



THE UNIVERSITY *of* EDINBURGH

Edinburgh Research Explorer

Is solicitation status related to rating conservatism and rating quality?

Citation for published version:

Zhao, S, Moreira, F & Wang, T 2021, 'Is solicitation status related to rating conservatism and rating quality?', *Journal of International Financial Markets, Institutions and Money*, vol. 72, 101341. <https://doi.org/10.1016/j.intfin.2021.101341>

Digital Object Identifier (DOI):

[10.1016/j.intfin.2021.101341](https://doi.org/10.1016/j.intfin.2021.101341)

Link:

[Link to publication record in Edinburgh Research Explorer](#)

Document Version:

Peer reviewed version

Published In:

Journal of International Financial Markets, Institutions and Money

General rights

Copyright for the publications made accessible via the Edinburgh Research Explorer is retained by the author(s) and / or other copyright owners and it is a condition of accessing these publications that users recognise and abide by the legal requirements associated with these rights.

Take down policy

The University of Edinburgh has made every reasonable effort to ensure that Edinburgh Research Explorer content complies with UK legislation. If you believe that the public display of this file breaches copyright please contact openaccess@ed.ac.uk providing details, and we will remove access to the work immediately and investigate your claim.



Is Solicitation Status Related to Rating Conservatism and Rating Quality?

Sheng Zhao^a, Fernando Moreira^b, Tong Wang^b

^a IBSS, Xi'an Jiaotong-Liverpool University, 8 Chongwen Road, Suzhou Dushu Lake Science and Education Innovation District, Suzhou Industrial Park, Suzhou, China, 215123

Corresponding author

^b University of Edinburgh Business School, 29 Buccleuch Place, Edinburgh, EH8 9JS, UK

Abstract

This paper discusses the association between rating solicitation status and rating quality. Our model shows that if firms with a declining trend of performance are less likely to solicit ratings from credit rating agencies, these firms are more conservatively rated, as their self-selection behaviour is seen as a signal of high credit risk. Our empirical results support the predictions of the model proposed in this study and show that: first, when controlling for fundamental factors, unsolicited ratings are lower than solicited ones, and; second, the rating qualities of both types of ratings are not significantly different from each other.

Keywords: Credit ratings; Solicitation Status; Self-selection Effect; Conflict of Interest

JEL code: G24; G41

1. Introduction

Conflict of interest is a widely discussed topic in the field of credit ratings. From an international perspective, the rating industry is dominated by three large credit rating agencies (CRAs): Moody's, S&P and Fitch.¹ This feature has commonly been criticised, as CRAs would have the motivation and the opportunity to make extra profits by taking advantage of information asymmetry (Kedia et al., 2017; Sangiorgi and Spatt, 2017).

The heart of the conflict of interest in this case is the rating service fee charged by CRAs (Fulghieri et al., 2014; Kashyap and Kovrijnykh, 2015). All of the 'Big Three' CRAs (Moody's, S&P and Fitch) follow the 'issuer-paid' model of rating service collection. In this model, firms requesting ratings when issuing debt/equity pay all of the service fees to the hired credit rating agencies. Some concerns have been raised (Griffin et al., 2013; Sangiorgi and Spatt, 2017) as to whether or not such a payment model would allow the CRAs who act as oligopolists to 'sell' their rating services to issuers. In other words, in the framework of the issuer-paid model, credit rating agencies have the incentives to issue over-optimistic ratings for the firms that purchase their rating services. The previous literature in this area has analysed the conflict of interest in rating payment models from two angles: the special cases of CRAs with an 'investor-paid' model and the regime of the ratings by 'issuer-paid' CRAs (Xia, 2014; Bhattacharya et al., 2019).

Some rating agencies—apart from the Big Three—follow the 'investor-paid' model, where the investors who are interested in the rated firms' performances subscribe to the rating reports issued by the rating agencies. Among the nine NRSRO (Nationally Recognized Statistical Rating Organization)

¹ In 2013, these three rating agencies took 95% of the market share of the rating sector. (Alessi, Christopher: 'The credit rating controversy. Campaign 2012' Council on Foreign Relations, 27 July 2013).

CRAs, one agency called the Egan-Jones Rating Company applies the investor-paid business model.² The reason for the adoption of the investor-paid model is mainly to challenge traditional big CRAs by ‘support(ing) the funding ecosystem which has so severely broken down’ and by preventing the serious ‘rating shopping’ before the 2008 financial crisis (Sean Egan, founder of Egan-Jones Rating Company, 2008).

