Punishment on the Rating Agencies

Abstract

We study the effect of regulatory punishment in the oligopolistic credit rating market. We exploit a unique feature of the Chinese credit rating market, where a government-backed rating agency (China Bond Rating Co. Ltd., CBR) provides independent ratings. Utilizing a policy shock of Dagong Global Credit Rating Co. Ltd.'s license suspension, we compare quality changes in the ratings of issuer-paid credit rating agency (CRA) around Dagong's market exit and re-entry. We show that the punishment only has a short-term deterring effect on Dagong but worsens the quality of its ratings in the post suspension periods. the suspension. Among non-punishee rating agencies, less competitive CRAs substantially lower their ratings' quality to compete for vacant market share while highly-reputable CRAs become more conservative. In addition, capital markets fully anticipate the impact of the punishment and respond accordingly in terms of the yield spread and the bond price. Our findings demonstrate that market competition in an oligopolistic credit ratings market undermines the effectiveness of regulatory punishment.

Keywords: punishment, competition, reputation, credit rating, oligopoly

JEL classification: G20, G24, G28, L50

1. Introduction

We study the effectiveness of regulatory punishment for credit rating agencies (CRAs) within an oligopolistic industry. The market is characterized by a high concentration of players and high barriers to entry/expansion profit; profit-maximizing competitors set their strategies by paying close attention to how their rivals are likely to react. In crime theory, punishment's deterrence effect is debatable; this becomes even more uncertain in an oligopolistic market where punishment outcome hinges on the interplay of market participants' reactions.

We take the credit rating market and auditing as examples to animate our point. The "death penalty" experienced by Arthur Andersen was arguably costly to society.[1] The deferred prosecution agreement in the KPMG tax-advice case reflected concern about the costliness of another potential full-blown criminal conviction. While the United States brought major lawsuits against S&P and Moody's in the aftermath of the global financial crisis, it agreed to a lawsuit settlement that left S&P and Moody's intact. These anecdotes demonstrate the potential limits on regulators' abilities to impose severe punishment given the concentration of the auditing industry or the credit rating agencies, highlighting an especially delicate aspect of regulatory punishment in an oligopolistic industry.

The consequences of punishment in such an oligopolistic market are uncertain. In such a market, firms might imitate their rivals' competitive behaviour in a process that harms consumer welfare without reaching an explicit agreement. Rating inflation resembles an outcome of the tacit collusion between competitors in an oligopolistic market. Thus, the payoff of committing a fraud/misdeed depends on the player's behavior, as well as the other players' behavior in the market.

Despite the regulator and societal concerns, there is limited empirical evidence in the literature on how punishment affects market dynamics. Identifying the effect of punishment is challenging as the peer non-punishees are often "contaminated" by the potential deterrence effect of punishment. There is a lack of counterfactuals. Moreover, the punishee and the non-

[1] The collapse of Arthur Andersen in 2002 led to a permanent change in the industrial organization of the auditing industry—a change from the "Big Five" to the "Big Four." This would be analogous to the United States taking down a major rating agency, such as S&P Global Ratings.

punishee CRAs/auditing firms have different customer bases. In addition, the customer selection effect presents further empirical challenges.

In this paper, we examine how market participants respond to regulatory punishment in the Chinese credit rating market. We utilize a policy shock of business suspension imposed by regulators on Dagong Global Credit Rating Co. Ltd from August, 2018 to November, 2019.[2] A unique feature of the Chinese credit market that appeals to our empirical identification is China Bond Rating Co. Ltd. (CBR), which is a government-backed rating agency. CBR randomly covers a representative sample of firms, and uses a hybrid of public utility and investor-paid business models (Amstad and He, 2020). In addition, CBR does not compete with other issuer-paid CRAs in rating financial corporate detbs, thus having no incentives to change their ratings upon Dagong's suspension.

The CBR model overcomes both the drawbacks of issuer-paid (e.g., "rating catering") and investor paid (e.g., "limited coverage") rating agencies and thus provides relatively unbiased ratings. As an independent rating agency, CBR is unlikely to be affected by the punishment of other issuer-paid CRAs; hence, it provides a benchmark to identify the effect of punishment on an issuer-paid CRA. Moreover, the business suspension includes an "exit" and a "re-entry" event of a major CRA in a short one-year window, alleviating the concern of correlated local shocks with the punishment and also allowing us to track the dynamics of the rating market in different punishment phases in a short window.

We are interested in the behavioral responses of the punishee CRA, their competitors, and the investors to a suddenly forced exit of a CRA by regulators and its re-entry. Does the punishment deter the punishee and competitor CRAs' wrongdoings and improve ratings quality afterwards? If so, did this effect last? Do investors react to the punishment, and why? The answers to these questions address the potential consequences of CRA punishment. We

[2] Dagong is one of the major CRAs in China, with a market share of 15% in 2017. In 2018, regulators suspended Dagong's ratings' license on August 18, 2018. Whether, when, and how Dagong will re-emerge was unknown to the market at the time. More than a year later, Dagong was re-organized and re-entered the market in November, 2019. While ratings inflation is phenomenal and has long existed among CRAs, Dagong's punishment was an unexpected and shocking event to the market.

compare CRA and CBR ratings for the same firm before and after the market exit (re-entry) of Dagong when the suspension starts (ends).

We find that Dagong significantly lowers its existing clients' credit ratings during their business suspension relative to the ratings assigned by CBR on the same firms. Its incidence of failed warning (Type I error) drops while the false warning rate (Type II error) increases. Markets react stronger to ratings upgrades than downgrades, indicating that investors perceive the ratings upgrades as more informative and downgrades as a temporary tactic taken by Dagong to avoid further regulatory actions when the business is under greater scrutiny during the suspension.

However, when Dagong returns to the market, it increases its ratings aggressively comparing to CBR to regain its market power, making its upgrades less informative but downgrades more useful. This finding is consistent with the "temporary suppression" view on punishment in crime economic theory (e.g., Sidman, 2000; Chalfin and McCrary, 2017).

Due to the changes in the CRA market structure caused by Dagong's exit and re-entry, non-Dagong issuer-paid CRAs also adjusted their rating strategies. The reactions differ between CRAs with higher market power (HMP) and those with lower market power (LMP). HMP CRAs lower their ratings during Dagong's suspension and do not inflate ratings when Dagong re-enters. This shows the "deterrence" effect on HMP CRAs because their potential loss would be magnificent if their licence were to be suspended. The benefits of committing ratings inflation to gain additional market share are marginally insignificant. In constast, LMP CRAs choose to rasie their ratings during both the Dagong's suspension period and its re-entry, indicating that competiting for more market share is the main consideration for them.

In terms of the market awareness, we find that bond prices react stronger to ratings changes made by HPM CRAs, indicating that their ratings are more informative in both Dagong's exit and re-entry periods. On the contrary, the ratings issued by LMP CRAs have lower quality and are less informative.

Our paper contributes to the literature in several ways. First, and at the broadest level, our findings add to the industrial organization literature by showing the impact of punishment on market competition dynamics in an oligopolistic market. The oligopolistic market structure is common in some product markets and prevalent in financial intermediaries (e.g., banking and insurance sector in some countries, rating agencies, and auditing). There is limited empirical evidence on how punishment affects the competitive dynamics among the main players in the oligopolistic market and to what extent punishment can effectively deter future wrongdoings.

Second, and more specifically, we contribute to the CRA literature. Distinct from previous studies analyzing the rating inflation problem from various angles of the conflict of interest and issuer-pay model (e.g., Cornaggia and Cornaggia, 2013; Kashyap and Kovrijnykh, 2016), we analyze the rating inflation problem from the industrial organization perspective.[3] We emphasize the change in market share and responses of related parties. In this regard, we see our study as part of the growing literature on the industrial organization of financial markets (e.g., Hortacsu and Kastl, 2012; Kastl, 2017; Dewatripont, Rochet, and Tirole, 2010).

Third, we provide new insights into regulating CRAs.[4] Credit rating plays an important role in capital markets, affecting real investment decisions (Goldstein and Huang, 2020) and financial system stability (Duffie, 2019; White, 2019). Despite extensive criticism of inaccurate ratings, the major CRAs remain central entities in the financial markets (White, 2019). An underlying rationale is that the market can self-correct inaccurate credit ratings through reputational incentives and competition.

But as shown in recent empirical studies, reputation and competition mechanisms fail to

[3] The role played by CRAs' competition in ratings quality is controversial. In principle, whether competition can reduce ratings inflation depends on how it affects the trade-off between the benefit of building a long-term reputation and the short-term profit of inflating ratings. Competition is seen as a crucial driver behind inflated ratings with softer rating criteria and less useful information (e.g., Faure-Grimaud et al., 2009; Skreta and Veldkamp, 2009; Becker and Milbourn, 2011; Bongaerts et al., 2012; Bolton et al., 2012; Chu and Rysman, 2019). But others argue the contrary (e.g., Manso, 2013; Xia, 2014; Bae et al., 2015). Nonetheless, most theoretical models consider the competition in a duopoly and ignore the market's dynamic properties. Empirical studies only focus on the entry of a new CRA (e.g., Becker and Milbourn, 2011). We are the first to provide empirical evidence on the impacts of an exit and re-entry of a CRA and supplement the studies on the dynamics of the market structure.

[4] Stolper (2009) suggests that a proper regulatory approval scheme for CRAs can prevent ratings inflation, where combining a threat to deny accreditation approval in future periods and a reward for CRAs deviating from collusive agreements. Mattingly (2013) and Hirth (2014) recommend that the ongoing monitoring of CRAs' performance and their possible punishment should be carried out by a regulator or a central market authority.

effectively contain rating inflation.[5] Hence, there are ongoing calls for monitoring CRAs' performance and punishment by a regulator or a central market authority rather than individual investors (Darbellay, 2013; Hirth, 2014; White, 2019). Currently, little is known about the impact of regulatory punishment on the credit ratings market. In most theoretical models for credit rating, the wrongdoings of CRAs (e.g., rating inflation) are the outcome of a trade-off between expected gains and the potential costs of the misdeeds, and punishment is treated as an add-on cost. There is a paucity of information in the literature on the role of punishment in reshaping market competition among CRAs and deterring future wrongdoings.

Our study is among the few that empirically examine the role of punishment for CRA wrongdoings. Our examination of Dagong's business suspension helps us to understand the potential impact of punishment in the CRA market. Despite the relevance to regulation practice, the effect on the entry and exit of one CRA is theoretically ambiguous (Chu and Rysman, 2019). Theoretical models in the CRA literature usually neglect the dynamic properties of the oligopolistic competition over an infinite horizon due to the lack of tractability.[6] We provide counterfactuals to the theoretical ambiguity by showing how credit ratings' quality will be affected when there is an exogenous reduction in the number of competitors.

The paper proceeds as follows. In Section 2, we provide the theoretical foundations and review the related literature. In Section 3, we give the background of the CRA market, Dagong's license suspension, and CBR. We describe our sample and variables in Section 4. In

[5] While some argue that reputation concerns incentivize CRAs to provide informative ratings (Cheng and Neamtiu, 2009; Bolton et al., 2012; Bar-Isaac and Shapiro, 2013), others show that CRAs' reputation mechanism does not work (Mathis et al., 2009; Baghai and Becker, 2020) when the exogenous reputation costs are lower or there are more naïve investors (Bolton et al., 2012).

[6] We are not aware of any papers in the literature that have empirically investigated this. One recent theoretical study in this spectrum is Chu and Rysman (2019). They use a structural model to identify the effect of removing one CRA from the three. In their model, they find that the rating in a duopoly market is less distorted when compared with the market with three CRAs. Importantly, Chu and Rysman (2019) cautioned readers that the real effect of removing one CRA could be different from their structural estimation. They hold the market share as static for comparability, but the market is dynamic in the real world. Indeed, we find that the impacts are complex when the market dynamics come into play. The exogenous exit can lead to further rating distortion in the real markets. CRAs with lower market power inflate ratings further to win the battle of freed-up market shares from the suspended CRA. And the rating qualities differ at the upper and lower end of the rating scales. Our results echo Chu and Rysman's (2019) sentiment on the complex market dynamics in the real market.

Section 5, we discuss the main results, and in Section 6 present additional results. We conclude in Section 7.

2. Theory and Literature Review

Moody's, S&P, and Fitch, the Big Three CRAs, collectively account for more than 90% of the global market share. They have been criticized for the lack of informative and timely ratings in revealing the credit risks of bond issuers and blamed for playing a significant role at various stages in the 2007-2009 global financial crisis (Mathis, McAndrews, and Rochet, 2009; Kisgen and Strahan, 2010; Bolton, Freixas, and Shapiro, 2012). The 2010 Dodd-Frank Wall Street Reform and Consumer Protection Act implemented several rules to improve credit rating quality in the U.S. (Dimitrov, Palia, and Tang, 2015). However, even with intensified regulations, the credit ratings quality has not been effectively improved in the U.S. (Dimitrov, Palia, and Tang, 2015) or other countries.[7]

Studies attribute the inflated credit ratings to the conflict of interest rooted in CRAs' issuer-paid business model (Cornaggia and Cornaggia, 2013; Kashyap and Kovrijnykh, 2016), credit ratings shopping (Griffin, Nickerson, and Tang, 2013; Sangiorgi and Spatt, 2017), and the rating-reliant regulation (Beaver, Shakespeare, and Soliman, 2006; Kisgen and Strahan, 2010; Bruno, Cornaggia, and Cornaggia, 2016). To date, how to regulate CRAs remains controversial.

