				
EA*Default6M		-0.100				
		(-1.123)				
ES			-0.004**	-0.004**		
			(-2.878)	(-2.593)		
ES*Default6M				0.001		
				(0.315)		
Controls	YES					
Fixed Effects	Year, CRA, Industry, Province, Bond Type					
Observations	7910	7910	9324	9324	9131	1827
R-squared	0.398	0.398	0.401	0.401	0.025	0.259

Notes: This table reports OLS regression results examining the role of the information environment in the relationship between bond defaults and credit ratings quality. Columns (1)-(4) focus on issuer self-disclosure. Column (1) includes earnings aggressiveness (*EA*) as a control, while Column (2) adds the interaction term *EA*Default6M*. Column (3) adds earnings smoothness (*ES*) as a control, and Column (4) incorporates the interaction *ES*Default6M*. In Column (5), we introduce the Baidu News Index for the six months before and after the bond issuance, while in Column (6), we introduce the number of reports published by stock analysts during the same period as the dependent variables. Control variables match those in Table 2. Fixed effects for year, CRA, industry of the issuer, province of the issuer, and bond type are included. Robust standard errors are clustered at the issuer level. T-statistics of the coefficient estimates are reported in parentheses. Symbols ***, **, * indicate statistical significance at the levels 1%, 5%, and 10%, respectively.

Table 12. The Role of Implicit Government Guarantee

Dep.Var.:	Ratings Inflation	
	(1)	(2)
Default6M	-0.054	0.027
	(-1.526)	(0.439)
LGFV	-0.052	
	(-1.310)	
LGFV*Default6M	-0.001	
	(-0.020)	
SOE		-0.520***
		(-10.102)
SOE*Default6M		-0.098
		(-1.564)
Controls	Yes	
Fixed Effects	Year, CRA, Industry, Province, Bond Type	
Observations	10136	10136
R-squared	0.392	0.392

Notes: This table reports the OLS regression results examining whether implicit government guarantees influence how defaults improve rating inaccuracy. *LGFV* is a dummy variable equal to 1 if the bond is issued by a Local Government Financing Vehicle (*Chengtou* bond) and 0 otherwise. *SOE* is a dummy variable equal to 1 if the bond is issued by a state-owned enterprise and 0 otherwise. Other variables are consistent with Table 2. Fixed effects for year, CRA, industry of the issuer, province of the issuer, and bond type are included. Robust standard errors are clustered at the issuer level. *T*-statistics of the coefficient estimates are reported in parentheses. Symbols ***, **, * indicate statistical significance at the levels 1%, 5%, and 10%, respectively.

Table 13. Adjust Selection Bias

	Issuer FE	PSM (1 vs.3)
Dep.Var.:	Ratings Inflation	
	(1)	(2)
Default6M	-0.042**	-0.050**
	(-2.320)	(-2.063)
Controls	YES	
Fixed Effects	Year, CRA, Industry, Province, Bond Type	
Issuer FE	YES	
Observations	10136	8518
R-squared	0.772	0.394

Notes: This table reports the OLS regression results examining the potential sample selection bias. Column(1) adds the issuer-level fixed effect to the baseline model. Column (2) presents results using the Propensity Score Matching (PSM) method with a 1-to-3 nearest neighbor matching algorithm and a caliper of 0.01. Control variables are identical to those in Table 2. Fixed effects for year, CRA, industry of the issuer, province of the issuer, and bond type are included. Robust standard errors are clustered at the issuer level. T-statistics of the coefficient estimates are reported in parentheses. Symbols ***, **, * indicate statistical significance at the levels 1%, 5%, and 10%, respectively.

Table 14. Instrumental Variable Approach

IVs:	NCSKEW		DUVOL		CRASH	
	Stage 1	Stage 2	Stage 1	Stage 2	Stage 1	Stage 2
Dep.Var.:	Default6M	Inflation	Default6M	Inflation	Default6M	Inflation
	(1)	(2)	(3)	(4)	(5)	(6)
IV	3.271***		2.671***		1.864***	
	(11.774)		(8.786)		(6.430)	
Default6M		-0.204***		-0.252**		-0.277***
		(-2.580)		(-2.559)		(-2.600)
Controls	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES	YES	YES
CRA FE		YES		YES		YES
Province FE		YES		YES		YES
Bond Type FE		YES		YES		YES
Observations	8321	8321	8321	8321	8321	8321
Pseudo/R-squared	0.510	0.361	0.487	0.357	0.482	0.355

Notes: This table reports two-stage instrumental variable regression results examining the impact of bond defaults on ratings inflation. Columns (1), (3), and (5) report the first-stage results, where the instrumental variables *NCSKEW*, *DUVOL*, *CRASH* are used, with *Default6M* as the dependent variable. Columns (2), (4), and (6) present the second-stage results, with *Ratings Inflation* as the dependent variable. Control variables are identical to those in Table 2. Fixed effects for year, CRA, industry of the issuer, province of the issuer, and bond type are included. Robust standard errors are clustered at the issuer level. T-statistics of the coefficient estimates are reported in parentheses. Symbols ***, **, * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Internet Appendix to "Reputation at Risk: How Bond Defaults Improve Credit Ratings Quality"

Haoyu Gao, Yuting Huang, Xiaoming Li, Ruochen Wang

A Model Extension: Duopolistic CRAs

We extend our baseline model to introduce competition between duopolistic CRAs. Specifically, the issuer is rated by two CRAs, denoted as i and j respectively. For simplicity, we focus on the symmetric equilibrium, where both CRAs have the same initial reputation q_0, and adopt the identical rating strategies in each period.

To secure financing from investors, the issuer must pass the screening of both CRAs. Otherwise, investors would treat the issuer as the bad type, and refuse to finance the issuer. With two CRAs, the possible rating sets in period t is, $(r_{1t}, r_{2t}) \in \{(\varnothing, \varnothing), (H, H)\}$. So the probability of a project to be a good one given two high ratings is

$$p_{HH} = \frac{p_G}{p_G + p_B \left[(1 - q_0)\, \hat{\epsilon}_t\right]^2}.$$

Thus, two high ratings assigned by duopolistic CRAs is more reliable than a single high rating assigned by the monopolistic CRA in the baseline model, i.e. $p_{HH} > p_H$. Additionally, each CRA will optimally set the agency fee as $\psi(q_0, \hat{\epsilon}_t) = \frac{1}{2}\left[p_{HH} V_G + (1 - p_{HH}) V_B - I\right]$.

At the end of period 1, the project payoff is realized, and investors would update their beliefs on the CRA's type. Specifically, we define q_{HH,y_1} as the investor's posterior belief on the CRA's type *conditional* on assigning high ratings in period 1 and the realized payoff y_1, and $q_{\varnothing\varnothing}$ as the investor's posterior belief on the CRA's type *conditional* on the issuer remaining unrated in period 1.

In the case of duopolistic CRAs, the issuer must be certified by two CRAs. As a result, the bad project with an inflated rating assigned by opportunistic CRAs are less likely to be mixed with the good project, and get financed. Conversely, the issuer remained unrated in period 1 whenever at least one CRA truthfully assigns the rating. Given the same rating strategy, ϵ_{it}, the opportunistic CRA experiences less severe reputational damage when inflating ratings, i.e. $q_{HH,y_1} > q_{H,y_1}$. However, it also has a smaller reputation improvement when truthfully assigning the rating, i.e. $q_{\varnothing\varnothing} < q_{\varnothing}$. We formally derive posterior beliefs and summarize the result in the Lemma 2.