In terms of scholars’ views, conflict of interest is examined by investigating the ratings given by agencies following the issuer-paid and the investor-paid models (Cornaggia and Cornaggia, 2013; Bonsall IV, 2014; Xia, 2014). However, research on the impact of payment models on credit rating agencies is restricted by the unobserved heterogeneity of different rating agencies. In this paper, we study another perspective of conflict of interest; the unsolicited rating regime (Fulghieri et al., 2014). This regime is applied by the Big Three agencies as an essential supplemental service: in contrast to the majority of cases where the agency collects fees from rated firms, the agency provides ratings to some firms that neither request the rating services nor pay any fees for them. Whether CRAs follow an alternative standard in issuing ratings to firms that do not pay is viewed as an indicator of conflict of interest. The literature has identified that credit rating agencies normally issue more conservative ratings for unsolicited rating recipients who do not request or pay for the rating services (Byoun and Shin, 2002; Poon, 2003; Poon et al., 2009; Bannier et al., 2009). However, this finding does not necessarily imply that there exists a conflict of interest unless evidence shows that the more conservative ratings issued for unsolicited rating recipients are biased.

² This new payment model is also used by some other small CRAs, such as Chengxin Credit Management Co. (China), Universal Credit Ratings Group (China) and RusRatings (Russia).

To answer this question, scholars have raised two contrary hypotheses (Byoun et al., 2014): the strategic behaviour hypothesis and the self-selection hypothesis. The former hypothesis states that the more conservative unsolicited ratings are biased and reflect a strategic behaviour of rating agencies that offer over-optimistic ratings for those firms paying them, in order to either compensate the firms that buy their services or blackmail the firms that do not pay for the ratings. In contrast, the self-selection hypothesis states that firms that do not purchase rating services from rating agencies are motivated by concerns about the disclosure of adverse information in the rating process. Nonetheless, rating agencies capture this self-selection incentive of the firms and rate them without being paid in order to provide transparency to market participants (Fulghieri et al., 2014). To reflect the conservatism towards the unobservable weak characteristics of firms, unsolicited ratings issued by CRAs are relatively lower than solicited ones.

Due to data availability, we only have access to the records of unsolicited ratings from the Moody's website. Therefore, in this paper, we focus on a sample of firms that receive Moody's unsolicited ratings. Our evidence suggests that: first, the levels of unsolicited ratings issued by Moody's are more conservative than solicited ones; and second, the rating quality of these two types of firms does not differ significantly. In general, our results support the hypothesis of self-selection. In particular, the first finding provides a necessary condition for the self-selection hypothesis and demonstrates that rating agencies observe firms' self-selection incentives and assign lower ratings to them. The second finding provides a sufficient condition for the hypothesis and shows that those lower unsolicited ratings are not biased but have the same rating quality of solicited ones, reflecting the same default risk predictability and the same rating action timeliness.

We contribute the literature from the following perspectives. First, in terms of the potential reasons for unsolicited ratings being lower than solicited ones, we provide novel evidence in favour of the self-selection hypothesis. Our theoretical model shows that under the self-selection hypothesis, if a CRA is rational and unbiased, then: first, unsolicited ratings are lower than solicited ratings; and second, both types of ratings should be identically able to provide predictions for the risk of firm defaults (i.e., have a similar rating quality). Our empirical tests confirm these findings. Hence, the theoretical model and empirical evidence together strengthen the self-selection hypothesis by justifying the lower levels of unsolicited ratings.

Second, when running our empirical tests, we not only make the baseline comparison between unsolicited ratings and their solicited counterparties offered by a single rating agency (as done by Byoun and Shin, 2002; Poon, 2003; Poon and Firth, 2005; Bannier et al., 2008; Poon et al., 2009; Bannier et al., 2009; Byoun et al., 2014), but we also introduce a ‘cross-agency’ comparison. We take advantage of a sample of firms that receive unsolicited ratings from one CRA and solicited ratings from other CRAs in order to compare their rating levels and rating qualities. In this cross-agency comparison, we conduct our test concerning the rating level by constructing a new measure — the gap between the unsolicited rating of a firm (provided by a CRA) and the unsolicited rating of that same (provided by another CRA) — in order to test whether or not solicitation status is a factor impacting the rating levels. As for the rating quality test, we take a measure — called the ‘lead-lag’ relationship — (Alsakka and ap Gwilym, 2010a; Güttler, 2011; Bowe and Larik, 2014) of rating actions between a CRA that provides solicited ratings and one that provides unsolicited ratings to reflect the rating quality. In tests regarding rating level and rating quality, we find that the results are similar to the single-agency test; thus it enhances our findings.