As mentioned above, the outcome of punishment is uncertain. In crime theory, the deterrence effect of punishment is debatable. The earliest economic model of optimal penalty theory by Becker (1968) suggests that criminals commit crimes rationally when the expected benefits of the crime outweigh the expected costs; they may be deterred from criminality with the appropriate combination of punishments and enforcement. Along this line, some papers suggest that criminals respond to increased enforcement by committing fewer crimes (e.g., Butterfield, Trevino, and Ball, 1996; McCrary, 2007, 2010; Hopfensitz and Reuben, 2009;

[7] For example, the CRAs issue highly inflated ratings in China (Hu et at., 2019; Amstad and He, 2020). CRAs in India involved in proving non-rating services that are in conflict of interest with their rating business (Baghai and Becker, 2018).

Balliet, Mulder, and Van Lange, 2011; Ambrus and Greiner, 2012). By contrast, Sidman (2000) questioned the effectiveness of punishment in controlling behaviour based on the transitory nature of the response suppression produced. The author argues that the suppression response is temporary, and punishment induces aggression in the offender; punishment may only have a short-term effect on the punished and, even worse, leads to more criminal behaviours after the punishment. Worse still, Chalfin and McCrary (2017) find that if offenders are myopic or have a high discount rate, deterrence effects will be less likely, even if they face heavy punishment.

The outcome of punishment in an oligopoly market is even more uncertain. The punishment is a "reputation loss" event, leading CRAs to reassess the probability and cost of being punished. At the same time, the punishment disadvantages the punishee (either temporarily or permanently); thus, it is also a "market competition" event. When faced with an explosion in the overall market, the inter-dependent CRAs inflate credit ratings to maintain their market shares. The conscious parallelism of credit rating inflation is thus worldwide. From the view of the economics of the oligopolistic market, inflation of credit ratings by CRAs is a natural one-shot equilibrium outcome of the implicit coordination game among the leading CRAs.

Two potential underlying mechanisms may mitigate the credit rating inflation problem: a reputation mechanism and a competition mechanism. In the reputation mechanism in a multiperiod reputation model (e.g., Klein and Leffler, 1981; Kreps and Wilson, 1982), if the interactions of CRAs are repeated and the credit ratings quality is visible, the formation of reputations can incentivize the CRAs to provide high-quality credit ratings to maintain their reputations for sustaining future business (Mathis et al., 2009; Bolton et al., 2012; Bouvard and Levy, 2018). In a competition mechanism, competition may enhance the effectiveness of the reputational mechanism if the existence of competitive choice is required to make the loss of reputation a real threat (Hörner, 2002). The quality of the credit ratings may increase with competition (at least over some range).

By contrast, competition may reduce the effectiveness of the reputational mechanism. Reputations are only valuable if future rents can be extracted from costly long-term reputation building. Since competition typically reduces rent, it reduces the incentive for maintaining a reputation. Short-term profit is more attractive than long-term reputational value, especially for those firms with lower market share (Doherty, Kartasheva, and Phillips, 2012; Flynn and Ghent, 2018).

Baghai and Becker (2020) show that the reputation mechanism fails to discipline the credit rating inflation problem; S&P employed rating inflation to occupy more market share and boost the short-term profit after it experienced a reputation loss. Introducing more players to the market to promote competition also fails to mitigate rating inflation. The entry of Fitch into the CRA market deteriorates credit ratings (Becker and Milbourn, 2011). In addition, introducing an investor-paid CRA to the market improves other CRAs' ratings quality as the ratings quality becomes visible to the market and thus disciplines CRAs' rating inflation behavior through the reputation channel (Xia, 2014). Little is known about how disciplinary actions affect the interplay between external regulatory punishment and CRA reputation and market competition.

3. Institutional Background

In this section, we provide background information for Chinese credit rating market, Dagong's suspension and CBR.

3.1 Credit Rating Market

In China, there are three major issuer-paid CRAs in the market: China Cheng Xin International Co. Ltd. (Chengxin_Moody), China Lianhe Credit Rating Co. Ltd. (Lianhe), and Dagong Global Credit Rating Co., Ltd. (Dagong) (Amstad and He, 2020).[8] These CRAs account for 75.33% (82.12%) of the market share measured by the number (issue size) of corporate debt securities they rated between 2006 and 2021; the other eleven issuer-paid CRAs[9] together take

[8] We summarize the characteristics of the existing CRAs in China in Appendix 1.

[9] The other nine CRAs including ten issuer-paid one investor-paid CRAs. The nine issuer-paid CRAs are Shanghai Brilliance Credit Rating & Investors Service Co., Ltd. (Brilliance). Golden Credit Rating International Co., Ltd. (Jincheng), Pengyuan Credit Rating Co., Ltd. (Pengyuan), Shanghai Far East Credit Rating Co., Ltd. (SFE), Anrong Credit Rating Co., Ltd. (Anrong) , Shanghai Credit Information Service Co. Ltd. (SCI), Beijing ZBL Credit Rating Co., Ltd. (ZBL), Dapu Credit Rating Co., Ltd. (Dapu), S&P Global China Ratings (S&P China) and

24.67% (17.88%) of the overall market. Entrants into the CRA market in China face high regulatory barriers. According to the 2009 Interim Measures for the Administration of Credit Rating Industry, CRAs must first register at the People's Bank of China (PBoC) to operate a credits ratings business in China. For each segment of the bond markets, CRAs need to be accredited in the market; each market is regulated by a different authority. [10] Like CRA markets in other countries, the CRA market in China is also an oligopoly market with a small number of major players.

The credit rating scale in China ranges from AAA to C. [11] There are two categories of credit ratings in China: long-term issuer ratings (LTIR) and bond ratings (BR). LTIR is a rating for a bond issuer that measures the issuer's creditworthiness and ability to repay the debt over a long horizon. BR is a rating that denotes the safety of debt securities. BR is normally equal to or higher than LTIR, depending on whether the bond is guaranteed. In addition to its crucial role in debt issuance in determining offering yield spread, the credit ratings are used to calibrate bank capital requirements and provide investment information for insurance funds and money market funds (Amstad and He, 2020). Banks and insurance firms are required to invest only in bonds rated A and above; money market funds can only invest in bonds with credit ratings of AA+ and above (CSRC, 2015). In addition, only debt issues rated AA and above are eligible for bond repurchases in the exchange-based market (CSDC, 2017; Chen et al., 2019).

3.2 Dagong's License Suspension

Dagong was founded in 1994 and was a privately owned company before the license suspension. Dagong was among the first domestic CRAs accredited with full rating licences from the National Association of Financial Market Institutional Investors (NAFMII), the

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Fitch (China) Bohua Credit Ratings Ltd (Fitch China). The one investor-paid CRA is China Bond Rating Co., Ltd. (CBR).

[10] NAFMII regulates the nonfinancial enterprise debt-financing instruments in the interbank market. NDRC approves the eligibility of a CRA for rating enterprise bonds, and CSRC decides who can rate exchange-listed corporate bonds. For example, if a CRA wants to rate both non-financial institution debt financing tools and corporate bonds, it must be accredited by both the NAFMII and the CSRC. NAFMII and NDRC use the examination and approve system to accredit CRAs, while CSRC shifts to registration system since February 2021.

[11] However, as documented in previous studies, the ratings in China centre around AA+ and AA.

National Development and Reform Commission (NDRC), and the Chinese Securities Regulatory Commission (CSRC) for bond rating in both the interbank and exchange markets. By the end of 2017, it was one of the three leading CRAs in China, with a 15% market share.

On August 17, 2018, both NAFMII and CSRC announced that Dagong's licence to rate interbank and exchange market products would be suspended for one year.[12] This punishment is the most drastic practice in the Chinese CRA industry. According to NAFMII, Dagong provided fee-paying consulting services to its rated companies,[13] which is subject to conflicts of interest and violates self-regulation rules. Dagong was also accused of submitting fake statements to NAFMII during the investigation. CSRC identified four issues from its special inspection on Dagong: (1) poor internal governance and misused official corporate seals; (2) providing advisory services to issuers and charging high fees, which violates the principle of independence; (3) unqualified senior management; and (4) missing manuscript data for ratings projects, and defective ratings models.

During the business suspension, Dagong was prohibited from rating new clients or new bonds but was still allowed to provide regular follow-up ratings to clients with outstanding debt securities. In April 2019, Dagong was taken over by China Reform Holdings, a state-owned investment company, and formally became a state-owned issuer-paid CRA.[14] In November 2019, after a fourteen-month reform and restructuring period, Dagong returned to the market

[12] See http://www.nafmii.org.cn/zlgl/zwrz/zlcf/201808/t20180817_71730.html and http://www.gov.cn/xinwen/2018-08/17/content_5314678.htm.

[13] Dagong and its affiliate companies "sell inflated ratings" through three "consulting services." The first service Dagong provided was to help issuers build their corporate credit management system, with a contract price of RMB 9.7 million, in exchange for promised rating upgrades. For example, Dagong upgraded Xinguang Holding's rating from AA to AA+, two days after receiving this service payment. Second, Dagong sold a valuation report of realizable assets to its ratings clients, and one report was worth RMB 2 million. This type of report was mainly to evaluate the value of the total assets of the issuers that can be quickly realized to meet the debt repayment. Dagong issued an evaluation report on a firm's financing ability and proposed short-, medium-, and long-term optimization solutions. This type of report was sold at RMB 2 million as well. Compared to the ratings fees ranging between RMB 0.01 and 0.015 million, the above consulting services are extremely profitable and suspicious. According to Hu et al. (2020), issuers can save 42.8 bps per year with a ratings upgrade from AA to AA+ when issuing corporate bonds in China. This translates to an approximate interest saving of RMB 6.42 million per year for an average size bond with an average maturity of five years.

[14] See https://www.ft.com/content/7079c7aa-6265-11e9-b285-3acd5d43599e.

and resumed its rating business.[15]

3.3. Government-backed Ratings Agency: China Bond Rating Co. Ltd. (CBR)

In August 2010, the NAFMII established CBR with 50 million RMB in registered capital contributed by all its members.[16] Under the supervision and guidance of the PBoC, NAFMII is responsible for the self-regulatory management of the Chinese interbank market and plays an important role in facilitating market expansion and guiding and regulating the primary and secondary markets. Although CBR claims that it is completely independent of PBoC, PBoC oversees its major shareholder, NAFMII, and both its chairmen of the board and the supervisory board once worked at PBoC. Therefore, the origin of CBR has its roots in the government with an embedded public utility model (e.g., Lynch, 2008; Diomande et al., 2009).[17]

CBR releases its credit ratings through ChinaBond, Wind Information Co. Ltd.,(WIND) and its websites.[18] All investors in the market can observe its ratings announcements and the associated ratings, but only subscribers have access to the comprehensive details. CBR provides a range of services for different subscription fees. The investors (e.g., banks, funds, securities firms, and insurance companies) subscribe directly to CBR for each rated asset class they are interested in. Besides the ratings it randomly provides, CBR also provides ratings at subscribers' requests.[19]

The business model for CBR is a hybrid model of investor-paid and government-owned CRA. CBR provides independent and objective ratings that are less influenced by the conflict

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[15] See https://www.reuters.com/article/china-bonds-ratings-idUSL3N27K1Z9.

[16] The registered capital contributed by NAFMII was increased to 150 million RMB in 2019.

[17] Lynch (2008) and Diomande et al. (2009) advocate for a non-profit public CRA in the U.S., to manage the conflicts of interest by imitating other successful public independent bodies, such as the U.S. Federal Reserve Board or the U.S. Supreme Court. The European Commission Consultative Paper proposes the creation of a public European CRA as well.

[18] ChinaBond is a bond market database maintained by the China Central Depository & Clearing Co. Ltd. (CCDC). CCDC is a central securities depository (CSD) approved by the State Council of China, and it is the only government bond depository authorized by the Ministry of Finance.

[19] If a subscriber requests a rating on an issuer, CBR will only accept the request if the issuer is willing to cooperate and/or CBR has sufficient resources to conduct the rating. However, this kind of ratings information is not made publicly.

of interest problem facing other issuer-paid CRAs, such as rating inflation to cater to issuers' demands (Kashyap and Kovrijnykh, 2016). Compared to investor-paid CRAs, the main advantage of this business model is to prevent catering investors' higher rating demand and the excessive free-riding problem (Deb et al., 2019). As a combined model, governmental fund support helps mitigate the concern of the lack of incentives to provide high-quality ratings, while additional subscription fees overcome the problems of the shortage of government funds facing a public utility model. Notably, CBR is a re-rating agency; its ratings are given after the bond issuances and have no influence on corporate debt securities' offering prices.

In China, bond issuers have to obtain a certain rating level for bond issuance (e.g., AA- or above for mid-term notes issued on the inter-bank market). Since regulators do not use CBR's ratings as an issuance assessment criterion, CBR has no incentives to inflate its ratings. A new CRA has two roles: as a competitor or an information provider (Xia, 2014). As CBR does not directly compete with other issuer-paid CRAs, it primarily acts as an information provider.

It is also worth noting that the coverage of CBR is sufficient to provide a valid control group to assess the impact of punishment on the issuer-paid CRAs. Since its inception in 2010, CBR has gradually enlarged its coverage of Chinese firms. As of 2017, CBR had rated approximately 58% of the firms covered by issuer-pay CRAs across 21 industries (classified by CSRC level I industry code).

4. Data, Sample, and Variables

In this section, we define our event windows in Subsection 4.1. Next, we describe our data and sample in Subsection 4.2, and we define the key variables Subsection 4.3.

4.1 Timeline and the Event Windows

Figure 1 provides a timeline of the three phases of Dagong's suspension. The suspension period runs from August 18, 2018 to November 31, 2019. To keep the sample period balanced in each phase we define three phases based on Dagong's market exit and re-entry: (1) the pre-punishment period (Phase 0) from May 1, 2017 to August 18, 2018; (2) the suspension period (Phase 1) from August 19, 2018 to November 31, 2019; (3) the re-entry period (Phase 2) from

December 1, 2019 to March 15, 2021. All three phases have an identical sample length. We create two dummy variables to identify the period of the sample: *Post1* equals one for the sample in Phase 1 and zero otherwise, and *Post 2* equals one if the sample is in Phase 2 and zero otherwise.