Lemma 2 *For the same realized project payoff $y_1 \in \{y_H, y_L\}$ and the CRA's ratings inflation strategy $\hat{\epsilon}_1$, the posterior beliefs on the CRA's quality, given CRA ratings, satisfies that $q_{H,y_1} \leq q_{HH,y_1} \leq q_0 \leq q_{\varnothing\varnothing} \leq q_{\varnothing}$.*

Proof. See the Appendix B. ■ For given the initial belief $\{q_0, \hat{\epsilon}_1\}$, the opportunistic CRA i's optimal strategy for a bad project, ϵ_{i1}, is to maximize its expected payoff

$$\pi^D(\epsilon_{i1}; \hat{\epsilon}_1, q_0) = (1-q_0)\hat{\epsilon}_1 \left\{ \epsilon_{i1} \left[\psi(q_0, \hat{\epsilon}_1) + \gamma \int_{y_1} \psi(q_{HH,y_1}, 1) f_B(y_1) dy_1 \right] + (1-\epsilon_{i1}) \gamma\psi(q_{\varnothing\varnothing}, 1) \right\}$$
$$+ (1-q_0)(1-\hat{\epsilon}_1)\gamma\psi(q_{\varnothing\varnothing}, 1) + q_0\gamma\psi(q_{\varnothing\varnothing}, 1) P_G$$

With probability q_0, the CRA j is a committed one, and will truthfully assign a low rating to the bad project. Therefore, the issuer will remain unrated, regardless of the rating assigned by the CRA i. Conversely, if the CRA j is an opportunistic one, it will inflate the rating with probability $\hat{\epsilon}_1$, and assign a truthful rating otherwise. Thus, the CRA i can only benefit from its inflated rating if the CRA j also inflates the rating simultaneously. In equilibrium, there exists a threshold of reputation cost, $\bar{\gamma}^D$, such that for $\gamma < \bar{\gamma}^D$, opportunistic CRAs always chooses to inflate their ratings, $\hat{\epsilon}_1 = 1$. Otherwise, they takes the interior solutions, i.e. $\hat{\epsilon}_1 \in (0, 1)$.

For simplicity, we use the superscript M to denote the case of a monopolistic CRA,

and D to denote the case of duopolistic CRAs. We assume that the initial reputation cost $\gamma_0 < \min\left\{\bar{\gamma}^M, \bar{\gamma}^D\right\}$, so opportunistic CRAs always inflate their ratings in both cases, i.e., $\hat{\epsilon}_1^M = \hat{\epsilon}_1^D = 1$. We then consider a reputation cost shock that raises the CRA's reputation concerns, and increases the reputation cost from γ_0 to γ_1, where opportunistic CRAs take interior solutions in both cases, i.e. $\gamma_1 > \max\left\{\bar{\gamma}^M, \bar{\gamma}^D\right\}$. In the Appendix B, we provide proofs for Proposition 4.

B Proofs and Derivations

This section provides the proofs of the lemmas and propositions.

Proof for Lemma 1

Proof. The probability of a CRA to be a committed one conditional on a high rating H and the realized project payoff y_1 is

$$\begin{aligned} q_{H,y_1} = Pr\left(\mathcal{C}|r_{i1} = H, y_1\right) &= \left\{1 + \frac{1-q_0}{q_0}\frac{Pr\left(H, y_1|\mathcal{O}\right)}{Pr\left(H, y_1|\mathcal{C}\right)}\right\}^{-1} \\ &= \left\{1 + \frac{1-q_0}{q_0}\frac{Pr\left(y_1, G\right) + Pr\left(y_1, B\right)\hat{\epsilon}_1}{Pr\left(y_1, G\right)}\right\}^{-1} \\ &= \left\{1 + \frac{1-q_0}{q_0}\left(1 + \frac{P\left(y_1, B\right)\hat{\epsilon}_1}{P\left(y_1, G\right)}\right)\right\}^{-1} \leq q_0. \end{aligned}$$

The above inequality holds only when $P\left(y_1, B\right) = 0$ or $\hat{\epsilon}_1 = 0$. Similarly, the probability of a CRA to be a committed one conditional on a null rating is

$$q_{\varnothing} = P\left(\mathcal{C}|\varnothing\right) = \left[1 + \frac{1-q_0}{q_0}\left(1 - \hat{\epsilon}_1\right)\right]^{-1} \geq q_0,$$

which is not related with the realized project payoff. Obviously, we have $\frac{\partial q_{H,y_1}}{\partial \hat{\epsilon}_1} < 0$, and $\frac{\partial q_{\varnothing}}{\partial \hat{\epsilon}_1} > 0$. ■

Proof for Proposition 1

Proof. Take derivations, we have

$$\begin{aligned}\frac{d\pi_i}{d\epsilon_{i1}} &= \psi\left(q_0, \hat{\epsilon}_i\right) + \gamma \int_{y_1} \psi\left(q_{H,y_1}, 1\right) f_B\left(y_1\right) dy_1 - \gamma\psi\left(q_\varnothing, 1\right) \\ &= \left(V_G - V_B\right)\left[p_H\left(q_0, \hat{\epsilon}_i\right) + \gamma \int_{y_1} p_H\left(q_{H,y_1}, 1\right) f_B\left(y_1\right) dy_1 - \gamma p_H\left(q_\varnothing, 1\right)\right] + V_B - I \\ &= \left(V_G - V_B\right)\left[\frac{p_G}{p_G + p_B\left(1 - q_0\right)\hat{\epsilon}_i} + \gamma \int_{y_1} \frac{p_G f_B\left(y_1\right) dy_1}{p_G + p_B\left(1 - q_{H,y_1}\right)} - \gamma \frac{p_G}{p_G + p_B\left(1 - q_\varnothing\right)}\right] + V_B - I\end{aligned}$$

Second-order derivation,

$$\frac{d}{d\hat{\epsilon}_1}\frac{d\pi_i}{d\epsilon_{i1}} = \left(V_G - V_B\right)\left[\frac{\partial p_H}{\partial \hat{\epsilon}_1} + \gamma \int_{y_1} \frac{\partial p_H}{\partial q_{H,y_1}} \frac{\partial q_{H,y_1}}{\partial \hat{\epsilon}_1} f_B\left(y_1\right) dy_1 - \gamma \frac{\partial p_H}{\partial q_\varnothing}\frac{\partial q_\varnothing}{\partial \hat{\epsilon}_1}\right] < 0$$

The above inequality is obtained as $\frac{\partial p_H}{\partial \hat{\epsilon}_1} < 0$, $\frac{\partial q_{H,y_1}}{\partial \hat{\epsilon}_1} < 0$, and $\frac{\partial q_\varnothing}{\partial \hat{\epsilon}_1} > 0$.