Third, we develop novel ex-post measures of rating quality using Distance to Default (DTD) and rating timeliness. DTD is applied to indicate the predictability of Moody's ratings in terms of the actual variation of default risk following ratings at different levels. We show evidence of the absence of the impact of solicitation status on DTD predictability (which is essential to prove the self-selection hypothesis) in light of two findings: first, ratings at the same levels are followed by statistically similar DTD performances, regardless of the solicitation status of the rated firms; and second, if we use firm fundamentals and rating levels to model DTD, the characteristic of whether the ratings are solicited and unsolicited does not significantly change the accuracy of the estimated DTD.

Our research can also be positioned in the literature flow about how external information sources are linked with firm risks. Credit ratings are an essential source of external information which is significantly linked with firm risks. Similar to other sources such as economic news (Gkillas et al., 2020), technology shocks (Kogan and Dimitris, 2014) and firm fundamentals (Campello and Chen, 2010), credit ratings also have a reflection on firm risk but with a more complicated way as a consequence of blending payment models. Our theoretical model and the corresponding empirical results capture an asymmetric relationship between firm risk and external signals: due to the information asymmetry, firms have more knowledge about their own risk level than CRAs and investors do; therefore, firms have asymmetric strategies on whether to solicit external assessment. CRAs capture such asymmetry and then assign asymmetric rating levels in line with different solicitation status. The firm risk observed later one justifies the risk asymmetry associated with different solicitation behaviour. Gkillas et al. (2020) show evidence of an asymmetric relationship between firm risk and news releases at different risk levels. We contribute to their study by showing that the asymmetry in the information-

risk relationship also exists in the context of interaction among different entities and may be a consequence of the self-selection nature of the information release.

Our findings are important to practitioners because they highlight the special role of credit rating agencies in the economy-wide business activities. Credit ratings play a key role to guide investors in their investment decisions. Normally, downgrades released by big rating agencies significantly deteriorate the market value of the respective firms due to investors' compulsory or voluntary sell-off activities. This reinforces the pro-cyclical pattern in which bad-performing firms tend to get worse (Ferri et al., 1999). Therefore, the absence of rating fairness and quality would negatively influence the economic development. Our results corroborate the fairness and quality of the ratings provided by the big CRAs and show that, in principle, it is safe and rational to follow their opinions when making investment decisions.

This paper is structured as follows. In Section 2, we describe the background of the unsolicited rating practice of Moody's, explain the motivation for studying unsolicited ratings, raise the self-selection hypothesis of conservative unsolicited ratings, and present the related literature. Section 3 introduces a theoretical model used as a background for our empirical tests and presents our main hypotheses. Section 4 describes the data source, data matching scheme and the setting of some essential variables. In Section 5, a series of empirical analyses test the self-selection hypothesis. Section 6 concludes.

2. Background and related literature

Our main objective in this study is to test whether or not the solicitation status causes a rating bias by comparing the levels and qualities between unsolicited and solicited rating services. In this section, the background and a summary of the existing research on rating bias and rating quality are presented.

2.1 Studies on rating bias

To study the rating bias potentially associated with fee payments, the existing literature mainly focuses on two issues: the rating gaps between investor-paid agencies and issuer-paid agencies (Jiang et al., 2012; Cornaggia and Cornaggia, 2013; Bonsall IV, 2014; Kashyap and Kovrijny, 2015) or the solicitation and its impact on rating levels. However, investor-paid agencies are newly-established and are ‘freshmen’ in the rating industry, so they may have a weaker rating ability than the big CRAs that follow an issuer-paid model. To compare investor-paid agencies with issuer-paid agencies, it is very difficult for researchers to determine whether the difference of rating performances is due to rating bias or rating ability. However, if comparing solicited ratings with unsolicited ratings offered by the same rating agency (Moody’s in our paper), the rating ability difference does not exist. Thus, we focus on the latter perspective in this paper.

2.1.1 Regime of solicitation status in the credit rating industry

Historically, Moody’s has issued unsolicited ratings since its establishment in 1909, however, it started publicly announcing the identification of unsolicited firms in 1999. Despite frequent complaints and investigations (Jefferson County case, 1983; US Justice Department case, 1996; Hannover Re case, 2004), Moody’s continues to claim that the activity of issuing unsolicited ratings is intended ‘to provide greater transparency to market participants’ and that the rating agency ‘reserves the right’ to issue them ‘not at the request of the rated equity and /or its agents’ (Moody’s, 2018).

Unsolicited ratings have two unique features: fee payment and information access. Moody's neither collects fees³ from rated firms for the issuance of unsolicited ratings nor has access to the internal information of those firms (Behr and Güttler, 2008).