[Insert Figure 1 Here]

4.2 Data

We sourced the data on credit ratings and firms' quarterly financial information from WIND and ChinaBond. Our sample includes all the LTIR assigned by all issuer- paid CRAs to Chinese firms on the onshore public debt market. We exclude ratings for issuers of financial institutions' bonds, Treasury and municipal bonds, structured rating products, private bonds, and other non-rated bond categories, either because they are not issued at the firm level or because their rating criteria are different (Hu et al., 2019; Chen et al., 2021). Our initial sample consists of 53,454 observations of 4,795 firms that have credit rating records from the issuer-paid CRAs in China from May 1, 2017 to March 15, 2021. We also collect the credit ratings issued by CBR from WIND and CBR's website for the same sample period, and there are 20,705 ratings provided by CBR for 2,372 unique firms. Each observation in our sample is an issuer's entity rating corresponding to a certain rating action from CRAs (i.e., new ratings assignment, rating affirmation, ratings upgrade or downgrade).

We employ a difference-in-difference (DiD) analysis. To conduct the DiD analysis, we further require for each firm in each phase, both issuer-paid CRAs and CBR have available rating records. Therefore, our final sample consists of 40,366 credit rating observations for 2,121 unique firms that are covered by both issuer-paid CRAs and CBR, and 20,183 rating observations provided by CBR.

We compare the credit ratings coverage distribution of firms in our final sample that are covered by both issuer-paid CRAs and CBR, with that of the initial sample in Figure 2. Panel A depicts the percentage distribution of rated firms across CSRC level I industries and Panel B presents the distribution of rated firms by size (i.e., total assets by the end of 2017). We can see that 24.3% of the firms in the initial sample are from the construction industry with industry code E, and 23.6% of firm in our final sample are from the same industry.[20] We find similar trends for all the other industries. We also find that the distribution of covered firms in various size categories is comparable between our initial sample and final sample. Hence, the reduced sample rated by both issuer-paid CRAs and CBR is not biased compared to the initial sample, and is representative of all the issuers on the market.

[Insert Figure 2 Here]

We test the characteristic differences between the initial sample (raw sample) and our final sample (reduced sample) to further validate its representativeness. Panel A of Table 1 presents the summary statistics of firm characteristics for our final sample, which are covered by both issuer-paid CRAs and CBR. The summary statistics for all onshore issuers rated by issuer-paid CRAs during the same period are reported in columns 1-3. Firms rated by both issuer-paid CRAs and CBR are largely the same as all firms covered by all issuer-paid CRAs. We only observe slight differences in the financial leverage ratio (0.46%), publicly listed (0.01), and ownership status (0.05), which confirm that our reduced sample can represent the raw sample. Panel B presents the summary of ratings provided by issuer-paid CRAs in the raw and reduced samples. In the full sample period and each phase, we find that the ratings from the issuer-paid CRAs on the reduced sample are indifferent from that of the raw sample. Therefore, our results are not likely driven by sample selection bias.

[Insert Table 1 Here]

We also sourced the bond default data and the daily bond trading data from WIND to estimate the credit rating accuracy and bond market reactions to credit ratings changes. The daily stock market data are from China Stock Market & Accounting Research (CSMAR) for the evaluation of stock market's reaction. We also collect new bond issuance data from WIND to examine how the primary bond market reacts to the punishment episode.

4.3 Variable Construction

4.3.1 Main variables

[20] In Appendix 2, we summarize the number of firms in each industry for the raw and reduced samples.

We next discuss the main variables. Rating levels (*Rating*) are a numerical transformation of the alphanumerical rating codes issued by CRAs (e.g., Hu et al., 2020; He et al., 2022), from 1 to 5 (AAA = 5, AA+ = 4, AA = 3, AA- = 2, A+ and below = 1). Following Dimitrov et al. (2015), we define Type I error as a dichotomous variable that equals one for a AA+ or above rated firm that defaults within one year and zero otherwise, to represent the failed warning of the rating. Similarly, we define Type II error as a dummy variable that equals one for a A+ or lower rated issuer that does not default within one year and zero otherwise, to measure the false warning of the rating. Type I and Type II errors that are higher indicate a higher failed warning ratio and a high false warning ratio, respectively.

To measure the bond market's reaction to ratings changes, we create the 7-day *ABR* ([*t*-3, *t*+3]), abnormal bond return following Bessembinder et al. (2009) and Dimitrov et al. (2015). The *ABR* is calculated as the difference between the observed bond return (*OBR*) and the benchmark bond return (*BBR*) as follows:

$$ABR_{i,t,7} = OBR_{i,t,7} - BBR_{i,t,7} \tag{1}$$

and

$$OBR_{i,t,7} = \frac{P_{i,t+3} - P_{i,t-4} + C_{i,t,[t-3,\ t+3]}}{P_{i,t-4}}, \tag{2}$$

where $ABR_{i,t,7}$ is the abnormal bond return of bond *i* over the event window [*t*-3, *t*+3] surrounding the ratings change date *t*. $P_{i,t+3}$ is the dirty price at the end of day 3 after the event date; $P_{i,t-4}$ is the dirty price at the end of day *n*-4 before the event date; and $C_{i,t,[t-3,t+3]}$ is the coupon paid in between day *t*-3 and *t*+3 if it happened. The dirty price is the sum of clean price and the accrued interest. $BBR_{i,t,7}$ is the index return of a rating/maturity matched portfolio of bond *i* retrieved from the ChinaBond website. Given the illiquidity of bond prices, we impose trading restrictions by requiring that at least one trading transaction be executed from day *t-3* to day *t+3*. We also require the bond to have a maturity longer than one year. Then for issuers with multiple outstanding bonds, we aggregate the ABR to the issuer level by calculating the (outstanding bond) volume-weighted average ABR for bonds issued by the same issuer.

Our estimation of stock market returns surrounding the ratings changes follows Field and

Hanka (2001) and Cheng et al. (2020):

$$AR_{i,t,n`} = R_{i,t,n`} - RM_{i,t,n`}, \text{ where } n` \in [-3, 3], \tag{3}$$

where $R_{i,t,n`}$ is the log return of the stock of firm $i$ on day *n* surrounding the ratings change date *t*, and $RM_{i,t,n`}$ is the log return of a corresponding market index of firm i.[21] The cumulative abnormal return (CAR) over the 7-day event window is computed as the sum of the daily ARs over the event window.

We measure the bond issuance cost on the primary bond market using the at-issue yield spread (*Spread*), which is the percentage difference between the bond offering yield and the yield on a Treasury note of comparable maturity. We also define three dummy variables to identify the rating agencies in our estimation: *Dagong* is a dummy variable that equals one if the credit rating is provided by Dagong and is zero otherwise; *HMP* is a dummy variable that equals one if the rating is issued by the CRAs with higher market power (i.e., Chengxin_Moody and Lianhe) and is zero otherwise; and *LMP* is an indicator for ratings provided by CRAs with lower market power (i.e., ratings issued by issuer-paid CRAs other than Dagong, Chengxin_Moody, or Lianhe).

4.3.2 Control variables

We also control for a raft of firm characteristics that may potentially affect credit ratings following Ziebart and Reiter (1992), Blume, Lim, and MacKinlay (1998), Campbell and Taksler (2003), and Livingston et al. (2018): profitability (*ROA*), which is operating income divided by average total assets; financial leverage ratio (*Leverage*), which is total liability divided by total assets; asset tangibility (*Tangibility*); cash holdings (*Cash*) as a proxy for asset liquidity (calculated as cash and cash equivalents scaled by the current liability; sales growth (*Sales*), which is the growth rate in operating revenue; firm size (natural logarithm of sales in 100 million RMB; denoted as *Sales*), the natural logarithm of firm age (*Age*); whether the issuer is a publicly listed company (*Listed*); and whether or not the issuer is a state-owned enterprise (*SOE*). In the estimation of the primary bond market response, we also control three bond issues characteristics: the years to maturity (*Maturity*), the issue size (*ISize*) measured by the par value

[21] For each stock, we define its corresponding market return as the return of the index the stock belongs to.

of a bond in RMB 1 billion, and whether the bond is secured by a third party or collateral (*Guarantee*). All variables are described in detail in Appendix 3.

4.4. Summary statistics

Panel A in Table 2 provides the descriptive statistics of the main and control variables for firms rated by both issuer-paid CRAs and CBR. The mean and median values of the credit ratings are 3.08 and 3.00, respectively, and are equivalent to a AA rating. The mean values of Type I and Type II errors of our sample are 0.01 and 0.00, respectively. The 7-day abnormal bond returns for ratings upgrades and downgrades are 0.14% and -4.70%, respectively, while the 7-day stock market CARs are 0.37% and -7.54% for rating upgrades and downgrades respectively. There are 4,550 new corporate bond issuances during our sample period with maturities longer than one year, and the average yield spread is 2.48%. In our sample, 4% of the ratings are provided by Dagong, 35% are issued by CRAs with higher market share, and 11% are rated by CRAs with lower market share. The other 50% of the ratings in our sample are from CBR. The sample is evenly distributed across the three phases (29% in Phase 0, 34% in Phase 1, and 37% in Phase 2). The summary statistics of the control variables are largely comparable to the previous studies (e.g., Livingston et al., 2018; Chen et al., 2020). A typical firm in the sample has a ROA of 3.59% with a 64% leverage ratio, a size of 1.35 billion RMB, and has been in business for 18 years. Eighty-four percent of our sample firms are SOEs and 18% are publicly listed companies.

Panel B of Table 2 provides the results of a comparison between issuer-paid CRAs' ratings to CBR's in the full sample and firms rated by Dagong, HMP, and LMP CRAs. On average, CBR's ratings are more than 2 notches higher (closer to the AA- of the rating spectrum) than ratings from issuer-paid CRAs (AA+), and the difference is significant at the 1% level. This is consistent with the literature that issuer-paid CRAs are more likely to provide issuer-friendly ratings (Xia, 2014). Among the 20,183 rating observations, CBR's ratings are lower than issuer-paid CRAs' ratings 89.4% of the time, equal to issuer-paid CRAs' 9.7% of the time, and higher than issuer-paid CRAs' 0.9% of the time. CBR's ratings are consistently lower than the ratings of different issuer-paid CRAs. Specifically, CBR issues 2.118 notches lower ratings than that of Dagong for the same firms, 1.873 notches lower than ratings provided by CRAs with higher market power, and 2.172 notches lower than LMP CRAs' ratings.

[Insert Table 2 Here.]

5. Methodology and Results

In this section, we present our main models and results on the impact of the punishment on the dynamics of credit ratings. We provide descriptive evidence in Section 5.1. We then show the impacts of Dagong's exit and re-entry on the ratings, Type I and Type II errors of Dagong and other issuer-paid CRAs in Sections 5.2 and 5.3, respectively, and market responses in Section 5.4.

5.1 Descriptive Evidence

Figure 3 depicts the quarterly average credit ratings issued by issuer-paid CRAs and CBR in Phases 0, 1, and 2. The average credit rating issued by CBR is stabilized near 2.2 (closer to AA-) across the three phases, which is independent of the exit or re-entry of Dagong. This confirms the validity of using CBR's ratings as a control group to evaluate the rating changes of Dagong and its competitors surrounding the events.

We observe an overall decrease in the average rating of all issuer-paid CRAs (red line). It starts to drop with the punishment announcement for Dagong on August 18, 2018 (from 4.08 to 3.95) and rise again after Dagong's re-entry. This result indicates that the overall CRA market becomes more conservative in issuing inflated ratings during the punishment period and tries to regain market share when Dagong re-joins the market and recovers from the punishment.

Looking into different issuer-paid CRAs separately, we find Dagong provides the highest ratings (4.3 on average) before its punishment (Phase 0), followed by HMP CRAs (~4.2) and LMP CRAs (~3.4). The significantly lower ratings issued by LMP CRAs might be due to the lower qualities of their covered firms. In Phase 1 when Dagong's business is suspended, we see a sharp ratings drop from Dagong (3.5, 0.8 notches lower than in Phase 0). HMP CRAs show similar ratings downward movement as Dagong (from 4.2 to 4.1), whereas LMP CRAs significantly increase their ratings by 0.5 notches to 3.9. When Dagong re-enters the market in November 2019, it quickly offers higher credit ratings in an attempt to regain its lost market share (average rating of 4.15). HMP CRAs exhibit a slight rating drop (0.07 notches) during this period, while LMP CRAs experience a ratings increase (0.1 notches).

The results indicate that Dagong and HMP CRAs are deterred by the punishment policy in Phase 1 and respond by reducing the offered ratings, while LMP CRAs use higher ratings to compete for market share. When Dagong re-enters, the deterrence effect weakens and all issuer-paid CRAs raise their ratings.

[Insert Figure 3 Here.]

One alternative explanation for the above results is the changes of rated firms' fundamentals: the credit risk of firms rated by Dagong and HPM CRAs soars in Phase 1 then recovers in Phase 2, while firms rated by LMP CRAs become more credible in both Phases 1 and 2. Another explanation might be the shift of the client composition: credible issuers shift from Dagong and HMP CRAs to LMP CRAs in Phase 1 and Dagong and HMP CRAs regain the high-quality issuers in Phase 2. To exclude the above two plausible explanations, we introduce the difference-in-difference analysis where ratings provided by CBR on the same firms as issuer-paid CRAs are used as the control sample. Thus, the rating changes of issuer-paid CRAs over time are compared to that of CBR on the same firms, and the firms' financials are irrelevant to the relative rating differences between issuer-paid CRAs and CBR. Moreover, we require the firms to have comparable ratings from one CRA in each pair of phases (i.e., when comparing the ratings on a firm rated by Dagong between Phase 0 and Phase 1), the firm needs to have rating records from Dagong and CBR in both Phase 0 and Phase 1 at the same time. In that sense, our results cannot be attributed to the change in client composition.