For boundary values, we have

$$\begin{aligned}\left.\frac{d\pi_i}{d\epsilon_{i1}}\right|_{\hat{\epsilon}_i = 0} &= \psi\left(q_0, 0\right) + \gamma \int_{y_1} \psi\left(q_0, 1\right) f_B\left(y_1\right) dy_1 - \gamma\psi\left(q_0, 1\right) \\ &= V_G - I > 0\end{aligned}$$

$$\left.\frac{d\pi_i}{d\epsilon_{i1}}\right|_{\hat{\epsilon}_i = 1} = \psi\left(q_0, 1\right) + \gamma \int_{y_1} \psi\left(q_{H,y_1}, 1\right) f_B\left(y_1\right) dy_1 - \gamma\psi\left(q_\varnothing, 1\right)$$

Define the cut-off value $\bar{\gamma}$ such that $\left.\frac{d\pi_i}{d\epsilon_{i1}}\right|_{\hat{\epsilon}_i = 1, \gamma = \bar{\gamma}} = 0$, and $\bar{\gamma}$ can be solved as

$$\bar{\gamma} \equiv \frac{\psi\left(q_0, 1\right)}{\psi\left(q_0, 1\right) - \int_{y_1} \psi\left(q_{H,y_1}, 1\right) f_B\left(y_1\right) dy_1} = \frac{p_H\left(q_0, 1\right) - \left(I - V_B\right)/\left(V_G - V_B\right)}{p_H\left(q_\varnothing, 1\right) - \int_{y_1} p_H\left(q_{H,y_1}, 1\right) f_B\left(y_1\right) dy_1},$$

where $q_\varnothing$ and q_{H,y_1} is evaluated at $\hat{\epsilon}_1 = 1$.

For $\gamma > \bar{\gamma}$, we have

$$\begin{aligned}\frac{\partial}{\partial\gamma}\frac{d\pi_i}{d\epsilon_{i1}} &= \int_{y_1} \psi\left(q_{H,y_1},1\right) f_B\left(y_1\right) dy_1 - \psi\left(q_{\varnothing},1\right) \\ &= \left(V_G - V_B\right)\left[\int_{y_1} \frac{p_G f_B\left(y_1\right) dy_1}{p_G + p_B\left(1-q_{H,y_1}\right)} - \frac{p_G}{p_G + p_B\left(1-q_{\varnothing}\right)}\right] < 0\end{aligned}$$

The above inequality holds as $q_{H,y_1} < q_{\varnothing}$ for any y_1. Therefore, we conclude that $\frac{\partial\hat{\epsilon}_1}{\partial\gamma} < 0$. ■

Proof for Proposition 2

Proof. Take partial derivation w.r.t. the issuer's safety p_G, we have that

$$\begin{aligned}\frac{\partial}{\partial p_G}\frac{d\pi_{it}}{d\epsilon_{it}} = &\frac{\left(1-q_0\right)\hat{\epsilon}_i/p_G^2}{\left[1+\left(1/p_G-1\right)\left(1-q_0\right)\hat{\epsilon}_i\right]^2} + \gamma\int_{y_1}\frac{\left(1/p_G-1\right)\frac{\partial q_{H,y_1}}{\partial p_G} f_B\left(y_1\right) dy_1}{\left[1+\left(1/p_G-1\right)\left(1-q_{H,y_1}\right)\right]^2} \\ &+\gamma\left\{\int_{y_1}\frac{\left(1-q_{H,y_1}\right)/p_G^2 f_B\left(y_1\right) dy_1}{\left[1+\left(1/p_G-1\right)\left(1-q_{H,y_1}\right)\right]^2} - \frac{\left(1-q_{\varnothing}\right)/p_G^2}{\left[1+\left(1/p_G-1\right)\left(1-q_{\varnothing}\right)\right]^2}\right\}\end{aligned}$$

Note that the posterior belief q_{H,y_1} is increasing with the issuer's safety p_G, as

$$\begin{aligned}\frac{\partial q_{H,y_1}}{\partial p_G} &= \frac{1-q_0}{q_0}\frac{P\left(y_1|B\right)\hat{\epsilon}_1}{P\left(y_1|G\right)}\left\{1+\frac{1-q_0}{q_0}\left(1+\frac{1-p_G}{p_G}\frac{P\left(y_1|B\right)\hat{\epsilon}_1}{P\left(y_1|G\right)}\right)\right\}^{-2}/p_G^2 \\ &= \frac{1-q_0}{q_0}\frac{P\left(y_1|B\right)\hat{\epsilon}_1}{P\left(y_1|G\right)} q_{H,y_1}^2/p_G^2 > 0.\end{aligned}$$

Moreover, for $\frac{(1-q)}{[p_G+(1-p_G)(1-q)]^2}$, take first-order derivation, we can obtain that

$$\begin{aligned}\frac{\partial}{\partial q}\frac{(1-q)}{\left[p_G+(1-p_G)(1-q)\right]^2} &= \frac{-1}{\left[p_G+(1-p_G)(1-q)\right]^2}+\frac{2(1-q)(1-p_G)}{\left[p_G+(1-p_G)(1-q)\right]^3}\\ &= \frac{-p_G+(1-q)(1-p_G)}{\left[p_G+(1-p_G)(1-q)\right]^3}<0,\end{aligned}$$

the above inequality holds under the the assumption that $p_G > (1-q)(1-p_G)$. As $q_{H,y_1} \leq q_0 \leq q_\varnothing$, for any $y_1 \in \{y_H, y_L\}$, we have that,

$$\frac{(1-q_{H,y_1})}{\left[p_G+(1-p_G)(1-q_{H,y_1})\right]^2} > \frac{(1-q_\varnothing)}{\left[p_G+(1-p_G)(1-q_\varnothing)\right]^2}.$$

So we can obtain that $\frac{\partial}{\partial p_G}\frac{d\pi_{it}}{d\epsilon_{i1}} > 0$. As $\frac{d\pi_{it}}{d\epsilon_{i1}} < 0$, we conclude that, in equilibrium, $\frac{\partial \hat{\epsilon}_1}{\partial p_G}\Big|_{\gamma=\gamma_1} > 0$. ■

Proof for Proposition 3

Proof. Take partial derivation w.r.t. the CRA's quality q_0, we have that

$$\begin{aligned}\frac{\partial}{\partial q_0}\frac{d\pi_i}{d\epsilon_{i1}} &= (V_G-V_B)\left[\frac{p_G p_B \hat{\epsilon}_i}{\left[p_G+p_B(1-q_0)\hat{\epsilon}_i\right]^2}+\gamma\int_{y_1}\frac{p_G p_B \frac{\partial q_{H,y_1}}{\partial q_0} f_B(y_1)\,dy_1}{\left[p_G+p_B(1-q_{H,y_1})\right]^2}-\gamma\frac{p_G p_B \frac{\partial q_\varnothing}{\partial q_0}}{\left[p_G+p_B(1-q_\varnothing)\right]^2}\right]\\ &= (V_G-V_B)\,p_G p_B\left[\frac{\hat{\epsilon}_i}{\left[p_G+p_B(1-q_0)\hat{\epsilon}_i\right]^2}+\gamma\int_{y_1}\frac{\left(1+\frac{P(y_1,B)\hat{\epsilon}_1}{P(y_1,G)}\right)\left(\frac{q_{H,y_1}}{q_0}\right)^2 f_B dy_1}{\left[p_G+p_B(1-q_{H,y_1})\right]^2}-\frac{\gamma(1-\hat{\epsilon}_1)\left(\frac{q_\varnothing}{q_0}\right)^2}{\left[p_G+p_B(1-q_\varnothing)\right]^2}\right]\\ &= (V_G-V_B)\,p_G p_B\left[\frac{\hat{\epsilon}_i}{\left[p_G+p_B(1-q_0)\hat{\epsilon}_i\right]^2}+\gamma\frac{\left(1+\frac{P_B\hat{\epsilon}_1}{P_G(1-f)}\right)\left(\frac{q_{H,y_L}}{q_0}\right)^2}{\left[p_G+p_B(1-q_{H,y_L})\right]^2}-\gamma\frac{(1-\hat{\epsilon}_1)\left(\frac{q_\varnothing}{q_0}\right)^2}{\left[p_G+p_B(1-q_\varnothing)\right]^2}\right]\end{aligned}$$