In terms of information access, Moody's claims that '(the) publication of an unsolicited credit rating will be conditioned, among other factors, on its determination that sufficient information is available to allow MIS⁴ to assign and maintain the credit rating' (Moody's, 2018). On the other hand, it also states that 'a rated entity does not have the ability to decline publication of an unsolicited credit rating', which implies that there is no negotiation between the rated firm and Moody's. Due to the absence of negotiation, CRAs do not have access to the internal information of the unsolicited rating recipients guaranteed by formal commercial contracts (Byoun and Shin, 2002).

Although Moody's claims that it 'does not distinguish between solicited and unsolicited credit ratings with respect to its credit rating methodologies' so as to demonstrate its fairness and absence of bias in the market, the bias of unsolicited ratings related to the fee payment and the lack of internal information are discussed by both regulators and scholars.

Regulators have long been sceptical about the issuance of unsolicited ratings due to the absence of payment, which may incur a conflict of interest, and to the lack of information access (Kedia et al., 2017; Klusak, Alsakka and ap Gwilym., 2017). However, recently regulators are changing their attitudes towards unsolicited ratings. In a policy document issued by SEC (the U.S. Securities and

³ Moody's does not disclose any factors related to profits (the centre of the criticism of conflict of interest) as criteria in order to select firms to which they issue unsolicited ratings. The criteria they list are: benefits to market participants, issuers' size, the issuance time of the issuers, and relevance to other firms that Moody's rates.

⁴ MIS: short for 'Moody's Investors Service'.

Exchange Commission) regarding credit rating agencies,⁵ the Commission states that it ‘preliminarily believes’ that CRAs registered as NRSROs (including Moody’s) have sufficient ability to collect non-public information, even in the activity of unsolicited rating issuance. Moreover, the Commission regards the mechanism of unsolicited rating issuance as a suggestive way of increasing the competition and pushing rating agencies to be more proficient.⁶ However, such optimistic opinions of regulators contradict scholars’ views regarding the information access ability (Behr and Güttler, 2008).

Therefore, literature has studied the gap between these two types of ratings to explore the rationality and neutrality of unsolicited ratings. Two research streams have investigated the gap between solicited and unsolicited ratings. One stream focuses on the comparison of levels of unsolicited and solicited ratings in order to study whether or not solicited ratings are higher than unsolicited ones. The majority of literature finds evidence that the solicited ratings are more likely to be higher (Byoun and Shin, 2002; Poon, 2003; Poon et al., 2009), however, the previous literature only compares the rating levels for different rated firms offered by one rating agency (either S&P or Fitch). The drawback for this setting is that only ratings offered for different firms can be compared, so the rating gaps may reflect the difference between firm fundamentals rather than the gap between rating conservatism. In this paper, we use the split of ratings⁷ offered for a firm but by the different rating agencies in order to provide new empirical evidence of rating gaps.

⁵ Annual Report on Nationally Recognized Statistical Rating Organizations. Available at <https://www.sec.gov/files/2016-annual-report-on-nrsros.pdf>.

⁶ Re-Proposed Rules for Nationally Recognized Statistical Rating Organizations. Available at <https://www.gpo.gov/fdsys/pkg/FR-2009-02-09/pdf/E9-2514.pdf>.

⁷ Rating split refers to the phenomenon that for one firm, different CRAs offer different credit ratings at the same time.

The second stream of research concerns the reason for lower unsolicited ratings by exploring the ex-post measures of performances of firms that receive both types of ratings. Two contrary hypotheses—the strategy hypothesis and self-selection hypothesis—are discussed (Byoun et al., 2014). In the strategy hypothesis, the lower unsolicited ratings are viewed as biased because a significant gap is observed between the ex-post performance measures of the recipients of unsolicited and solicited ratings, given the same rating levels. For example, if the ex-post performances of unsolicited rating recipients are better than their peers, given the same level of ex-ante ratings, this indicates that rating agencies ‘under-estimate’ the quality of unsolicited rating recipients. In other words, this reflects the strategy of rating agencies to issue systematically lower unsolicited ratings. The incentives of rating agencies to offer biased unsolicited ratings are summarised in different aspects: first, the ‘blackmail’ effect, which is used by rating agencies to ‘blackmail’ other firms to purchase rating services from them to avoid being offered unsolicited ratings (Fulghieri, 2014); second, upward bias due to being paid, which means that rating agencies cater to their customers by inflating their ratings (Poon, 2003; Poon and Firth, 2005); and third, information access, whereby rating agencies do not have access to the internal information of rated firms so they prefer offering more conservative ratings to them so as to be safe (Bannier et al., 2009).