5.2 The Impact on Dagong

To investigate the impact of punishment on Dagong, we keep the observations rated by Dagong and CBR. As the business suspension involves two events, market exit and re-entry, we first treat them as two separate events, and compare Dagong's rating and CBR's rating pre and post each event by employing the DiD model as follows:

$$Dep.var_{it} = \beta_0 + \beta_1 Dagong_{it} \times POST_{it} + \beta_2 POST_{it} + \beta_3 Dagong_{it} + \beta_4 X_{it-1} + \gamma_i + \varepsilon_{it}, \quad (1)$$

where $Dep.var_{it}$ denotes the credit rating level (*Rating*), *Type I* and *Type II* for firm *i* at time *t*. *Rating* ranges from 1 to 5 to measure the credit rating levels; *Type I* is a dummy variable, which equals one for a AA+ or above rated firm that defaults within one year and is zero otherwise, to represent the failed warning of the rating. Similarly, we define *Type II* error as a dummy variable, which equals one for a A+ or lower rated issuer that does not default within one year and is zero otherwise. *Dagong* is a dummy variable that equals one if the rating is issued by Dagong, and zero if the rating is issued by CBR. *POST* denotes *Post1* for the analysis of Dagong's market exit period and *Post2* for Dagong's market re-entry. X_{it} denotes a list of firm-level control variables; industry fixed effects (γ_i) are also included. We cluster our standard error by firm and correct for heteroskedasticity.

To address the concern that the market exit and re-enter events are correlated, we employ the two-period model to include both events, as follows:

$$Dep.var_{it} = \beta_0 + \beta_1 Dagong_{it} \times Post1_{it} + \beta_2 Dagong_{it} \times Post2_{it} + \beta_3 Post1_{it} + \beta_4 Post1_{it} + \beta_5 Dagong_{it} + \beta_6 X_{it-1} + \gamma_i + \varepsilon_{it}. \quad (2)$$

Columns 1-3 of Table 3 present the results on credit ratings from Dagong relative to CBR, while columns 4-5 (7-8) present the results on Type I (Type II) error. Columns 1, 4, and 7 (columns 2, 5, and 8) provide the results of the impact of business suspension (re-entry) on Dagong from Phase 0 (Phase 1) and Phase 1 (Phase 2) in Eq. (1), and columns 3, 6, and 9 present the results from the two-period model in Eq. (2).

We find a significantly negative coefficient on *Dagong×Post1* in column 1, indicating that compared with the control group (CBR's rating), Dagong rated firms experience a decline in credit ratings subsequent to the punishment, which is economically significant. That is, Dagong's ratings experience a decline of 0.7 (close to one notch) in ratings relative to that of CBR during its suspension. This suggests that the punishment has a significant effect on alleviating the Dagong's ratings inflation problem, reflecting a deterrence effect. As for the control variables, the coefficient on *Dagong* is positive and significant, confirming the results in Figure 3 that Dagong assigned a higher credit rating in Phase 0 compared to CBR. The coefficients on *Post1* in column 1 are significantly negative, which indicates a rating reduction from CBR in Phase 1. Other control variables exhibit the expected signs. For instance, consistent with previous studies (e.g., Kedia et al., 2014; Korkeamäki et al., 2014; Xia, 2014; Jiang and Packer, 2017), we find that firms with a larger sales volume and state ownership are associated with a more favorable rating, while a higher leverage ratio leads to a lower rating.[22] In column 2, the positive and significant sign on *Dagong×Post2* indicates that relative to CBR, Dagong offers higher ratings to its rated firms when it re-enters the market, potentially with the expectation to retain the clients and attract new clients. The relative rating increase from Dagong in Phase 2 shows a similar scale as its decrease in Phase 1 (0.014), when its average credit rating level returns to that before the punishment (Phase 0), indicating that the alleviation of the rating inflation from the policy is only temporary. The results in column 3 from the two-period model confirm our findings in columns 1 and 2.

[Insert Table 3 Here]

Moving to the incidence of failed warnings (Type I error), we find that Dagong significantly decreased its Type I error in the Phase 1 relative to that of CBR (column 4). The coefficient on *Dagong×Post1* is -0.022, which means that after the suspension, the odds of a failed rating provided by Dagong are 2.3 times lower in Phase 1, relative to that of CBR. When Dagong re-enters the market, we do not find significant changes in its Type I error relative to CBR (column 5), and the results are consistent in the two-period model (column 6). We can also find that Dagong is consistently associated with a higher incidence of a failed warning than CBR in Phase 0 across models.

In columns 7-9, we find that Dagong tends to issue more low ratings to firms that do not default in the future (i.e., a false warning). This might be due to Dagong's reputation concern that it intentionally lowered ratings to protect itself from more stringent regulation. As a result, this reduces the usefulness of ratings for predicting actual defaults, echoing the results in

[22] For brevity, we do not tabulate the coefficients on the firm controls in the tables 4-8.

Dimitrov et al. (2015). In the analysis of Dagong's re-entry, we do not find any significant change in its Type II error in column 8, but do find a reduction of the false waring in the two-period model (column 9).[23]

In summary, our results show that Dagong adjusted the average credit rating of their customers downward compared to that of CBR during its business suspension. When Dagong re-entered the market, it gave out higher ratings compared to CBR for the same pool of firms. The accuracy of Dagong's ratings differs: during the suspension in Phase 1, Dagong provides lower failed warnings that the odds of default of its AA+ and AA rated firms, while it provides more downward-biased ratings, which leads to a higher false warning ratio. Collectively, our results suggest that the punishment had only a short-term deterrence effect on Dagong and led to its further wrongdoings.

5.3 Impact on Other CRAs

We next examine whether Dagong's market exit and re-entry had a deterrence effect on other CRAs in the market. On the one hand, Dagong's punishment makes the other CRAs reassess the probability and consequences of future punishment, hence inducing a change in their operating behavior (D'Acunto, Weber, and Xie, 2019). Dagong's punishment also increases the other CRAs' perceived probability of being caught for dishonest ratings, and thus the expected costs (e.g., reputation and monetary equivalent penalty imposed by regulators) of dishonest ratings, which could have had positive externalities in disincentivizing other CRAs from issuing inflated ratings. On the other hand, Dagong's exit at the time changed the market competition status, resulting in competition for the freed-up market share among the remaining CRAs. To gain market share, these CRAs could inflate ratings to attract customers. Therefore, the consequences of Dagong's punishment are a trade-off between the incremental expected costs and benefits, and this also depends on the market share its competitors. As short-term profit is more attractive than long-term reputational value for firms with lower market share

[23] We examine the robustness of the results with respect to the definition of failed and false warnings. We define Type I error (Type II error) as firms with AA+ and above (A+ and below) ratings and default (do not default) within one and a half years, and our results are unchanged. We also define the false warning as firms with AA- and below ratings and do not default within one year, and our results remain unchanged.

(Hörner, 2002), the CRAs with lower market share may seize the opportunity and more aggressively inflate ratings to gain market share. When Dagong re-enters the market, the competition structure of the credit ratings industry changes again. First, exiting CRAs observe the recovery of Dagong, which may lead to an adjustment on the probability of being punished and the expectation on the penalty's consequence. Second, incumbent CRAs may change their ratings strategies based on their expectations on Dagong's re-entry strategies.

As the expected gains and costs are different between CRAs with high market share (i.e., dominating CRAs in the oligopolistic CRA market) and CRAs with low market share, the impacts of Dagong's suspension and re-entry on the ratings of the two groups can be different. To test how other issuer-paid CRAs react to Dagong's suspension and re-entry, we split the non-Dagong issuer-paid CRA sample into two groups: the high market power (HMP) and the low market power (LMP) groups as defined in Section 4.3.1. Similarly, we compare their ratings, Type I and Type II errors with that of CBR using the DiD model in Eq. (3) and present the results for the HMP CRAs and LMP CRAs in Panels A and B of Table 4 respectively. A two-period model similar to Eq. (2) is also applied, as follows:

$$Dep.var_{it} = \beta_0 + \beta_1 HMP_{it}(LMP_{it}) \times POST_{it} + \beta_2 POST_{it} + \beta_3 HMP_{it}(LMP_{it}) + \beta_4 X_{it-1} + \gamma_i + \varepsilon_{it}, \quad (3)$$

where $Dep.var_{it}$ denotes the credit rating level (*Rating*), *Type I* and *Type II* errors for firm *i* at time *t*. *POST* and control variables are the same as Eq. (1). HMP (LMP) is a dummy variable that equals one if the rating is issued by Chengxin_Moody or Lianhe (issuer-paid CRAs other than Dagong, Chengxin_Moody or Lianhe), and zero if the rating is issued by CBR. Industry fixed effects are also included and the standard errors are cluster at the firm level.

Panel A of Table 4 only includes the sample covered by both HMP CRAs and CBR. In columns 1-3, we document a rating reduction for HMP CRAs during the Dagong suspension (coeff. = -0.179, significant at 1%). This indicates that the reputational concern stimulated by the punishment spreads to HMP CRAs, which suggests they may worry more about losing business if they are punished in the future. In Phase 2, when Dagong re-enters the market, we still find the rating reduction from HMP CRAs in the two-period model, which indicates the deterrence effect of the punishment policy has a lasting effect for HMP CRAs. The incidence of Type I error exhibits a slight reduction for HMP CRAs in columns 4-6 with 10% confidence; we find only a slight rise of Type II error in columns 7-9, significant at 10%. To summarize, HMP CRAs tend to mildly downward adjust their credit ratings to reflect the true creditworthiness of their rated firms, without impairing the accuracy (Type I and II errors) of the ratings.

[Insert Table 4 Here]

We present the results for LMP CRAs in Panel B of Table 4, where the sample only includes the firms rated by both LMP CRAs and CBR. Consistent with our expectations, we find a continuous increase in ratings issued by LMP CRAs in Phases 1 and 2 relative to that of CBR. This means that after controlling the changes of firm financials, for the same firms, LMP CRAs increase their average ratings by 0.358 notches (column 1) during Dagong's suspension and another 0.168 notches (column 2) when Dagong re-enters the market. The coefficients on *LMP ×Post1* and *LMP ×Post2* are both significant at the 1% level. The incidence of a failed warning (Type I error) of LMP CRAs significantly rises in both Phases 1 and 2. The coefficient of β_1 in column 4 (column 5) is 0.017 (0.011), which means that after the punishment, the odds of a failed rating provided by LMP CRAs are 3.4 (1.5) times lower in Phase 1 (Phase 2), relative to that of CBR. For its false warning ratio (Type II error in columns 7-9), we document a slight reduction in Phase 1 and a significant rise in Phase 2. Overall, LMP CRAs have stronger incentives to use higher ratings to compete when Dagong left as well as when Dagong re-enters the market. And their ratings are less useful in both defining creditworthy firms and revealing risky ones.

Taken together, we show that HMP CRAs become more conservative after Dagong's punishment and when Dagong re-enters the market, while LMP CRAs are more aggressive. The results suggest that the penalty on Dagong only has a sobering effect on HMP CRAs. But for LMP CRAs, competing for market share dominates the concern of being caught up.

5.4 Market Reactions

5.4.1 Secondary market reactions

So far, we provide evidence that Dagong's punishment has no curbing effect on ratings inflation in the long run due to market competition. A natural question would then be how do investors react to the dynamic changes in the credit ratings market. Bond and stock market abnormal returns surrounding rating changes are widely used to estimate rating informativeness (e.g., Xia, 2014; Dimitrov et al., 2015; Agarwal et al., 2016). We expect different market reactions for different issuer-paid CRAs, i.e., Dagong, HMP and LMP CRAs in different phases since they react differently to the punishment as we document in Section 5.3. If the punishment improves the credit ratings' quality, both upgrades and downgrades become more informative and a more positive (negative) market reaction is expected for ratings upgrades (downgrades). This is the disciplining hypothesis as stated in Dimitrov et al. (2015). If CRAs artificially reduce their ratings in Phase 1 to protect their reputation (reputation hypothesis), ratings downgrades are less informative in Phase 1. However, rating upgrades in Phase 1 become more costly as upgrade actions expose CRAs to a higher probability of being penalized (i.e., lesson from Dagong's punishment). To avoid being perceived as inflating ratings, CRAs may spend more effort to issue an upgrade, which is potentially more informative.

We present the results of the secondary market reaction in Table 5. Panel A presents the summary statistics of the 7-day ABRs in each phase and the full sample period for upgrades and downgrades. We find that the upgrades made before the punishment have no market reaction (0.07% and insignificant), while bond investors positively react to the ratings upgrades after the punishment in Phases 1 and 2 (0.17% and 0.16%, respectively, significant at the 5% level). Comparing the market reactions in different phases, we find a significantly stronger reaction to upgrades in Phase 1 relative to Phase 0, potentially reflecting the quality improvement of credit ratings. However, there is no significant difference in market reactions between Phase 1 and Phase 2 for rating upgrades. This might be because the deterrence effect of punishment weakens (see Section 5.3), and credit ratings are inflated again. Investors perceive rating upgrades as milking the market instead of providing useful information. For rating downgrades, the market shows negative and significant reactions in Phases 1, 2 and 3, which is consistent with previous studies that find that investors are more sensitive to rating downgrades than upgrades (e.g., Holthausen and Leftwich, 1986; Hand et al., 1992; Dichev and Piotroski, 2001; Norden and Weber, 2004). Comparatively, the negative market reaction to rating downgrades in Phase 1 is indifferent from that in Phase 0, which is consistent with the reputation mechanism that investors treat downgrades as conservative consideration of CRAs rather than as stronger information. However, contrary to ratings upgrades, the market reacts more strongly to ratings downgrades in Phase 2 than Phase 1 (a difference of 0.93% in 7-day abnormal bond returns). This suggests that investors place more value on ratings downgrades when Dagong returns to the market. The results in Panel A of Table 5 suggest that investors are aware of the dynamic changes in market structure and CRAs' rating strategy.