The last equality holds as $Pr\left(y_L\middle|\theta=B\right)=1$, and $Pr\left(y_L\middle|\theta=G\right)=1-f$. Substitute q_{H,y_1} and $q_{\varnothing}$, we have,

$$\begin{aligned}
&\frac{\left(1+\frac{P_B\hat{\epsilon}_1}{P_G(1-f)}\right)\left(\frac{q_{H,y_L}}{q_0}\right)^2}{\left[p_G+p_B\left(1-q_{H,y_L}\right)\right]^2}-\frac{\left(1-\hat{\epsilon}_1\right)\left(\frac{q_{\varnothing}}{q_0}\right)^2}{\left[p_G+p_B\left(1-q_{\varnothing}\right)\right]^2}\\
=&\frac{\left(1+\frac{P_B\hat{\epsilon}_1}{P_G(1-f)}\right)}{\left[q_0p_G+\left(1-q_0\right)\left(1+\frac{P_B\hat{\epsilon}_1}{P_G(1-f)}\right)\right]^2}-\frac{\left(1-\hat{\epsilon}_1\right)}{\left[q_0p_G+\left(1-q_0\right)\left(1-\hat{\epsilon}_1\right)\right]^2}\\
=&\frac{\left(\hat{\epsilon}_1+\frac{P_B\hat{\epsilon}_1}{P_G(1-f)}\right)\left[q_0^2p_G^2-\left(1-q_0\right)^2\left(1-\hat{\epsilon}_1\right)\left(1+\frac{p_B\hat{\epsilon}_1}{p_G(1-f)}\right)\right]}{\left[q_0p_G+\left(1-q_0\right)\left(1+\frac{P_B\hat{\epsilon}_1}{P_G(1-f)}\right)\right]^2\left[q_0p_G+\left(1-q_0\right)\left(1-\hat{\epsilon}_1\right)\right]^2}
\end{aligned}$$

Therefore, one sufficient condition to ensure that $\frac{\partial}{\partial q_0}\frac{d\pi_i}{d\epsilon_{i1}}>0$ is $q_0p_G>(1-q_0)$. As $\frac{d\pi_{it}}{d\epsilon_{i1}}<0$, so we conclude that, in equilibrium, $\frac{\partial\hat{\epsilon}_1}{\partial p_G}\Big|_{\gamma=\gamma_1}>0$. ■

Proof for Lemma 2

Proof. The probability of a CRA to be a committed one conditional on high ratings HH and the realized project payoff y_1 is

$$\begin{aligned}
q_{HH,y_1}=P\left(\mathcal{C}|HH,y_1\right)&=\left\{1+\frac{1-q_0}{q_0}\frac{P\left(HH,y_1|\mathcal{O}\right)}{P\left(HH,y_1|\mathcal{C}\right)}\right\}^{-1}\\
&=\left\{1+\frac{1-q_0}{q_0}\frac{P\left(y_1,G\right)+P\left(y_1,B\right)\left(1-q_0\right)\hat{\epsilon}_1^2}{P\left(y_1,G\right)}\right\}^{-1}\\
&=\left\{1+\frac{1-q_0}{q_0}\left[1+\frac{P\left(y_1,B\right)\left(1-q_0\right)\hat{\epsilon}_1^2}{P\left(y_1,G\right)}\right]\right\}^{-1}\\
&\geq\left\{1+\frac{1-q_0}{q_0}\left[1+\frac{P\left(y_1,B\right)\left(1-q_0\right)\hat{\epsilon}_1}{P\left(y_1,G\right)}\right]\right\}^{-1}=q_{H,y_1}
\end{aligned}$$

Similarly, the probability of a CRA to be a committed one conditional on the issuer remained unrated is

$$q_{\varnothing\varnothing} = P\left(\mathcal{C}|\varnothing\varnothing\right) = \left[1 + \frac{1-q_0}{q_0}\left(1-\left(1-q_0\right)\hat{\epsilon}_1^2\right)\right]^{-1}$$
$$\leq \left[1 + \frac{1-q_0}{q_0}\left(1-\hat{\epsilon}_1\right)\right]^{-1} = q_{\varnothing}.$$

■

Proof for Proposition 4

Proof. For the case of duopolistic CRAs,

$$\frac{d\pi^D}{d\epsilon_{i1}} = \left(1-q_0\right)\hat{\epsilon}_1 \left[\underbrace{\psi\left(q_0,\hat{\epsilon}_1\right) + \gamma\int_{y_1}\psi\left(q_{HH,y_1},1\right)f_B\left(y_1\right)dy_1 - \gamma\psi\left(q_{\varnothing\varnothing},1\right)}_{\equiv A(\hat{\epsilon}_1)}\right]$$

Thus, for $\gamma = \gamma_1 > \bar{\gamma}^D$, $\hat{\epsilon}_1^D$ solves that $A\left(\hat{\epsilon}_1\right) = 0$, or equivalently,

$$p_{HH}\left(q_0,\hat{\epsilon}_1\right) + \gamma\int_{y_1} p_{HH}\left(q_{HH,y_1},1\right)f_B\left(y_1\right)dy_1 - \gamma p_{HH}\left(q_{\varnothing\varnothing},1\right) = \frac{I-V_B}{V_G-V_B}$$

$$\frac{p_G}{p_G + p_B\left[\left(1-q_0\right)\hat{\epsilon}_1\right]^2} + \gamma\int_{y_1}\frac{p_G f_B\left(y_1\right)dy_1}{p_G + p_B\left(1-q_{HH,y_1}\right)^2} - \gamma\frac{p_G}{p_G + p_B\left(1-q_{\varnothing\varnothing}\right)^2} = \frac{I-V_B}{V_G-V_B}$$

For the case of the monopolistic CRA, $\hat{\epsilon}_1^M$ solves that

$$\psi\left(q_0,\hat{\epsilon}_1\right) + \gamma\int_{y_1}\psi\left(q_{H,y_1},1\right)f_B\left(y_1\right)dy_1 - \gamma\psi\left(q_{\varnothing},1\right) = 0.$$

$$\frac{p_G}{p_G + p_B\left(1-q_0\right)\hat{\epsilon}_1} + \gamma\int_{y_1}\frac{p_G f_B\left(y_1\right)dy_1}{p_G + p_B\left(1-q_{H,y_1}\right)} - \gamma\frac{p_G}{p_G + p_B\left(1-q_{\varnothing}\right)} = \frac{I-V_B}{V_G-V_B}$$