The literature has widely discussed the strategy hypothesis in the context of conflict of interest. The existence of a strategic selection of unsolicited ratings by CRAs is a negative signal of their reputation because it implies that the CRAs issue unfair ratings to those firms that do not pay them. However, some authors (e.g., Bannier et al., 2008) discuss an alternative hypothesis: self-selection.

According to the self-selection hypothesis, although unsolicited ratings are systematically lower, they are not regarded as biased. Due to the information asymmetry between firms and investors, firms always

have more information about themselves than they do for investors. However, the firms' selection of whether or not to solicit the rating services can be observed as a way to infer the actual condition of firms, which is not released to investors. Firms with an unsatisfactory performance choose not to solicit the rating services because they know that the rating information released by rating agencies would not be favourable in terms of their aim to attract investors. Correspondingly, the rating agencies take this behaviour as a negative signal when deciding the unsolicited rating levels for the firms. Therefore, rating agencies tend to rate unsolicited rating recipients at a lower level than solicited rating recipients, even when their observable characteristics are similar.

In this paper, we establish a theoretical model to show that if the self-selection hypothesis holds, two phenomena should be observed: first, rating levels for unsolicited cases should be more conservative than for solicited cases, which reflects rating agencies' reaction to the self-selection incentives of firms; and second, ratings should provide information to the market even though they are unsolicited (the rating quality should be as good as that of solicited ratings).

2.1.2 Academic studies of unsolicited ratings

From the theoretical perspective, some studies have analysed the roles of unsolicited ratings in the rating market. Fulghieri et al. (2014) establish a game-theory model to study the behaviour of rating agencies that issue unsolicited ratings. A series of empirical papers also discuss the effect of solicitation on the level of credit ratings. The majority of these papers support the hypothesis of strategic behaviour (Byoun and Shin, 2002; Poon, 2003; Poon and Firth, 2005; Poon et al., 2009; Bannier et al, 2009; Byoun et al., 2014).

In contrast to the aforementioned papers, others support the hypothesis of 'self-selection', which implies that the performances of recipients of unsolicited and solicited ratings should not be significantly

different. Poon (2003) shows weak evidence of this by finding that firms receiving unsolicited ratings are not more likely to perform poorly than those receiving solicited ratings. Bannier et al. (2008) use non-U.S. firms and their ratings by S&P and find that—except for the banking sector—for all the other firms, ex-post default performances are not related to the status of solicitation.

Besides the two strands of research, some papers mention the market reaction of the rating solicitation. Behr and Guttler (2008) test the stock reactions of the announcements of solicitation and conclude that even though unsolicited ratings are based only on the public information, they still impact the stock market to some extent. Byoun and Shin (2002) and Han et al. (2013) find similar results for the bond yield cases. Klusak et al. (2017) use the disclosure of sovereign rating solicitation status as a shock to study its market impact.

2.2. Rating quality

The ex-post measurement of the rating quality is an essential component in our analysis. Theoretical papers measure the rating quality in the context of the economic cycle (Bar-Isaac and Shapiro, 2013), while other papers focus on the measurement of the rating quality.

Three categories of rating quality measures are applied in the current empirical work: relative timeliness comparison, the degree of information content and the predictive power of default.

A number of papers view the timeliness (i.e., lead-lag relationship among different CRAs) as a relative measure of the rating quality (Alsakka and ap Gwilym, 2011a; Güttler, 2011; Berwart et al., 2016). A rating agency is viewed as ‘better’ if it takes action prior to its peers. Another type of quality measure concerns how much information the ratings provide. To define this information, scholars use different indices, such as stock returns (Behr and Guttler, 2008; Byoun et al., 2014; Bruno et al., 2015) and bond

yields (Han, 2013; Bruno et al., 2015). Moreover, the power of ratings to forecast firms' defaults is regarded as an alternative measure of rating quality by many researchers. Becker and Milbourn (2011) use the default events within a three-year window following credit rating actions in order to measure the rating quality. Baghai and Becker (2018) analyse the default rates of firms rated at each of the rating levels so as to imply the predictability of rating agencies. Hilscher and Wilson (2016) update the traditional measurement of the probability of default estimation by applying a concept of 'failure score', by which a series of fundamentals—with or without rating factors—are applied to estimate the default events. The rating quality is reflected by a comparison between the baseline score (which is established only by the fundamentals) and the supplemental score (which is established not only by the fundamentals but by also adding the credit ratings).

In this paper, we apply default risk predictability and rating timeliness as indicators of the rating quality. Ratings are issued by CRAs to estimate firms' default risk, therefore, the predictability of default by its nature should be considered as an indicator to reflect the rating quality. As for timeliness, this can be intuitively measured by the lead-lag relationship between one rating agency and another. We do not use information content as an indicator because one of the essential components to measure the information contents is stock returns and some of the firms that receive unsolicited ratings by Moody's are not listed on the secondary market.