[Insert Table 5 Here]

We conduct a more formal test in Eq. 4 to investigate the secondary market reactions to credit rating changes made by different CRAs in different phases:

$$ABR_{it}(CAR_{it}) = \beta_0 + \beta_1 POST_{it} + \beta_2 X_{it-1} + \gamma_i + \varepsilon_{it}, \quad (4)$$

where *ABR* is the issuer-level abnormal bond return, which is the (outstanding bond) volume-weighted average 7-day *ABR* for bonds issued by the same issuer for rating changes; and *CAR* is the 7-day cumulative abnormal stock return surrounding rating changes. *POST* and the control variables *X* are the same as in Eq. (1). Industry fixed effects are also included and we cluster the standard errors at the firm level.

We present the results of bond and stock market reactions in Panels B and C of Table 5, respectively. Since we observe largely consistent results for the bond and stock markets, we focus on interpreting the results in Panel B for the bond market, where bond prices are more directly affected by the changes of default probability as measured by credit ratings. Consistent with the evidence from our univariate tests and our results in Tables 3 and 4, investors have stronger positive reactions to ratings upgrades made by Dagong and HMP CRAs in Phase 1 than Phase 0 since they decrease their ratings overall (columns 1 and 2). Upgrades made by HMP CRAs in Phase 1 only cause a mild market reactions (column 3, significant at the 10% level), which might be because investors do not value the additional information in their upgrades since they are upward biased. We document results for downgrades made in Phase 1 in columns 4-5 of Table 5 Panel B. The market does not react to downgrades made by Dagong in Phase 1 compared to Phase 0, indicating an insignificant change in its informativeness. In columns 5 and 6, we find the market stronger reacts to downgrades made by HMP and LMP CRAs in Phase 1.

In columns 7-12 in Table 5 Panel B, we present the results of a comparison of the bond market reactions to ratings changes made in Phase 2 to those made in Phase 1. Since Dagong re-enters the market in Phase 2 and use aggressively higher ratings in an attempt to regain market share, its rating upgrades cause bond prices to drop relative to that during Phase 1.. It indicates Dagong's upgrades become less informative in Phase 2. We do not find significant differences in bond market reactions for the ratings upgrades made by HMP and LMP CRAs in Phase 2 compared to those made in Phase 1. This is consistent with the idea that investors are aware of the overall credit ratings increase in Phase 2, and are therefore not responsive to ratings upgrades. For ratings downgrades in columns 10-12, under the rating inflation era in Phase 2, which is largely driven by Dagong and LMP CRAs, investors may believe that ratings downgrades issued by them provide more useful information.

In summary, our results on the secondary bond and stock markets likely reflect the investors' awareness of the dynamic changes in the credit ratings market after Dagong's suspension and react accordingly.

5.4.2 Primary market reactions

In this section, we examine the sensitivity of the bond issuance spread on the credit ratings surrounding Dagong's market exit and re- entry to evaluate the primary bond market's reactions to the punishment. We find that credit ratings have a negative relation with the bond offering yield spread (i.e., the cost is lower for bonds with higher ratings). Therefore, if investors believe there is an improvement in the quality of ratings, we expect to see a stronger negative relation between the bond offering yield spread and its credit rating. Otherwise, we may observe a less negative relation when investors lose their confidence in credit ratings.

We collect all the newly issued corporate debt securities with maturity longer than one year between May 1, 017 and March 15, 2021.[24] Since Dagong does not rate any new bonds in Phase 1, we only keep the issues rated by non-Dagong issuer-paid CRAs. The regression is as follows:

$$Spread_{it} = \beta_0 + \beta_1 Rating_{it} * POST_{it} + \beta_2 POST_{it} + \beta_3 X_{it-1} + \beta_4 Z_i + \gamma_i + \mu_i + \varepsilon_{it}, \quad (5)$$

where *Spread* is the percentage difference between the bond offering yield and the yield on a Treasury note of comparable maturity for bond i issued at time t. *Rating* denotes the credit rating levels ranging from 1 to 5. *POST* and *X* are defined the same as for Eq. (1). We also control three issue characteristics (*Z*), i.e., maturity of the bond, bond issuance size and the secured status of the bond, as defined in Section 4.3.2. Industry fixed effects (γ_i) and rating fixed effects (μ_i) are also included. We cluster our standard errors by firm and correct for heteroskedasticity. A negative (positive) coefficient of β_1 indicates that the offering yield spread is more (less) sensitive to credit ratings in the Phase 2 relative Phase 1. The results of Eq. (5) are in Table 6.

In columns 1-3 in Table 6, we present the results of a comparison of the relation between offering yield spread and credit ratings between Phase 1 and Phase 0, while the results for the comparison between Phase 2 and Phase 1 are in columns 4-6. In column 1, we find a negative coefficient on *Rating* ×*Post1* for all non-Dagong rated issues (-0.220, significant at the 5% level), indicating a stronger relation between issuance price and ratings in Phase 1 than in Phase 0. However, the effects are different between issues rated by HMP and LMP CRAs. For HMP CRAs, the coefficient on *Rating* ×*Post1* is -0.137, significant at the 1% level, which suggests the ratings provided by HMP CRAs' are more useful to investors. In column 3, investors do not allocate more weighting on the bonds issued by LMP CRAs in Phase 1 relative to Phase 0. When we compare the sensitivity of primary market bond price to ratings in Phase 2 to that in Phase 1 in columns 4-6, we find consistently positive coefficients on *Rating*×*Post2*, suggesting that investors re-adjust their perception on the informativeness of credit ratings in Phase 2 when the market competition status changes upon Dagong's return, and they realize the ratings inflation.

[24] Our results are qualitatively unchanged if we include the new issues with less than one-year maturity.

The results from the primary bond market are consistent with the secondary market reactions, and reflect investors' awareness of the rating quality changes over Dagong's suspension.

[Insert Table 6 Here]

To summarize, the punishment on Dagong directly affects its credit rating strategies and rating informativeness during its business suspension and market re-entry. We find more conservative ratings from Dagong in Phase 1 (i.e., the suspension period) than in the pre-punishment period (Phase 0). Its incidence of failed warnings drops while the false warning rate increases. Markets react stronger to Dagong's ratings upgrades but not for downgrades. These results suggest that after the punishment, Dagong intentionally adjusts its strategy by lowering ratings. Higher ratings from Dagong show a quality improvement while its lower ratings indicate an informativeness reduction. When Dagong re-enters the market (Phase 2), in order to regain its market power, Dagong increases its ratings aggressively, making its upgrades less informative and downgrades more useful.

Due to the changes in market dynamic due to Dagong's exit and re-entry, non-Dagong issuer-paid CRAs also adjust their strategies. The reactions are different between CRAs with higher market power and lower market power. Deterred by the punishment, HMP CRAs reduce their ratings in Phase 1 and do not inflate ratings again in Phase 2. This may because they want to avoid being punishment and protect their existing market power. We also observe rating quality improvement and markets react stronger to rating changes made by HPM CRAs. On the other hand, LMP CRAs are not disciplined by the punishment on Dagong. Instead, they aggressively raise their ratings in both Phase 1 and Phase 2 to compete in the market with lower ratings quality and informativeness.

6. Additional Tests and Discussion

6.1 Punishment Timing

To more clearly interpret the estimates of the coefficients on the interaction term *Dagong (HMP/LMP)×POST* as the causal effects of Dagong's exit and re-entry, we conduct a placebo test by replacing the punishment date and re-entry date with hypothetical dates 6 or 9 months before or after the actual event dates and re-run our tests on the changes in credit ratings.

We present the regression coefficients on the interaction terms for *CRA×Post1(Post2)* in Table 7. *CRA* is a dummy variable that equals one if the rating is from Dagong (HMP/LMP) and zero if the rating is issued by CBR in columns 1-2 (3-4/5-6). The dependent variable in Table 7 is *Rating*. Columne 1-2 show the results for Dagong. We do not find significant changes of ratings provided by Dagong compared to that of CBR when we assume the punishment and re-entry events happen 6 or 9 months before the actual dates. If we assume these events happen after the actual dates, we document similar results as in Table 3 that Dagong reduces its ratings in Phase 1 and inflate it in Phase 2. We document consistent results for HMP CRAs in columns 3-4, compared to columns 1-2 in Panel A of Table 4. For LMP CRAs in columns 5-6, significant rating increases are documented when the hypothetical events happened after the acutal events.

The significance in column 6 for the *CRA×Post2* before the real event is due to its overlapping with the Dagong suspension period, when LMP CRAs already start to increase their ratings. Therefore, the results in Table 7 confirm the causal relationship between Dagong's punishment and the ratings strategy changes made by issuer-paid CRAs.

[Insert Table 7 Here]

6.2 Ordinal Regression Model for Baseline Results

In our main models, we use the OLS estimation, where we assume the distance between nearby ratings categories is the same. To further check the robustness of our results with loosened assumptions, we use an alternative method, the ordinal regression model (ORM). The ORM is commonly presented as a latent-variable model. We re-run our tests and report the results of these alternative models in Table 8. We find that the ORM results are consistent with our main results in Table 4.

[Insert Table 8 Here]

6.3 Random Sample Simulation for Dagong

In this section, we investigate the possibility that our results are purely driven by chance following Gao, Shi, and Zhao (2021). Specifically, we employ a random sample of 1,776 Dagong covered observations (the same number of the actual samples in our treatment group) and this is the "pseudo-treatment group" of our issuer-paid CRAs covered group; the CBR covered samples are the control group. Based on this "pseudo" group, we re-estimate the regression for Table 4 and save the coefficients on *Dagong*×*Post*. Then we repeat this procedure 10,000 times.

Figure 4 shows the distribution of the coefficients on *Treat*×*Post*. The coefficients on *Dagong*×*Post* are located at reasonable positions (consistent with signs and significant levels) in histograms. These results indicate that our results are indeed driven by Dagong's punishment and are unlikely to be driven by chance.

[Insert Figure 4 Here]

7. Conclusion

In this study, we investigate how does regulatory punishment affects the dynamics of the credit ratings market in China. In 2018, regulators in China suspended Dagong Global Credit Rating Co. Ltd.'s license from rating newly issued bonds. Employing the business suspension and re-entry of Dagong, one of the largest credit rating agencies in China as exogenous shocks, we examine how this punishment affects the rating strategies and rating qualities of different CRAs, and how investors react to the events.

We use the DiD method to rule out the business cycle effects or the effects of firm fundamental changes. Using the ratings provided by CBR on the same firms as the control group, we find that Dagong is more conservative after the business suspension was imposed, but again aggressively inflates ratings when re-entering the market in an attempt to regain lost market share. Dagong's ratings upgrades are more informative during its business suspension but less useful when it re-enters the market. Its downgrades are less useful during its suspension but more informative when it re-enters the market.

Other non-Dagong issuer-paid CRAs are affected by the punishment. The punishment improves the ratings quality of other major non-Dagong rating agencies in the market, a deterring effect, but worsens the rating quality of less competitive crediting rating agencies. These less competitive rating agencies take the suspension as an opportunity to grab market shares by issuing inflated ratings. Investors are able to identify the rating quality changes in different punishment phases and react accordingly.

We strengthen the uncertain impacts of legal or regulatory punishment on CRAs due to market dynamics changes and CRAs' incentives. Our results suggest that regulators should be cautious when attempting to suspend the license of major players in the credit ratings market, which might lead to biased ratings. We suggest that regulators develop different regulations against different types of CRAs.

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Figure 1: Timeline and the Event Windows

Figure 1 depicts the timeline and the event windows of our sample. Phase 0 is the pre-punishment period from May 1, 2017 to August 18, 2018; Phase 1 is the Dagong business suspension period from August 19, 2018 to November 31, 2019; and Phase 2 is the Dagong re-entry period from December 1, 2019 to March 15, 2021.

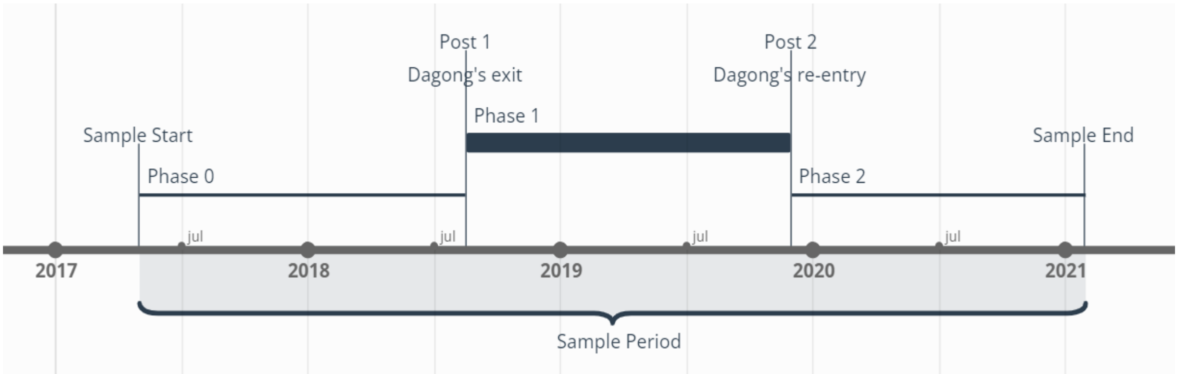

Figure 2: Sample Distribution of Firms in the Raw Sample and Reduced Sample

Panel A presents the percentage distribution of firms in the raw sample and reduced sample across industries. Panel B presents the percentage distribution of firms in the raw sample and reduced sample across size categories.