So $\hat{\epsilon}_1^M(\gamma_1) < \hat{\epsilon}_1^D(\gamma_1)$ is equivalent to $A\left(\hat{\epsilon}_1^M\right) > 0$, or

$$\begin{aligned}
A\left(\hat{\epsilon}_1^M\right) =& \frac{p_G}{p_G + p_B\left[(1-q_0)\hat{\epsilon}_1\right]^2} + \gamma\int_{y_1}\frac{p_G f_B(y_1)\,dy_1}{p_G + p_B\left(1-q_{HH,y_1}\right)^2} - \gamma\frac{p_G}{p_G + p_B(1-q_0)^2} - \frac{I-V_B}{V_G-V_B} \\
=& \frac{p_G}{p_G + p_B\left[(1-q_0)\hat{\epsilon}_1\right]^2} + \gamma\frac{p_G p_B\left[(1-q_{H,y_L}) - (1-q_{HH,y_L})^2\right]}{\left[p_G + p_B(1-q_{H,y_L})\right]\left[p_G + p_B\left(1-q_{HH,y_L}\right)^2\right]} \\
& - \gamma\frac{p_G p_B\left[(1-q_\varnothing) - (1-q_{\varnothing\varnothing})^2\right]}{\left[p_G + p_B(1-q_\varnothing)\right]\left[p_G + p_B\left(1-q_{\varnothing\varnothing}\right)^2\right]}
\end{aligned}$$

One sufficient condition for $A\left(\hat{\epsilon}_1^M\right) > 0$ is that

$$B\left(\hat{\epsilon}_1^M\right) = \gamma\frac{p_G p_B\left[(1-q_{H,y_L}) - (1-q_{HH,y_L})^2\right]}{\left[p_G + p_B(1-q_{H,y_L})\right]\left[p_G + p_B\left(1-q_{HH,y_L}\right)^2\right]} - \gamma\frac{p_G p_B\left[(1-q_\varnothing) - (1-q_{\varnothing\varnothing})^2\right]}{\left[p_G + p_B(1-q_\varnothing)\right]\left[p_G + p_B\left(1-q_{\varnothing\varnothing}\right)^2\right]} > 0.$$

Specifically, for $\hat{\epsilon}_1^M = 0$, we have $q_{H,y_L} = q_{HH,y_L} = q_\varnothing = q_{\varnothing\varnothing} = q_0$, and $B(0) = 0$. For $\hat{\epsilon}_1^M = 1$, we have $q_\varnothing = 1$, and $q_{\varnothing\varnothing} = \frac{1}{2-q_0} < 1$, so that $B(1) > 0$.

(i) Take derivation, for the first term of $B\left(\hat{\epsilon}_1^M\right)$, we have

$$\begin{aligned}
& \frac{\partial}{\partial\hat{\epsilon}_1^M}\left\{\gamma\frac{p_G p_B\left[(1-q_\varnothing) - (1-q_{\varnothing\varnothing})^2\right]}{\left[p_G + p_B(1-q_\varnothing)\right]\left[p_G + p_B\left(1-q_{\varnothing\varnothing}\right)^2\right]}\right\} \\
=& \gamma p_G p_B\frac{-\frac{\partial q_\varnothing}{\partial\hat{\epsilon}_M}\left[p_G + p_B\left(1-q_{\varnothing\varnothing}\right)^2\right]^2 + 2\left(1-q_{\varnothing\varnothing}\right)\frac{\partial q_{\varnothing\varnothing}}{\partial\hat{\epsilon}_M}\left[p_G + p_B(1-q_\varnothing)\right]^2}{\left[p_G + p_B(1-q_\varnothing)\right]^2\left[p_G + p_B\left(1-q_{\varnothing\varnothing}\right)^2\right]^2} \\
=& \gamma p_G p_B\frac{1-q_0}{q_0}\frac{-q_\varnothing^2\left[p_G + p_B\left(1-q_{\varnothing\varnothing}\right)^2\right]^2 + 4\left(1-q_{\varnothing\varnothing}\right)(1-q_0)\hat{\epsilon}_1 q_{\varnothing\varnothing}^2\left[p_G + p_B(1-q_\varnothing)\right]^2}{\left[p_G + p_B(1-q_\varnothing)\right]^2\left[p_G + p_B\left(1-q_{\varnothing\varnothing}\right)^2\right]^2} < 0
\end{aligned}$$

The last inequality holds as $q_\varnothing > q_{\varnothing\varnothing} > q_0 > \frac{1}{2}$, and $\hat{\epsilon}_1^M \leq 1$.

Take derivations for the second term of $B\left(\hat{\epsilon}_1^M\right)$, we have

$$\begin{aligned}
&\frac{\partial}{\partial \hat{\epsilon}_1^M}\gamma\frac{p_G p_B\left[(1-q_{H,y_L})-(1-q_{HH,y_L})^2\right]}{\left[p_G+p_B(1-q_{H,y_L})\right]\left[p_G+p_B(1-q_{HH,y_L})^2\right]} \\
=&\gamma p_G p_B\frac{-\frac{\partial q_{H,y_L}}{\partial \hat{\epsilon}_M}\left[p_G+p_B(1-q_{HH,y_L})^2\right]^2+2(1-q_{HH,y_L})\frac{\partial q_{HH,y_L}}{\partial \hat{\epsilon}_M}\left[p_G+p_B(1-q_{H,y_L})\right]^2}{\left[p_G+p_B(1-q_{H,y_L})\right]^2\left[p_G+p_B(1-q_{HH,y_L})^2\right]^2} \\
=&\gamma\frac{(1-q_0)p_B^2}{q_0(1-f)}\frac{q_{H,y_L}^2\left[p_G+p_B(1-q_{HH,y_L})^2\right]^2-4(1-q_{HH,y_L})(1-q_0)\hat{\epsilon}_M q_{HH,y_L}^2\left[p_G+p_B(1-q_{H,y_L})\right]^2}{\left[p_G+p_B(1-q_{H,y_L})\right]^2\left[p_G+p_B(1-q_{HH,y_L})^2\right]^2}<0
\end{aligned}$$

The above inequality holds for sufficiently small $\hat{\epsilon}_1^M$. Therefore, for relatively small $\hat{\epsilon}_1^M$, we have that $\frac{\partial B\left(\hat{\epsilon}_1^M\right)}{\partial \hat{\epsilon}_1^M}>0$, and hence, $B\left(\hat{\epsilon}_1^M\right)>B(0)=0$.

(ii) Furthermore, one sufficient condition to ensure that $(1-q_\varnothing)<(1-q_{\varnothing\varnothing})^2$ is

$$\left(1-(1-q_0)\hat{\epsilon}_1^2\right)\left[1-(1-q_0)\hat{\epsilon}_1\right]<q_0\hat{\epsilon}_1,$$

which holds for relatively large $\hat{\epsilon}_1^M$. Therefore, for relatively large $\hat{\epsilon}_1^M$., the first term of $B\left(\hat{\epsilon}_1^M\right)$ is positive, while the second term of $B\left(\hat{\epsilon}_1^M\right)$ is negative.