3. Theoretical model and hypotheses

3.1 Theoretical model

To better motivate our empirical analysis, we build a simplified model to reflect how rating agencies react to firms' self-selection of soliciting rating services and how ratings provide information for the

market. This theoretical model aims to show that, under the condition of the self-selection effect, first, a rational and non-biased CRA would offer a firm lower ratings if that firm does not solicit the rating service, and second, the information provided by CRA's rating would be same (i.e., the same rating quality), despite the rating being solicited (or not).

We define 'self-selection effect' by assuming that 'bad' firms are less likely to solicit rating services from CRAs because bad firms do not want their information to be released to public through the rating process. To define 'rational' CRA, we assume that CRAs know the self-selection effect. To define 'non-biased' CRA, we assume that CRAs do not hold stereotype or prejudice on non-soliciting firms; their only aim is to predict the probability of default of firms based on the information they gained (i.e., whether or not firms solicit ratings).

We denote parameters as follows. SL stands for solicitation status, where $SL=1$ means that the rating is solicited. S denotes the actual status of the firm. In this model, we assume that there are only two status of firms: Good (G) and Bad (B). CA is the rating given by rating agencies to the firm. We simplify the model by only assuming two rating notches, 1 and 0. $CA=1$ indicates that the rating is high and $CA=0$ indicates that the rating is low.

In the following analysis, we denote:

$\theta = P(S = G)$; as the prior distribution of good firms;

$\tau_i = P(SL = 1|S = i)$, $i \in \{G, B\}$ as the probability that a type- i firm is in a solicited status (G is for a good firm and B is for a bad firm) ; and $p_j = P(CA = 1|SL = j)$, $j \in \{1,0\}$ as the probability that a firm in status j will obtain a good rating ($j=1$ is for solicited ratings and $j=0$ for unsolicited ratings).

We assume that CRAs in our model only have one incentive: to infer the actual probability of the firm to be good or bad based on the observation of firms' solicitation. Specifically, rating agencies observe

the solicitation status (SL) as either G or B . If the observation is $SL = 1$, rating agencies have the information of conditional probability of $S = G$ as $P(S = G|SL = 1) = \frac{P(S=G,SL=1)}{P(S=G,SL=1)+P(S=B,SL=1)} = \frac{\theta\tau_G}{\theta\tau_G+(1-\theta)\tau_B}$.

The difference between the conditional probability and unconditional probability with no observation of solicitation status is:

$$P(S = G|SL = 1) - P(S = G) = \frac{\theta\tau_G}{\theta\tau_G + (1 - \theta)\tau_B} - \theta = \frac{\theta(1 - \theta)(\tau_G - \tau_B)}{\theta\tau_G + (1 - \theta)\tau_B} \quad (3.1)$$

If the observation is $SL = 0$, rating agencies have the information of conditional probability of $S = B$ as $P(S = B|SL = 0) = \frac{P(S=B,SL=0)}{P(S=B,SL=0)+P(S=G,SL=0)} = \frac{(1-\theta)(1-\tau_B)}{(1-\theta)(1-\tau_B)+\theta(1-\tau_G)}$.

The difference between the conditional probability and unconditional probability with no observation of solicitation status is:

$$\begin{aligned} P(S = B|SL = 0) - P(S = B) &= \frac{(1 - \theta)(1 - \tau_B)}{(1 - \theta)(1 - \tau_B) + \theta(1 - \tau_G)} - (1 - \theta) \\ &= \frac{\theta(1 - \theta)(\tau_G - \tau_B)}{(1 - \theta)(1 - \tau_B) + \theta(1 - \tau_G)} \end{aligned} \quad (3.2)$$

Analysing Equations (3.1) and (3.2), we see that their denominators are always positive and hence their signs depend on those of the numerators. For numerators, the fraction $\theta(1 - \theta)$ is always positive. Therefore, the signs of both results in Equations (3.1) and (3.2) depend on the sign of $(\tau_G - \tau_B)$.

Now we introduce the mathematical expression of self-selection of rated firms:

$$\tau_G > \tau_B \quad (3.3)$$

Equation (3.3) describes the selection bias: good firms are more likely to solicit the rating services than bad firms. Under the condition of (3.3), the mathematical results of (3.1) and (3.2) are always positive:

$$P(S = G|SL = 1) - P(S = G) > 0 \quad (3.4)$$

$$P(S = B|SL = 0) - P(S = B) > 0 \quad (3.5)$$

Equation (3.4) shows that if rating agencies observe that the firm *requests* solicited ratings, the probability of it being a *good* firm is larger than when no information of solicitation status is obtained.