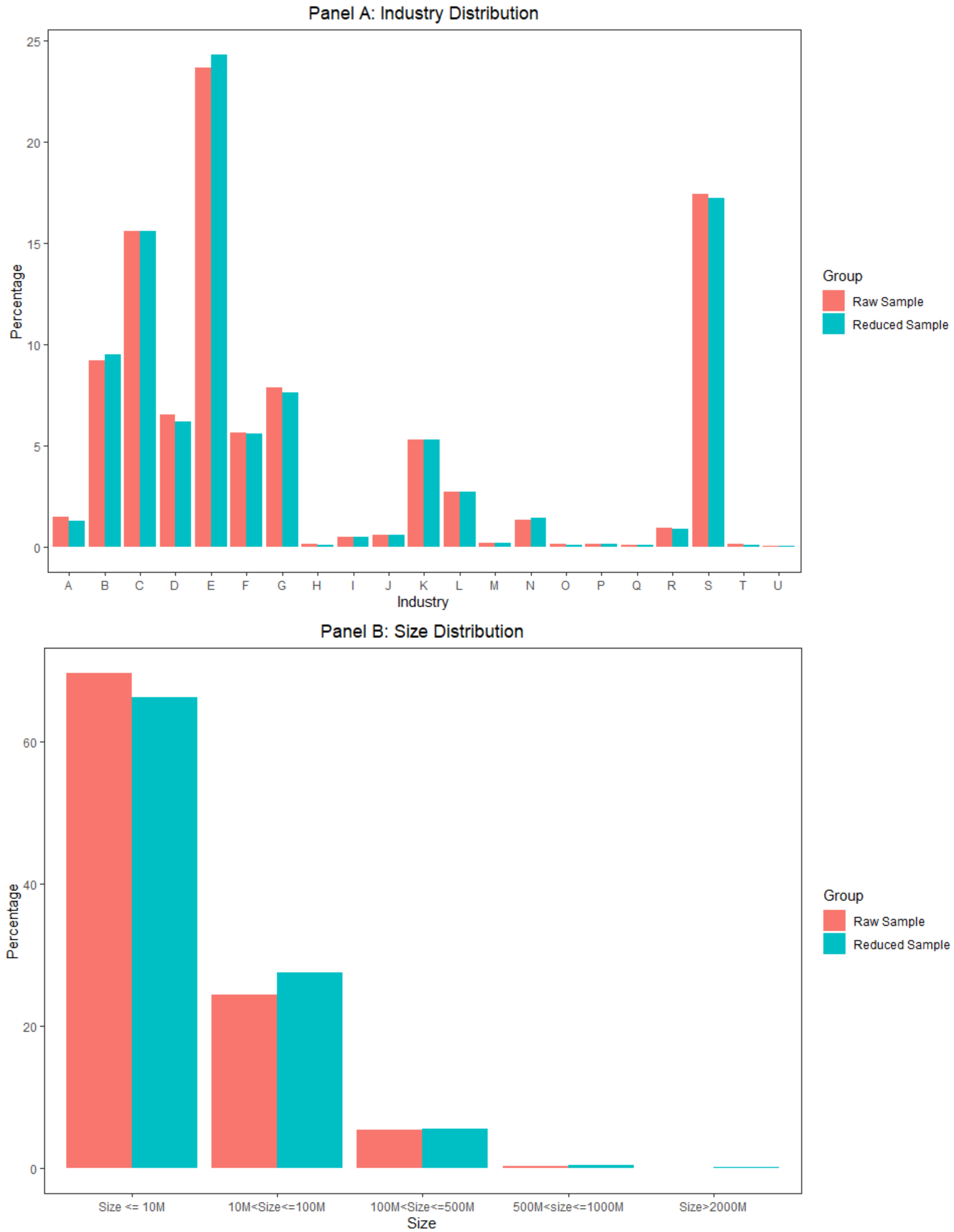

Figure 3: Credit Ratings of Issuer-paid CRAs and CBR in Three Phases

Figure 3 presents the quarterly average credit ratings issued by issuer-paid CRAs and CBR surrounding Dagong's market exit and re-entry.

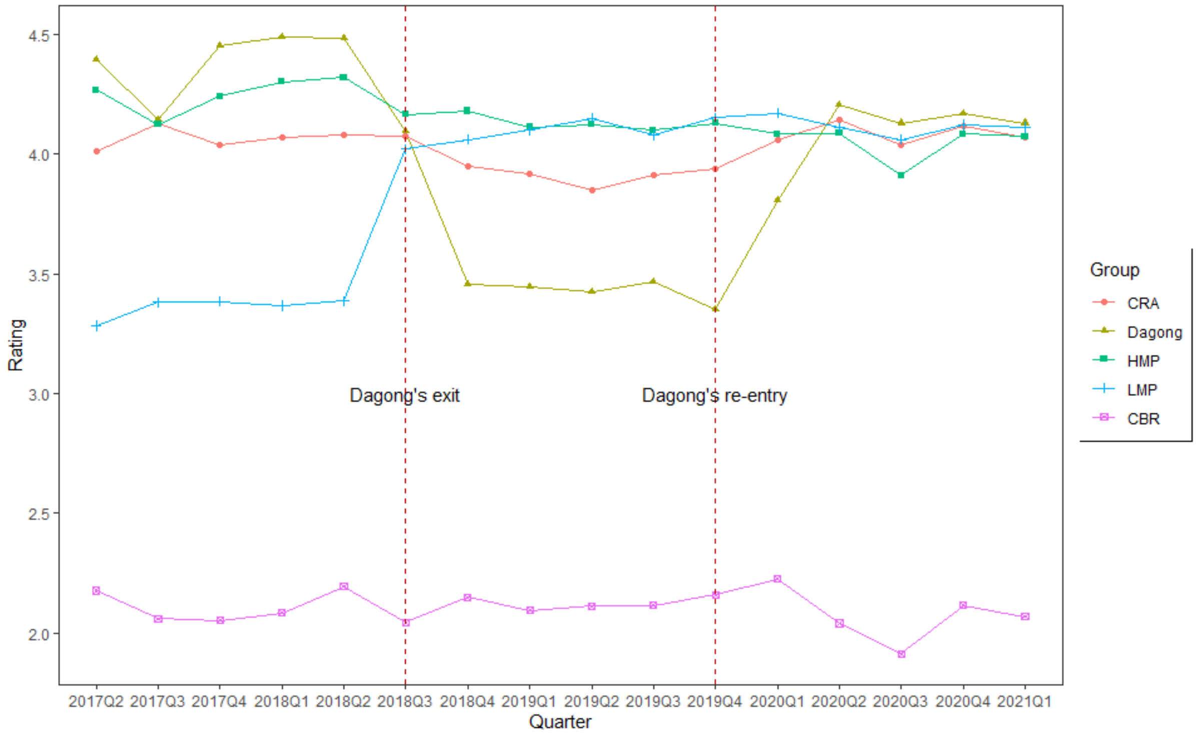

Figure 4: Random Sample Simulation of Dagong

This figure shows a histogram of the coefficients on *Dagong*×*Post* from 10,000 bootstrap simulations of the model in Eq. (1). For each iteration, we draw a random sample of 1,776 Dagong covered observations (the same number of the actual samples in our treatment group) as the "treatment group" from our issuer-paid CRAs covered group, and then treat the CBR covered samples as the control group. Based on these randomized treated samples, we re-estimate the results in Table 4 and save the coefficients on *Dagong*×*Post*. We also indicate the true coefficients of *Dagong*×*Post* in each plot.

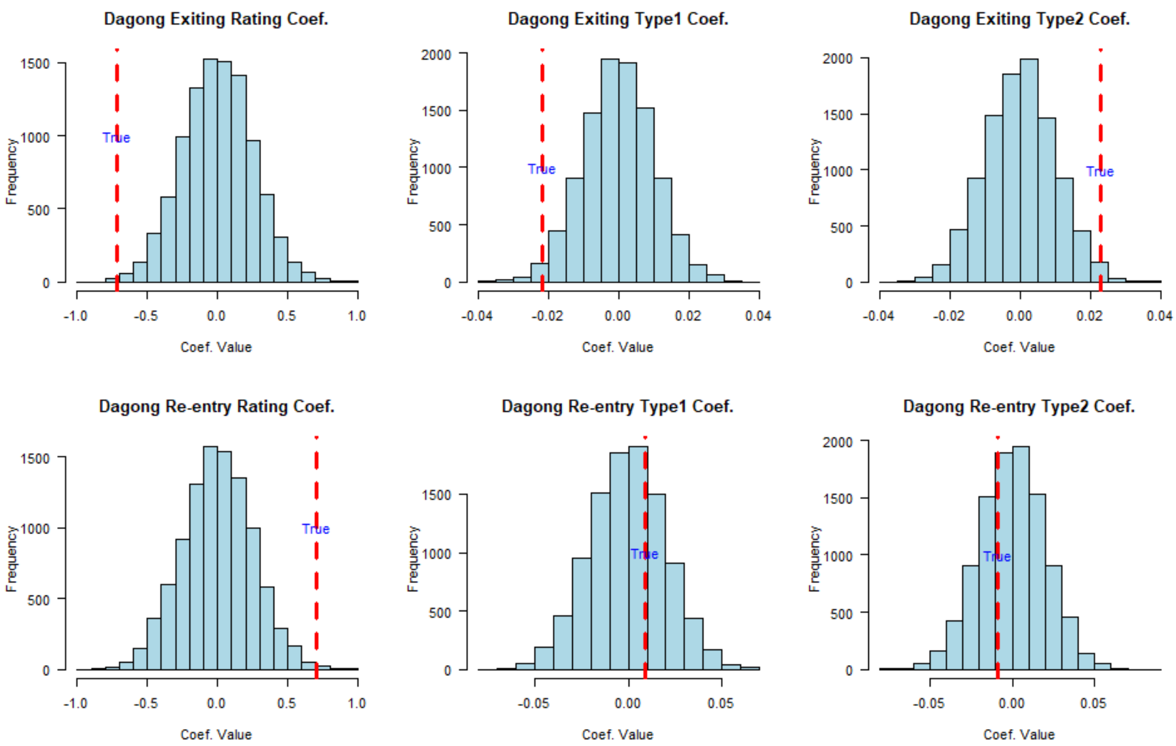

Table 1: Raw Sample and Reduced Sample

Panel A presents the firm characteristics in the raw and reduced samples, while Panel B presents the summary statistics of credit ratings for the raw and reduced samples for different estimation periods. We conduct t-tests for the difference-in-means. All the variables are defined in Appendix 3. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Firm characteristics in raw sample and reduced sample

	Raw Sample			Reduced Sample			
	N	**Mean**	**Std. Dev.**	***N***	**Mean**	**Std. Dev.**	***T*-test**
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(5)-(2)**
ROA	53,454	3.57	2.45	20,183	3.59	2.55	0.02
Leverage	53,454	64.58	18.39	20,183	64.12	14.77	-0.46***
Tangibility	53,454	30.19	18.60	20,183	30.26	18.54	0.07
Cash	53,454	56.90	20.15	20,183	56.76	45.69	-0.14
Growth	53,454	43.68	898.56	20,183	41.23	847.95	-2.45
Sales	53,454	2.62	1.53	20,183	2.60	1.95	-0.02
Age	53,454	2.89	0.56	20,183	2.91	2.01	0.02
Listed	53,454	0.18	0.34	20,183	0.19	0.38	0.01**
SOE	53,454	0.79	0.35	20,183	0.84	0.36	0.05***

Panel B: Credit ratings in raw sample and reduced sample

	Raw Sample		Reduced Sample		
	N	**Mean**	***N***	**Mean**	***T*-test**
	(1)	**(2)**	**(3)**	**(4)**	**(4)-(2)**
All periods	53,454	4.07	20,183	4.06	-0.01
Phase 0	20,223	4.08	5,836	4.06	-0.02
Phase 1	16,514	4.02	6,944	4.04	0.02
Phase 2	16,717	4.11	7,403	4.09	-0.02

Table 2 Summary statistics

Panel A presents the number of observations, the mean value, median value, standard deviation, 25 percentile (P25), and 75 percentile (P75) of the main variables. The sample consists of 40,366 observations from May 2017 to March 2021 for 2,121 unique firms covered by both issuer-paid CRAs and CBR. Panel B presents the credit ratings issued by issuer-paid CRAs and CBR. We conduct *t*-tests for the difference-in-means. All the variables are defined in Appendix 3. ***, ** and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Summary statistics of main variables						
	N	**Mean**	**Median**	**Std. Dev.**	**P25**	**P75**
Rating	40,366	3.08	3.00	1.52	1.00	5.00
Type1	40,366	0.01	0.00	0.09	0.00	0.00
Type2	40,366	0.00	0.00	0.03	0.00	0.00
ABR_Up	641	0.14	0.12	1.10	0.05	0.22
ABR_Down	531	-4.70	-4.53	2.70	-6.74	-2.43
CAR_Up	102	0.37	0.29	2.29	0.16	0.56
CAR_Down	127	-7.54	-7.35	4.52	-10.77	-3.06
Spread	4,550	2.48	2.21	1.18	1.61	3.12
Dagong	40,366	0.04	0.00	0.21	0.00	0.00
HMP	40,366	0.35	0.00	0.48	0.00	1.00
LMP	40,366	0.11	0.00	0.31	0.00	0.00
Post1	40,366	0.34	0.00	0.48	0.00	1.00
Post2	40,366	0.37	0.00	0.48	0.00	1.00
ROA	40,366	3.59	3.14	2.55	2.50	4.27
Leverage	40,366	64.12	65.87	14.77	57.08	72.84
Tangibility	40,366	30.26	30.97	18.54	17.31	42.44
Cash	40,366	56.76	45.86	45.69	33.69	65.97
Growth	40,366	41.23	11.65	847.95	-1.16	28.77
Sales	40,366	2.61	2.50	1.95	1.10	4.01
Age	40,366	2.92	3.00	2.01	2.64	3.25
Listed	40,366	0.18	0.00	0.38	0.00	0.00
SOE	40,366	0.84	1.00	0.36	1.00	1.00