Above all, we can conclude that $B(\hat{\epsilon}_M)>0$, and thereby, $\hat{\epsilon}_1^M(\gamma_1)<\hat{\epsilon}_1^D(\gamma_1)$. ■

C Institutional Background

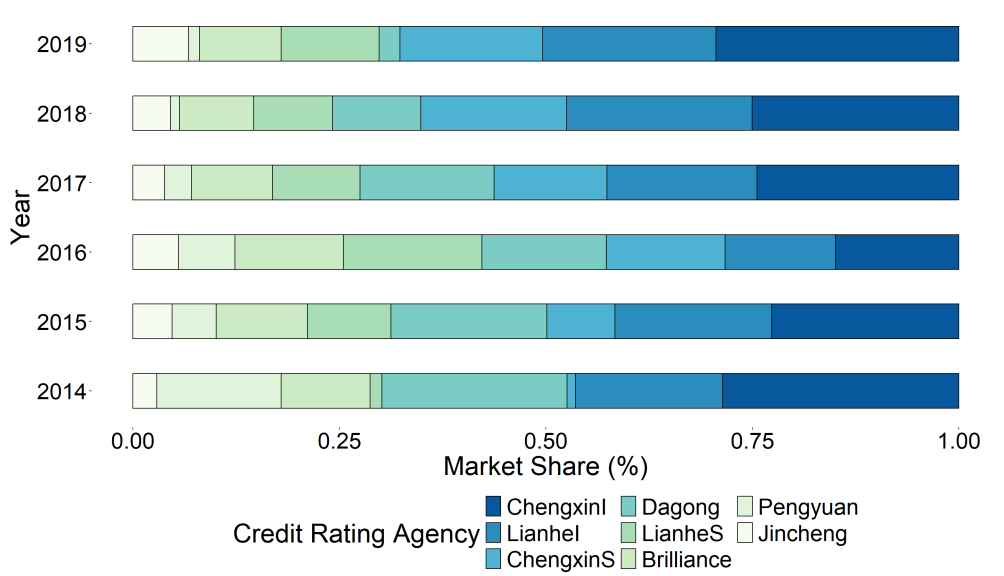
During the past two decades, the Chinese bond market has developed dramatically, with its market value reaching approximately 100 trillion RMB (around $14 trillion) at the end of 2019. It surpasses Japan and is now the second-largest market in the world behind the United States. However, this rapid market growth has been accompanied by significant problems, particularly regarding the quality of credit ratings. Credit ratings, which serve as crucial intermediaries by bridging information asymmetries between bond issuers and investors, are expected to be accurate and timely in predicting issuers' credit quality. However, in the Chinese corporate bond market, there is a notable prevalence of inflated ratings, with more than 95% of bonds rated in the top three categories (AAA, AA+, or AA). Consequently, AA is generally considered the lowest investment grade level in China, whereas this threshold is BBB in global ratings (Amstad and He, 2020). This excessive concentration of high ratings impairs investors' ability to differentiate between varying risk profiles effectively. Furthermore, the lack of comparability with international rating scales complicates investment decisions for foreign investors, who may struggle to accurately assess the true creditworthiness of Chinese bonds (Livingston et al., 2018).

There are mainly three reasons for the ratings inflation phenomenon in the Chinese corporate bond market:

Firstly, the Chinese credit rating industry is highly competitive compared to its US counterpart. Although the US market is dominated by S&P, Moody's, and Fitch, the Chinese market features eight major issuer-paid CRAs that operate in various sectors (see Livingston et al., 2018; Jiang and Packer, 2019; Hu et al., 2019, 2020, for a more detailed discussion of Chinese CRAs). As shown in Figure C1, which illustrates the year-by-year market share of each credit rating agency, the Chinese credit rating industry resembles a competitive environment without a dominant market player, unlike the oligopoly seen in the US (Livingston et al., 2018). The distribution of CRA market share within each sector, as shown in Fig-

ure C2, also supports this observation, with most CRAs actively participating in multiple sectors rather than specializing in a specific one.[15] In such a fiercely competitive market environment, CRAs tend to gain market share by catering to bond issuers, leading to more frequent rating shopping behaviors, as issuers can more easily switch between CRAs (Becker and Milbourn, 2011; Bolton et al., 2012).[16]

Figure C1. CRA market share by year (amount%)

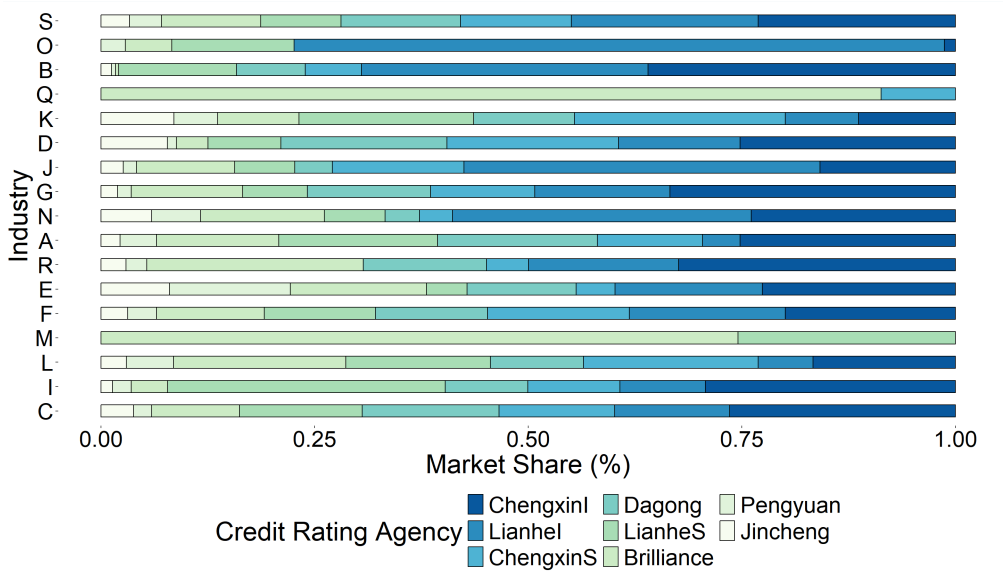


Notes: This figure plots the annual distribution of market shares for each of the eight CRAs between 2014 and 2019.

[15] Although some exceptions exist, such as the sectors of scientific research and technological services or healthcare and social services being primarily occupied by two CRAs, these anomalies are due to the limited number of bond issuances in these fields.

[16] As noted by Livingston et al. (2018) and Amstad and He (2020), dual ratings and unsolicited ratings are quite uncommon in China. Standard long-term corporate bonds issued in the Chinese market are typically required to be rated by only one credit rating agency.

Figure C2. CRA market share by industry (amount%)



Notes: This figure plots the distribution of market share across 17 sectors for the eight CRAs. Industry classification follows the categories defined by the China Securities Regulatory Commission.

Secondly, regulators are heavily dependent on bond ratings to conduct regulation and manage risks, which in turn increases the demand for elevated bond ratings. For example, money market funds are only allowed to invest in bonds rated higher than AA, as stipulated by the CSRC decree No. [2018] 120. Additionally, only AAA enterprise bonds with issuer ratings of AA and above can be used for bond-pledged repurchase agreements, according to CSDC No. [2014] 149. This regulatory reliance on bond ratings drives bond issuers to seek higher ratings in order to broaden their investor base and meet regulatory requirements, thereby contributing to the phenomenon of ratings inflation.