Equation (3.5) shows that if rating agencies observe that the firm *does not request* solicited ratings, the probability of it being a *bad* firm is larger than when no information of solicitation status is obtained.

Recall that we assume CRAs are ‘rational’ (i.e., they fully know the self-selection effect). So, they know parameters θ , τ_1 and τ_2 . Then a rational CRA would adjust p_1 and p_0 as:

$$\frac{p_1}{p_0} = \frac{\tau_G[\theta(1-\tau_G)+(1-\theta)(1-\tau_B)]}{(1-\tau_G)[\tau_G\theta+\tau_B(1-\theta)]} \quad (3.6)$$

The proof of Equation 3.6 is presented in Appendix A. This equation demonstrates that a CRA is able to adjust the ratio of probabilities of giving high ratings to recipients between solicited and unsolicited ratings.

By subtracting the denominator from the numerator, we get:

$$\tau_G[\theta(1-\tau_G)+(1-\theta)(1-\tau_B)] - (1-\tau_G)[\tau_G\theta+\tau_B(1-\theta)] = (\tau_G-\tau_B)(1-\theta) \quad (3.7)$$

Recall that $(\tau_G-\tau_B) > 0$ (the assumption of self-selection) and θ is always less than 1, so Equation 3.7 is positive, which means the ratio in Equation 3.7 is larger than 1. Hence, we have

$$p_1 > p_0 \quad (3.8)$$

According to Equation 3.8, we find that if the self-selection hypothesis holds and CRAs are rational, it is reasonable that a CRA rates firms that do not solicit rating services with a lower rating (i.e., with a lower probability of rating as ‘good’). This conclusion supports the non-strategic hypothesis of lower unsolicited ratings. It suggests that CRAs capture the different strategies applied by firms with different inherent risks and assign asymmetric rating levels. It is also consistent with the conclusions of Hao et al. (2011) and Gkillas et al. (2020), who show that external information has an asymmetric relationship with firm risks.

The next assumption introduced below is the non-bias assumption of CRAs, namely: CRAs do not have prejudice towards the solicited and unsolicited rating recipients. In other words, given the actual condition of the rated firm ($S=G$ or B), the opinion given by CRAs is not relevant to the solicitation status.

$$P(CA = 1|S = G, SL = 1) = P(CA = 1|S = G, SL = 0) \quad (3.9)$$

$$P(CA = 1|S = B, SL = 1) = P(CA = 1|S = B, SL = 0) \quad (3.10)$$

Under the condition of CRAs' rationality (3.6) and fairness (3.9 and 3.10), we measure the information provided by CRAs to the market (the investors) by calculating the conditional probability of the firms' status given the credit rating agencies' opinion (CA), as well as their solicitation status (SL):

$$P(S = G|SL = 1, CA = 1) = \frac{P(S = G)P(SL = 1|S = G)P(CA = 1|S = G, SL = 1)}{P(SL = 1)P(CA = 1|SL = 1)}$$

$$P(S = G|SL = 0, CA = 1) = \frac{P(S = G)P(SL = 0|S = G)P(CA = 1|S = G, SL = 0)}{P(SL = 0)P(CA = 1|SL = 0)}$$

The proof of these two equations is also shown in Appendix A.

Given the rationality assumption (3.6) and the non-biased assumption (3.9 and 3.10), we conclude that

$$P(S = G|SL = 1, CA = 1) = P(S = G|SL = 0, CA = 1) \quad (3.11)$$

Equation 3.11 shows that the information given by the CRA's opinion regarding the status of the rated firms is not related to the solicitation status: the conditional probability that the firm is 'good' is the same whether $SL=1$ or 0 .

We further test whether or not the CRA's opinion (CA) is informative by calculating the difference between the conditional probability of being good and the unconditional probability. We measure the rating quality by examining whether or not ratings provide extra information to investors who do not take solicitation status into consideration (uninformed investors). Uninformed investors do not realise

the factor of solicitation status but only observe the rating opinion ($CA=1$ or 0) given by the rating agencies. Their aim is also to infer the probability of the firm to be good/bad.

$$P(S = G|CA = 1) - P(S = G) = \frac{\theta(1 - \theta)(p_1 - p_0)(\tau_G - \tau_B)}{\theta\tau_G p_1 + \theta(1 - \tau_G)p_0 + (1 - \theta)\tau_B p_1 + (1 - \theta)(1 - \tau_B)p_0} \quad (3.12)$$

The derivation of this equation is shown in Appendix B. We find that the denominators in both algebraic fractions are always positive and hence their signs depend on those of the numerators. As for the numerators, the fraction $\theta(1 - \theta)$ is always positive. Therefore, the signs of Equation 3.12 depend on the sign of $(p_1 - p_0)(\tau_G - \tau_B)$.