Panel B: Issuer-paid CRAs' and CBR's ratings							
	Ratings by issuer-paid CRAs			**Ratings by CBR**			
	N	**Mean**	**Std. dev.**	**N**	**Mean**	**Std. dev.**	**T-test**
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(5)-(2)**
Full sample	20,183	4.061	0.966	20,183	2.100	1.318	-1.961***
Dagong	1,776	4.068	0.955	1,776	1.950	1.235	-2.118***
HMP	13,930	4.146	0.968	13,930	2.274	1.364	-1.873***
LMP	4,477	3.792	0.915	4,477	1.620	1.052	-2.172***

Table 3: The impact on Dagong

This table shows the impact of Dagong's suspension and re-entry on Dagong's ratings and rating quality. We present the regression results from Eq. (1) in columns 1-2, 4-5, and 7-8, and the results from Eq. (2) in columns 3, 6, and 9, to estimate the changes of rating levels and rating qualities surrounding the Dagong's market exit and re-entry. The sample for columns 1, 4, and 7 includes ratings issued by Dagong and CBR for the same firms in Phases 0 and 1. The sample for columns 2, 5, and 8 includes ratings issued by Dagong and CBR for the same firms in Phases 1 and 2. The sample for columns 3, 6, and 9 includes ratings issued by Dagong and CBR for the same firms in Phases 0, 1 and 2. The dependent variable in the regression for the results in columns 1-3 is *Rating*, which is a numerical value between 1-5 to represent the rating notches. The dependent variable in the regression for the results in columns 4-6 is *Type I* error, which is a dummy variable that equals one for a AA+ or above rated firm that defaults within one year and zero otherwise, to represent the failed warning of the rating. The dependent variable in the regression for the results in columns 7-8 is *Type II* error as a dummy variable which equals one for a A+ or lower rated issuer that does not default within one year and zero otherwise. *Dagong* is a dummy variable that equals one if the rating is issued by Dagong, and zero if the rating is issued by CBR. *Post1* (*Post2*) is a dummy variable that equals one if the rating is issued in Phase 1 (Phase 2) and zero otherwise. All variables are defined in Appendix 3. The continuous issuer-specific variables are winsorized at the top and bottom 5% of the sample distribution. The robust standard errors are clustered at the firm level are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	Rating			***Type I***			***Type II***		
	Exit	**Re-entry**	**Two-period**	**Exit**	**Re-entry**	**Two-period**	**Exit**	**Re-entry**	**Two-period**
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**
Dagong×Post1	-0.720***		-0.720***	-0.022**		-0.022**	0.023**		0.023**
	(0.073)		(0.073)	(0.011)		(0.011)	(0.010)		(0.010)
Dagong×Post2		0.706***	0.702***		0.009	-0.013		-0.010	-0.013*
		(0.080)	(0.084)		(0.013)	(0.018)		(0.013)	(0.008)
Dagong	2.314***	1.594***	2.314***	0.045***	0.023	0.045***	-0.001	0.023**	-0.001
	(0.078)	(0.072)	(0.078)	(0.015)	(0.019)	(0.015)	(0.005)	(0.010)	(0.004)
Post1	0.002		0.006	0.001		0.000	0.001*		0.001
	(0.048)		(0.048)	(0.002)		(0.002)	(0.001)		(0.001)
Post2		-0.146	-0.142		-0.003	-0.002		0.002	0.003
		(0.154)	(0.163)		(0.004)	(0.006)		(0.003)	(0.002)
ROA	-0.065***	-0.021	-0.040*	-0.001	-0.002*	-0.001	-0.003	-0.006	-0.004
	(0.020)	(0.024)	(0.021)	(0.003)	(0.001)	(0.002)	(0.004)	(0.004)	(0.003)
Leverage	-0.011***	-0.007***	-0.009***	0.002	-0.0004	0.002	0.001	0.003	0.002
	(0.003)	(0.002)	(0.002)	(0.003)	(0.001)	(0.002)	(0.001)	(0.003)	(0.002)
Tangibility	0.001	0.002	0.002	-0.001	-0.001**	-0.001	-0.000	-0.000	-0.000
	(0.002)	(0.002)	(0.002)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Cash	-0.000	-0.001	-0.000	0.001	0.004	0.010	-0.001	-0.001	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.005)	(0.004)	(0.002)	(0.001)	(0.002)
Growth	0.001	-0.001	-0.000	0.000	0.000	0.000	-0.000	-0.000	-0.000
	(0.003)	(0.002)	(0.002)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Sales	0.367***	0.289***	0.329***	-0.002	-0.001	-0.001	-0.001	-0.001	-0.0002
	(0.024)	(0.026)	(0.024)	(0.002)	(0.002)	(0.002)	(0.001)	(0.002)	(0.001)
Age	0.056	0.116	0.088	0.005	0.003	0.004	-0.005	-0.009*	-0.005*
	(0.089)	(0.095)	(0.087)	(0.008)	(0.007)	(0.007)	(0.003)	(0.005)	(0.003)
Listed	0.176*	0.088	0.142	0.006	0.014	0.011	0.012	0.026	0.014*
	(0.093)	(0.117)	(0.097)	(0.017)	(0.016)	(0.016)	(0.010)	(0.016)	(0.008)
SOE	0.680***	0.803***	0.747***	-0.041	-0.035**	-0.041**	-0.019**	-0.033**	-0.020**
	(0.092)	(0.120)	(0.098)	(0.025)	(0.016)	(0.021)	(0.009)	(0.014)	(0.009)
Industry fixed	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	2,492	2,006	3,552	2,492	2,006	3,552	2,492	2,006	3,552
Adj. R^2	0.667	0.656	0.676	0.074	0.112	0.093	0.044	0.066	0.047

Table 4: The impact on non-Dagong issuer-paid CRAs

This table shows the results of an examination of the impact of Dagong's suspension and re-entry on the ratings and rating quality of HMP CRAs in Panel A and LMP CRAs in Panel B. We present the regression results from Eq. (1) in columns 1-2, 4-5, and 7-8, and the results from Eq. (2) in columns 3, 6, and 9, to estimate the changes of rating levels and rating qualities surrounding the Dagong's market exit and re-entry. The sample for Panel A (B) columns 1, 4, and 7 includes ratings issued by HMP (LMP) CRAs and CBR for the same firms in Phases 0 and 1. The sample for Panel A (B) columns 2, 5, and 8 includes ratings issued by HMP (LMP) CRAs and CBR for the same firms in Phases 1 and 2. The sample for Panel A (B) columns 3, 6, and 9 includes ratings issued by HMP (LMP) CRAs and CBR for the same firms in Phases 0, 1 and 2. The dependent variable in columns 1-3 is *Rating*, which is a numerical value between 1-5 to represent the rating notches. The dependent variable in the regression for the results in columns 4-6 is *Type I* error, which is a dummy variable that equals one for a AA+ or above rated firm that defaults within one year and zero otherwise, to represent the failed warning of the rating. The dependent variable in the regression for the results in columns 7-8 is *Type II* error as a dummy variable that equals one for a A+ or lower rated issuer that does not default within one year and zero otherwise. *HMP* (*LMP*) is a dummy variable that equals one if the rating is issued by HMP (LMP) CRAs, and zero if the rating is issued by CBR. *Post1* (*Post2*) is a dummy variable that equals one if the rating is issued in Phase 1 (Phase 2) and zero otherwise. The untabulated controls include *ROA*, *Leverage*, *Tangibility*, *Cash*, *Growth*, *Sales*, *Age*, *Listed*, and *SOE*. All variables are defined in Appendix 3. The continuous issuer-specific variables are winsorized at the top and bottom 5% of the sample distribution. The robust standard errors clustered at the firm level are reported in parentheses. ***, ** and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively

Panel A: HMP sample									
	Rating			***Type I***			***Type II***		
	Exit	**Re-entry**	**Two-period**	**Exit**	**Re-entry**	**Two-period**	**Exit**	**Re-entry**	**Two-period**
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**
HMP × Post1	-0.179***		-0.179***	-0.006		-0.006	0.002*		0.002*
	(0.035)		(0.035)	(0.005)		(0.005)	(0.001)		(0.001)
HMP × Post2		0.055*	-0.124***		-0.005*	-0.011*		-0.001	0.001*
		(0.030)	(0.037)		(0.003)	(0.006)		(0.001)	(0.001)
HMP	1.981***	1.802***	1.981***	0.017***	0.011***	0.017***	0.000	0.002**	0.000
	(0.042)	(0.046)	(0.042)	(0.006)	(0.003)	(0.006)	(0.000)	(0.001)	(0.000)
Post1	0.033		0.037	0.001		0.001	0.000		0.000
	(0.034)		(0.034)	(0.001)		(0.001)	(0.000)		(0.000)
Post2		-0.014	-0.030		0.000	0.001		-0.000	0.000
		(0.022)	(0.036)		(0.0003)	(0.001)		(0.001)	(0.000)
Firm Controls	YES	YES	YES	YES	YES	YES	YES	YES	YES
Industry fixed	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	17,758	19,986	27,860	17,758	19,986	27,860	17,758	19,986	27,860
Adj. R^2	0.647	0.619	0.638	0.042	0.028	0.036	0.026	0.018	0.015

Table 4 (Cont.)

Panel B: LMP samples									
	Rating			***Type I***			***Type II***		
	Exit	**Re-entry**	**Two-period**	**Exit**	**Re-entry**	**Two-period**	**Exit**	**Re-entry**	**Two-period**
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**
LMP ×Post1	0.358***		0.358***	0.017***		0.017***	-0.002*		-0.002*
	(0.046)		(0.045)	(0.005)		(0.006)	(0.001)		(0.001)
LMP ×Post2		0.168***	0.526***		0.011*	0.028***		0.003***	0.005***
		(0.039)	(0.043)		(0.006)	(0.006)		(0.001)	(0.002)
LMP	1.836***	2.194***	1.836***	0.007*	0.024***	0.007	0.004**	0.003***	0.004***
	(0.035)	(0.029)	(0.034)	(0.004)	(0.004)	(0.005)	(0.002)	(0.001)	(0.001)
Post1	0.007		0.018	0.002		0.003	0.001		0.001
	(0.033)		(0.032)	(0.004)		(0.004)	(0.002)		(0.001)
Post2		-0.050*	-0.032		0.005	0.006		0.000	0.001
		(0.028)	(0.031)		(0.004)	(0.004)		(0.001)	(0.001)
Firm Controls	YES	YES	YES	YES	YES	YES	YES	YES	YES
Industry fixed	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	5,310	6,702	8,954	5,310	6,702	8,954	5,310	6,702	8,954
Adjusted R^2	0.667	0.724	0.700	0.065	0.058	0.050	0.009	0.011	0.009

Table 5: Secondary Market Reaction

This table provides the results of a comparison of secondary market reactions to credit ratings changes made by issuer-paid CRAs in different phases during the Dagong's suspension. Panel A presents the mean and median values of the 7-day abnormal bond returns (ABRs) in each phase and the full sample period for upgrades and downgrades, as well as the *t*-tests for the difference-in-means between periods. Panels B and C present the regression results from Eq. (4) for the bond market and stock markets, respectively. The dependent variable in the regression for Panel B results is the ABRs while the dependent variable in the regression for Panel C is the 7-day cumulative stock returns (CARs). The sample for columns 1-4 includes market reactions for rating changes in Phases 0 and 1, and the sample for columns 5-8 includes market reactions for ratings changes in Phases 1 and 2. Columns 1 and 7 (4 and 10) present the results for Dagong's rating upgrades (downgrades). Columns 2 and 8 (5 and 11) present the results for ratings upgrades (downgrades) made by HMP CRAs. Columns 3 and 9 (6 and 12) present the results for ratings upgrades (downgrades) made by LMP CRAs. *Post1* (*Post2*) is a dummy variable that equals one if the rating is issued in Phase 1 (Phase 2) and zero otherwise. The untabulated controls include *ROA*, *Leverage*, *Tangibility*, *Cash*, *Growth*, *Sales*, *Age*, *Listed*, and *SOE*. All variables are defined in Appendix 3. The continuous issuer-specific variables are winsorized at the top and bottom 5% of the sample distribution. The robust standard errors clustered at the firm level are reported in parentheses. ***, ** and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Rating announcement bond return

	Credit Rating Upgrades			**Credit Rating Downgrades**		
	N	**Mean**	**Median**	**N**	**Mean**	**Median**
Phase 0 (1)	191	0.07	0.06	161	-4.25***	-4.36***
Phase 1 (2)	217	0.17***	0.16***	192	-4.48***	-4.61***
Phase 2 (3)	233	0.16**	0.15**	178	-5.31***	-5.34***
Total	641	0.14***	0.12**	531	-4.70***	-4.53***
Difference (2)-(1)		0.10***	0.10***		-0.23	-0.25
t-value		3.18	3.18		-0.98	-1.06
Difference (3)-(2)		-0.01	-0.01		-0.93***	-0.74***
t-value		-0.48	-0.48		-3.11	-2.47

Table 5 (Cont.)