Lastly, and perhaps most importantly, the prevalent existence of implicit government guarantees and the historically low default probabilities place CRAs in a less disciplined environment. The first corporate bond default in China occurred only in March 2014 (Shanghai Chaori), and although there have been several waves of defaults since then, the default rate

remains below 1% according to the Wind dataset, which is significantly lower than the international average (Zhang and Wu, 2019). Due to the rarity of bond defaults and the consequent weak visibility of rating performance, CRAs in China have less incentive to improve their ratings quality. The common practice of implicit guarantees further contributes to inflated bond ratings (Dong et al., 2021), as these guarantees reduce the perceived risk associated with the bonds, thereby diminishing the motivation for CRAs to rigorously assess and reflect the true credit risk.

This ratings inflation issue and the underlying institutional reasons underscore the need for regulatory reforms to improve the credibility and functionality of the Chinese credit rating system, thus better serving the overall healthy development of the bond market. In response to these challenges, the regulatory authorities issued a notice in 2021 aimed at promoting the healthy development of the credit rating industry in the bond market.[17] The notice explicitly outlines several key requirements: strengthening the construction of rating methodology systems to improve ratings quality and differentiation; improving corporate governance and internal control mechanisms within credit rating agencies to maintain rating independence; strengthening information disclosure and enhancing market discipline mechanisms by encouraging fair competition and building a market-based evaluation system based on ratings quality and led by investor opinions; optimizing the rating ecosystem and creating a fair and just market environment by reducing regulatory reliance on external ratings; and increasing supervision of credit rating agencies, along with the imposition of stricter penalties for noncompliance.

[17]Source: https://www.gov.cn/zhengce/zhengceku/2021-08/08/content_5630150.htm

D Appendix Tables & Figures

Table D1. Variable Definitions

Variables	Definitions
Dependent Variable	
Ratings Inflation	Difference between the bond rating given by the issuer-paid rating agency and the initial bond market-implied rating at issuance.
Issuer-paid Ratings	Bond ratings assigned by issuer-paid rating agencies at issuance.
Market-implied Ratings	The initial bond market-implied ratings.
Independent Variable	
Default6M	Indicator variable equal to one if there were bond defaults in the issuer's industry during the six months prior to the bond issuance and zero otherwise.
Issuer-level Variables	
SOE	Indicator variable equal to one if the bond issuer is a state-owned enterprise and zero otherwise.
Listed	Indicator variable equal to one if the bond issuer is publicly listed at issuance and zero otherwise.
Log(Assets)	The natural logarithm of one plus bond issuer's total amount of assets (in million RMB).
Leverage	The ratio of a firm's total long-term debt to its total assets.
ROE	The ratio of a firm's earnings before interest, taxes, depreciation, and amortization (EBITDA) to its total equity.
Cash flow/Assets	The ratio of a firm's operating cash flow to its total assets.
Bond-level Variables	
Log(Amount)	Natural logarithm of bond's issuance amount (in billion RMB).
Maturity	Bond maturity (in years).

Continued on next page

Table D1 – *Continued from previous page*

Variables	Definitions
Cross-listed	Indicator variable equal to one if the bond is dual-listed in both the interbank and the exchange market and zero otherwise.
Guaranteed	Indicator variable equal to one if the bond is embedded with an external guarantee and zero otherwise.

Notes: This table presents the definitions of the variables in the baseline regression model.

Table D2. Validation of Ratings Quality Proxy

Dep. Var.:	Ratings Inflation	Ratings Inflation	Ex-post Default Probability	Uprating	Downrating
	(1)	(2)	(3)	(4)	(5)
Frequent Issuer		0.100***			
		(4.340)			
Ratings Inflation			0.039***	-0.617***	0.604***
			(4.671)	(-7.746)	(3.066)
SOE	-0.561***	-0.560***	-0.198***	-0.580***	-1.823***
	(-12.514)	(-12.532)	(-7.907)	(-3.501)	(-4.578)
Listed	-0.049	-0.054	0.012	0.107	-0.417
	(-1.330)	(-1.496)	(0.576)	(0.660)	(-1.304)
Log(Assets)	0.002	-0.016	0.013**	-0.163***	-0.219
	(0.155)	(-1.004)	(2.396)	(-2.783)	(-1.294)
Leverage	0.005***	0.005***	0.000	0.010***	0.025**
	(5.116)	(5.059)	(1.510)	(2.796)	(2.507)
ROE	-0.008***	-0.008***	0.002**	0.020**	-0.018
	(-3.389)	(-3.250)	(2.052)	(2.499)	(-0.948)
Cash flow/Assets	-0.550***	-0.576***	-0.158**	-1.607**	-2.751*
	(-2.983)	(-3.132)	(-2.430)	(-2.050)	(-1.702)
Bond Controls			Yes		
Fixed Effects			Year, CRA, Industry, Province, Bond Type		
Observations	10136	10136	10136	10136	10136
R-squared	0.391	0.393	0.281	0.151	0.332

Notes: This table reports results validating the ratings inflation proxy. Columns (1)–(3) report OLS regression results, while Columns (4)–(5) report logit regression results. In Columns (1) and (2), the dependent variable is *Ratings Inflation*, defined as the difference between the issuer-paid and market-implied ratings. In Column (2), the key independent variable, *FrequentIssuer*, is a dummy equal to 1 if an issuer's annual bond issuance volume exceeds the yearly median, and 0 otherwise. In Columns (3)–(5), the key independent variable is *Ratings Inflation*. The dependent variable in Column (3), *Ex-post Default Probability*, equals 1 if the bond defaults by 2023, and 0 otherwise. In Column (4), the dependent variable, *Uprating*, equals 1 if the first subsequent issuer-paid rating exceeds the initial rating, and 0 otherwise. In Column (5), the dependent variable, *Downrating*, equals 1 if the first subsequent issuer-paid rating is lower than the initial rating, and 0 otherwise. Control variables follow those in Table 2. Fixed effects for year, CRA, industry of the issuer, province of the issuer, and bond type are included. Robust standard errors are clustered at the issuer level. T-statistics or z-statistics of the coefficient estimates are reported in parentheses. Symbols ***, **, * indicate statistical significance at the levels 1%, 5%, and 10%, respectively.

Table D3. Compare Intra-industry Defaults vs. Inter-industry Defaults

Dep.Var.:	Ratings Inflation	
	(1)	(2)
Intra- vs. Intra-+Inter-Defaults	-0.087	
	(-0.536)	
Inter- vs. Intra-+Inter-Defaults		-0.074***
		(-3.095)
Controls	YES	
Fixed Effects	Year, CRA, Industry, Province, Bond Type	
Observations	5812	10781
R-squared	0.407	0.398

Notes: This table reports OLS regression results comparing the effects of intra-industry and inter-industry defaults on ratings inflation. Column (1) contrasts cases with only intra-industry defaults against those with both intra- and inter-industry defaults in the past six months. Column (2) compares cases with only inter-industry defaults to those with both types in the same period. The dependent variable, *Ratings Inflation*, captures the deviation between assigned ratings and market-implied ratings, serving as a measure of rating quality. Control variables align with those in Table 2. Fixed effects for year, CRA, industry of the issuer, province of the issuer, and bond type are included. Robust standard errors are clustered at the issuer level. T-statistics of the coefficient estimates are reported in parentheses. Symbols ***, **, * indicate statistical significance at the levels 1%, 5%, and 10%, respectively.

Table D4. Robustness: Alternative Definitions of Bond Defaults

	Drop interval>6M	Industry 1st default	2-digit industry
Dep.Var.:	Ratings Inflation		
	(1)	(2)	(3)
Default6M	-0.071***	-0.110***	-0.047**
	(-3.086)	(-3.683)	(-2.130)
Controls	YES		
Fixed Effects	Year, CRA, Industry, Province, Bond Type		
Observations	9695	11701	11088
R-squared	0.392	0.422	0.416

Notes: This table reports robustness results using alternative definitions of the default indicator. Column (1) excludes the bond issuances with a term lag being more than 6 months after bond defaults. Column (2) uses the industry-level first default *industry 1st default* as the indicator variable. In Column (3), we modify the industry classification by using the 2-digit code. Control variables are identical to those in Table 2. Fixed effects for year, CRA, industry of the issuer, province of the issuer, and bond type are included. Robust standard errors are clustered at the issuer level. T-statistics of the coefficient estimates are reported in parentheses. Symbols of ***, **, * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table D5. Robustness: Alternative Window Horizons

Dep.Var.:	Ratings Inflation			
	(1)	(2)	(3)	(4)
Default6M	-0.056**			
	(-2.428)			
Default9M		-0.081***		
		(-3.262)		
Default1Y			-0.070***	
			(-2.645)	
Default1.5Y				-0.076**
				(-2.561)
Controls	Yes			
Fixed Effects	Year, CRA, Industry, Province, Bond Type			
Observations	10136	9801	9589	9364
R-squared	0.392	0.394	0.396	0.396

Notes: This table reports robustness results using different time windows. Columns (1)-(4) show the results for six months, nine months, one year, and one and a half years, respectively. Control variables are identical to those in Table 2. Fixed effects for year, CRA, industry of the issuer, province of the issuer, and bond type are included. Robust standard errors are clustered at the issuer level. T-statistics of the coefficient estimates are reported in parentheses. Symbols ***, **, * indicate statistical significance at the levels 1%, 5%, and 10%, respectively.

Table D6. Robustness: Issuer Ratings Quality

Dep.Var.:	Ratings Inflation		
	(1)	(2)	(3)
Default6M	-0.012*	-0.016**	-0.009*
	(-1.680)	(-2.103)	(-1.762)
Issuer Controls		YES	
Fixed Effects		Issuer, CRA	
YearQuarter FE	YES		
Province*YearQuarter FE		YES	
Issuer-paid Ratings*YearQuarter FE			YES
Observations	14376	14376	14376
R-squared	0.911	0.919	0.962

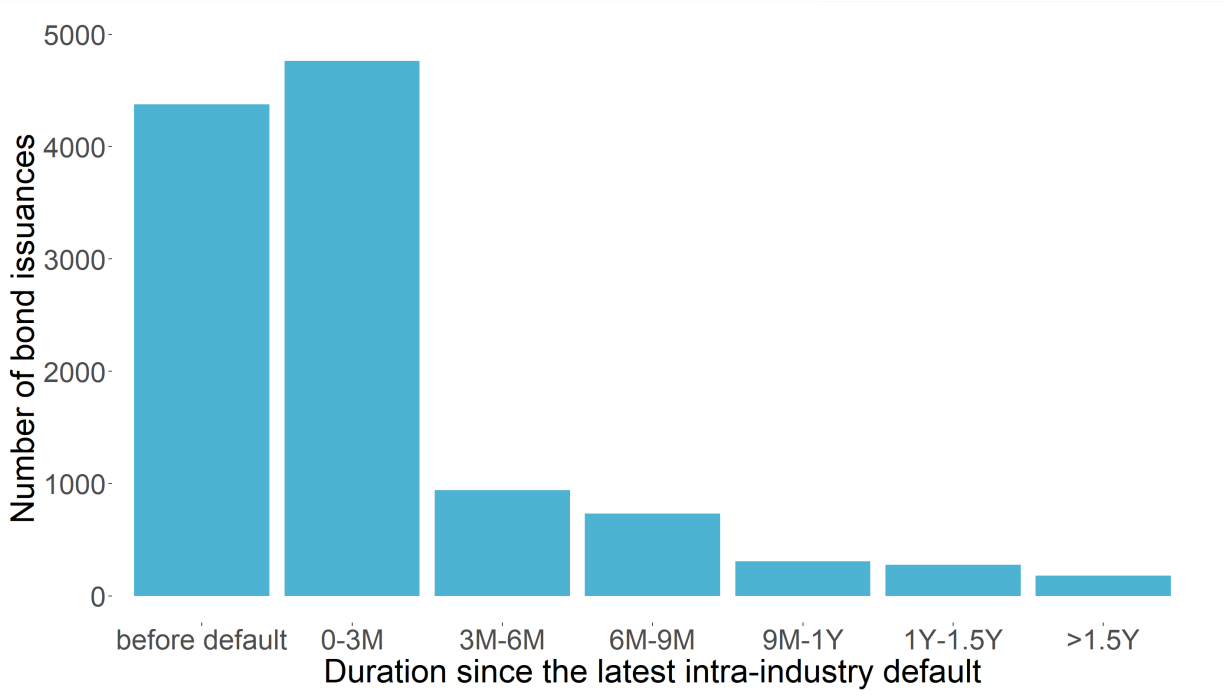
Notes: This table reports robustness results using issuers' ratings. *Ratings Inflation* is measured as the difference between issuer-paid ratings and China Bond Ratings, which are issued by the government-backed, investor-paid rating agency China Bond Rating Co., Ltd. *Default6M* captures whether any bond defaults occurred within the same industry in the past six months. All models include issuer and CRA fixed effects. Column (1) additionally includes year-quarter fixed effects. Column (2) incorporates province*year-quarter fixed effects to account for time-varying unobservables within each province. Column (3) further adds issuer-paid ratings*year-quarter fixed effects to control for dynamic unobservables within each rating level. Issuer control variables remain consistent with those in Table 2. Robust standard errors are clustered at the issuer level. T-statistics of the coefficient estimates are reported in parentheses. Symbols ***, **, * indicate statistical significance at the levels 1%, 5%, and 10%, respectively.

Table D7. Coverage of Bond Issuers by China Bond Rating (CBR) Co., Ltd.

	Total Number of Bond Issuers	CBR Coverage	Coverage Rate
Year	(1)	(2)	(3)
2014	1113	242	21.74%
2015	1205	263	21.83%
2016	1636	373	22.80%
2017	968	249	25.72%
2018	1021	510	49.95%
2019	1120	587	52.41%
2014-2019 Average			32.41%

Notes: This table reports the annualized number of bond issuers and the corresponding coverage by China Bond Rating Co., Ltd. from 2014 to 2019. Column (1) represents the total number of bond issuers each year, while Column (2) refers to those rated by China Bond Rating Co., Ltd. Column (3) reports Coverage Rate, calculated as the percentage of CBR-rated issuers relative to the total issuers.

Figure D1. Bond default timeline distribution



Notes: This figure shows the distribution of the number of bond issues based on the duration between the latest default within the same industry and the bond issuance date.