Panel B: OLS bond market reaction

	Phase 1 vs. Phase 0						Phase 2 vs. Phase 1					
	Credit rating upgrades			Credit rating downgrades			Credit rating upgrades			Credit rating downgrades		
	Dagong	HMP	LMP	Dagong	HMP	LMP	Dagong	HMP	LMP	Dagong	HMP	LMP
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Post1	0.126***	0.106***	0.035*	-0.322	-1.294***	-1.316**						
	(0.021)	(0.011)	(0.019)	(0.542)	(0.398)	(0.512)						
Post2							-0.074***	-0.002	-0.026*	-1.868**	0.448	-1.375**
							(0.024)	(0.015)	(0.015)	(0.738)	(0.382)	(0.684)
Observations	34	240	134	86	160	107	58	213	179	65	202	103
Adjusted R^2	0.550	0.315	0.014	-0.067	0.065	0.042	0.300	0.015	0.035	0.089	-0.006	0.008

Panel C: OLS stock market reaction

	Phase 1 vs. Phase 0						Phase 2 vs. Phase 1					
	Credit rating upgrades			Credit rating downgrades			Credit rating upgrades			Credit rating downgrades		
	Dagong	HMP	LMP	Dagong	HMP	LMP	Dagong	HMP	LMP	Dagong	HMP	LMP
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Post1	0.322***	0.336***	0.000	0.988	-4.518**	-0.350						
	(0.055)	(0.080)	(0.254)	(2.672)	(1.809)	(1.573)						
Post2							-0.316	-0.119	0.397*	-4.519*	2.803	-2.138
							(0.065)	(0.156)	(0.173)	(2.310)	(2.137)	(2.142)
Observations	15	44	15	19	43	17	11	27	18	23	51	23
Adjusted R^2	0.899	0.202	0.300	-0.184	0.032	0.268	0.958	0.148	0.242	0.017	0.008	-0.308
Firm controls	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Industry fixed	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES

Table 6: Primary Market Reactions

This table resents the regression results of the bond offering yield spread against the interaction term between *Rating* and *Post1* (*Post2*), together with a list of firm and issue control variables, from Eq. (6). The sample for columns 1-3 includes new bond issuance rated by non-Dagong issuer-paid CRAs in Phases 0 and 1, and the sample for columns 5-8 includes new bond issuance rated by non-Dagong issuer-paid CRAs in Phases 1 and 2. *Spread* is the percentage difference between the bond offering yield and the yield on a Treasury note of comparable maturity. *Rating* is a numerical value between 1-5 to represent the rating notches. *Post1* (*Post2*) is a dummy variable which equals one if the rating is issued in Phase 1 (Phase 2) and zero otherwise. The untabulated controls include *ROA*, *Leverage*, *Tangibility*, *Cash*, *Growth*, *Sales*, *Age*, *Listed*, *SOE*, *Maturity*, *Isize*, and *Guarantee*. All variables are defined in Appendix 3. The continuous issuer-specific variables are winsorized at the top and bottom 5% of the sample distribution. The robust standard errors clustered at the firm level are reported in parentheses. ***, ** and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	Phase 1 vs. Phase 0			**Phase 2 vs. Phase 1**		
	Non-Dagong	**HMP**	**LMP**	**Non-Dagong**	**HMP**	**LMP**
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Rating×Post1	-0.220***	-0.137**	-0.133			
	(0.058)	(0.064)	(0.183)			
Rating×Post2				0.146***	0.146**	0.225**
				(0.049)	(0.057)	(0.105)
Post1	0.015	-0.583*	0.146			
	(0.267)	(0.299)	(0.741)			
Post2				-0.900***	-0.881***	-1.312***
				(0.226)	(0.270)	(0.460)
Firm controls	YES	YES	YES	YES	YES	YES
Issue controls	YES	YES	YES	YES	YES	YES
Industry fixed	YES	YES	YES	YES	YES	YES
Rating fixed	YES	YES	YES	YES	YES	YES
Observations	1,337	907	430	1,072	694	378
Adjusted R^2	0.338	0.407	0.200	0.579	0.604	0.534

Table 7: Placebo Test

This table gives the results when we re-run the analysis in Eq. (1) and replace the punishment date and re-entry date with hypothetical dates 6 or 9 months before or after the actual event dates. The dependent variable is *Rating*, which is a numerical value between 1-5 to represent the rating notches. The untabulated controls include *ROA*, *Leverage*, *Tangibility*, *Cash*, *Growth*, *Sales*, *Age*, *Listed*, *SOE*, *Maturity*, *Isize*, and *Guarantee*. All variables are defined in Appendix 3. The continuous issuer-specific variables are winsorized at the top and bottom 5% of the sample distribution. The robust standard errors clustered at the firm level are reported in parentheses. ***, ** and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Dep.Var=Rating	**Dagong**		**HMP**		**LMP**	
	Exit	**Re-entry**	**Exit**	**Re-entry**	**Exit**	**Re-entry**
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
CRA×Post1 (*t*-9)	-0.071		-0.024		0.053	
	(0.061)		(0.021)		(0.034)	
CRA×Post2 (*t*-9)		0.107		-0.048		0.122***
		(0.083)		(0.043)		(0.031)
CRA×Post1 (*t*-6)	-0.117		-0.041		0.042	
	(0.079)		(0.037)		(0.037)	
CRA×Post2 (*t*-6)		0.113		-0.015		0.136***
		(0.092)		(0.028)		(0.041)
CRA×Post1	**-0.720*****		**-0.179*****		**0.358*****	
	(0.073)		**(0.035)**		**(0.046)**	
CRA×Post2		**0.706*****		**0.055***		**0.168*****
		(0.080)		**(0.030)**		**(0.039)**
CRA×Post1 (*t*+6)	**-0.969*****		**-0.226*****		**0.524*****	
	(0.077)		**(0.049)**		**(0.069)**	
CRA×Post2 (*t*+6)		**1.069*****		**0.069**		**0.384*****
		(0.358)		**(0.056)**		**(0.108)**
CRA×Post1 (*t*+9)	**-1.065*****		**-0.284*****		**0.823*****	
	(0.089)		**(0.059)**		**(0.067)**	
CRA×Post2 (*t*+9)		**1.246*****		**-0.097**		**0.481*****
		(0.398)		**(0.086)**		**(0.117)**

Table 8: Ordinal Regression Model

This table gives the results when we re-run the analyses in Tables 4-5 using ordinal regression model where we treat the dependent variable, *Rating*, as a categorical variable. The samples in columns 1-3 include ratings The untabulated controls include *ROA*, *Leverage*, *Tangibility*, *Cash*, *Growth*, *Sales*, *Age*, *Listed*, *SOE*, *Maturity*, *Isize*, and *Guarantee*. All variables are defined in Appendix 3. The continuous issuer-specific variables are winsorized at the top and bottom 5% of the sample distribution. The robust standard errors clustered at the firm level are reported in parentheses. ***, ** and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Dep.Var=Rating	**Dagong**			**HMP**			**LPM**		
	Exit	**Re-entry**	**Two-period**	**Exit**	**Re-entry**	**Two-period**	**Exit**	**Re-entry**	**Two-period**
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**
Dagong×Post1	-1.764***		-1.884***						
	(0.168)		(0.169)						
Dagong ×Post2		1.903***	1.309***						
		(0.184)	(0.166)						
HMP×Post1				-0.312***		-0.303***			
				(0.060)		(0.060)			
HMP×Post2					0.177	-0.122			
					(0.156)	(0.160)			
LMP×Post1							0.756***		0.762***
							(0.116)		(0.116)
LMP×Post2								0.341***	1.109***
								(0.103)	(0.113)
Firm controls	YES	YES	YES	YES	YES	YES	YES	YES	YES
Industry fixed	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	2,160	1,196	2,694	10,330	10,234	15,870	4,138	4,102	6,308
Pseudo R^2	0.527	0.516	0.533	0.539	0.562	0.509	0.594	0.635	0.621

Appendix 1: Summary of Credit Rating Agents in Chinese Onshore Debt Market

This table provides the founding year, the market of accreditation, and the regulator's recognition of the ten existing CRAs by the end of 2021.

CRAs	Founding Year	Market of Accreditation	Regulatory Accreditations
China Cheng Xin International Co. Ltd. (Chengxin_Moody)[a]	1999	Interbank Exchange	NAFMII, NDRC, CSRC
China Lianhe Credit Rating Co. Ltd. (Lianhe)[b]	1995	Interbank Exchange	NAFMII, NDRC, CSRC
Dagong Global Credit Rating Co. Ltd. (Dagong)	1994	Interbank, Exchange	NAFMII, NDRC, CSRC
Shanghai Brilliance Credit Rating & Investors Service Co. Ltd. (Brilliance)[c]	1992	Interbank, Exchange	NAFMII, NDRC, CSRC
Golden Credit Rating International Co. Ltd. (Jincheng)	2005	Interbank, Exchange	NAFMII, NDRC, CSRC
Pengyuan Credit Rating Co. Ltd. (Pengyuan)	1993	Interbank, Exchange	NAFMII, NDRC, CSRC
Shanghai Far East Credit Rating Co. Ltd. (SFE)	1988	Interbank, Exchange	NAFMII, NDRC, CSRC
Anrong Credit Rating Co. Ltd. (Anrong)[d]	2015	Interbank, Exchange	NAFMII, NDRC, CSRC
Shanghai Credit Information Service Co. Ltd. (SCI)	1999	Exchange	CSRC
Beijing ZBL Credit Rating Co. Ltd. (ZBL)	2015	Exchange	CSRC
Dapu Credit Rating Co. Ltd. (Dapu)	2016	Exchange	CSRC
China Bond Rating Co. Ltd. (CBR) [f]	2010	Interbank	NAFMII
S&P Global China Ratings (S&P China)	2018	Interbank, Exchange	NAFMII, CSRC
Fitch (China) Bohua Credit Ratings Ltd. (Fitch China)[e]	2018	Interbank	NAFMII

[a]Chengxin_Moody and China Cheng Xin Rating Co., Ltd. (CCXR) are both held by China Chengxin Credit Management Co. In February 2020, CCXR's rating business merged with Chengxin_Moody. Chengxin_Moody acquired the accreditation for exchange market from the CSRC. Moody's formed a joint venture with Chengxin_Moody in 2006; in December 2016, Moody's reduced its equity ownership in this joint venture from 49% to 30%.

[b]Lianhe and United Rating Co., Ltd. (UR) are both held by Lianhe Credit Information Service Co. (LCIS). In October 2020, UR's rating business merged with Lianhe. Lianhe acquired the accreditation for an exchange market from the CSRC. Lianhe became a joint venture with Fitch in August 2007. Fitch purchased 49% ownership of Lianhe from LCIS. Fitch sold its equity stake to Singapore's sovereign wealth fund GIC in January 2018.

[c]Brilliance formed a technical partnership with S&P in 2008.

[d]Anrong can only rate the financial bonds in the interbank market.

[e]Fitch China can only rate the financial bonds and structure bond in the interbank market.

[f]CBR is a government-backed CRA.

Appendix 2: Industry Distribution of Firms in Raw Sample and Reduced Sample

Industry Code	Industry Name	Raw Sample	Reduced Sample
		N	***N***
A	Agriculture, forestry, animal husbandry and	72	28
B	Mining	443	202
C	Manufacturing	750	331
D	Electric power, heat, gas and water production	314	132
E	Construction	1134	515
F	Wholesale and retail	271	119
G	Transport, storage and postal service	378	162
H	Accommodation and catering	7	3
I	Information transmission, software and	25	11
J	Financial	28	13
K	Real estate	255	113
L	Leasing and commercial service	131	58
M	Scientific research and technical service	11	5
N	Water conservancy, environment and public	64	31
O	Resident service, repair and other services	7	3
P	Education	9	4
Q	Health and social work	5	2
R	Culture, sports and entertainment	46	19
S	Diversified	835	366
T	Other service supply	7	3
U	Other	3	1
Total		4,795	2,121

Appendix 3: Variable Definitions

Variable	Definition	Data Source
Dependent Variables		
Rating	An numerical variable to measure the issuer's credit rating on a notch basis defined as follows: AAA = 5, AA += 4, AA = 3, AA- = 2, A+ and below =1.	WIND, ChinaBond, CBR
Type I	a dichotomous variable which equals one for a AA+ or above rated firm that defaults within one year and zero otherwise, to represent the failed warning of the rating.	WIND
Type II	a dummy variable which equals one for a A+ or lower rated issuer that does not default within one year and zero otherwise, to represent the false warning of the rating.	WIND
ABR	Abnormal bond return 7-day surrounding the rating change date. For issuers with multiple outstanding bonds, we aggregate the *ABR* to issuer level by calculating the (outstanding bond) volume-weighted average *ABR* for bonds issued by the same issuer.	WIND
CAR	The 7-day cumulative abnormal stock return surrounding the rating change date.	WIND, CSMAR
Spread	The percentage difference between the bond offering yield and the yield on a Treasury note of comparable maturity.	WIND
Independent Variables		
Dagong	A dummy variable that equals one if the issuer rated by Dagong, and zero otherwise.	WIND
HMP	A dummy variable that equals one if the issuer is rated by a high market power rating agent, i.e., Chengxin_Moody and Lianhe, and zero otherwise.	WIND
LMP	A dummy variable that equals one if the issuer is rated by a low market power rating agent, i.e., issuer-paid CRAs rather than Dagong, Chengxin_Moody and Lianhe, and zero otherwise.	WIND
Post1	A dummy variable that equals one if the sample is from Phase 1, and zero otherwise.	WIND
Post2	A dummy variable that equals one if the sample is from Phase 2, and zero otherwise.	WIND
Control Variables		
ROA	Operating income divided by average total assets.	WIND
Leverage	Total liabilities divided by total assets.	WIND
Tangibility	Tangible asset divided by total asset.	WIND
Cash	Cash and cash equivalents scaled by current liability.	WIND
Growth	Change in operating revenues from the previous year.	WIND
Sales	Natural log of sales in 100 million RMB.	WIND
Age	Natural logarithm of firm age.	WIND
Listed	A dummy variable that equals one if the issuer is a publicly listed company and zero otherwise.	WIND
SOE	A dummy variable that equals one if the issuer is a state-owned enterprise, and zero otherwise.	WIND