According to the assumption stated in (3.3), which reflects the self-selection of firms, we know that $(\tau_G - \tau_B) > 0$. Furthermore, according to the rational rating agency assumption obtained in (3.7), we know that $(p_1 - p_0) > 0$. Therefore, under the condition of (3.3) and (3.8), we get:

$$P(S = G|CA = 1) - P(S = G) > 0 \quad (3.13)$$

Equation (3.13) states that the signal of a *positive* rating given by rating agencies provides extra information for investors by showing a *higher probability of the firm to be good* than where no rating information is provided. In other words, the rating is informative for the investors.

Taking the conclusions drawn in (3.11) and (3.13) into consideration together, we can draw a conclusion that if the CRA is rational and unbiased, the quality of its ratings in terms of the predictability of firms' status is not related to the solicitation status and the ratings are informative to the investors.

In summary, we obtain three testable predictions in this discussion. First, it is reasonable for CRAs to assign lower ratings in unsolicited cases if the self-selection assumption holds (Equation 3.6). This conclusion is empirically tested in Section 5.1. Second, the ability of ratings to predict whether a firm is good or bad is the same, regardless of the solicitation status (Equation 3.11). Third, the ratings are

informative to the market by providing extra information about the rated firms (Equation 3.13). The second and the third predictions are tested in Section 5.3. In order to have empirically testable statements, we use the default risk, measured by DTD (Distant to Default), as an indicator of firm status and use rating change timeliness as an indicator of the rating information degree.

3.2 Hypotheses

Motivated by our theoretical model, we raise two hypotheses, as follows:

H1(Rating level hypothesis): the ratings are lower if they are issued as unsolicited ones;

H2 (Rating quality hypothesis): the rating is informative in terms of the future default risk of the rated firms, and the rating quality is not significantly different between solicited and unsolicited ratings.

In the remainder of this paper, we empirically test these two hypotheses using historical records of Moody's ratings for sample firms. For Hypothesis 2, an essential factor is the measure of the rating quality. Rating quality has been widely discussed in terms of its empirical measurement, including the default risk predictability of ratings (Becker and Milbourn, 2011; Baghai and Becker, 2018) and rating change timeliness measures (Bannier et al., 2009; Berwart et al., 2016). Default predictability is the key indicator for assessing the rating quality because the most important role that a credit rating should play is to inform the rated firm's risk of default to market participants (Ammer and Packer, 2000; Cantor and Packer, 1994). The absence of gaps of default risk predictability between unsolicited and solicited ratings implies that given the same level of ratings, the ex-post measures of default risk are not significantly different, regardless of the whether or not the ratings are solicited. Thus, the rating quality regarding the ratings predictability of a firm's default risk is not associated with the solicitation status. If both of these hypotheses hold, according to our theoretical model's conclusion, we can claim that the self-selection effect is able to explain the lower ratings of unsolicited ratings. Firms with weak

characteristics opt to not purchase the rating services, while rating agencies still correctly identify those firms and offer unsolicited ratings.

Besides the predictability of default, the speed of ratings is another measure of rating quality (Cheng and Neamtiu, 2009), because it indicates the CRAs' ability to capture the variation of rated firms' fundamentals and mirrors the information contents of the rating actions. The absence of gaps of rating action timeliness for solicited and unsolicited ratings implies that although unsolicited ratings are lower, the speed of Moody's revising them is not impacted by the solicitation status.

In summary, our model can be empirically tested by examining the rating quality gap, which is measured by the ratings' predictability and the rating action speed (timeliness). The absence of a weaker rating quality for unsolicited ratings shows evidence for firms' self-selection behaviour. It indicates that: first, the lack of internal information does not seriously undermine the rating quality of unsolicited ratings, which corroborates the statement of regulators and questions the conclusions drawn by Behr and Güttler (2008); and second, the fact that unsolicited ratings are lower does not necessarily reflect a strategic behaviour of CRAs but rather may reflect the self-selection effect regarding the solicitation status. In light of these two conclusions, we reject the hypothesis of the strategic behaviour of CRAs, as we are not able to find evidence showing that CRAs—for whatever reason—strategically under-rate firms that do not pay them.

4. Data

The data used in this research (historical ratings, fundamentals and market-based information) is retrieved from the Bloomberg database. Our sample period starts in 2010 when Moody's unsolicited ratings started to be disclosed in online reports and ends in 2017 when we commenced this study.

4.1 Identification of treatment and control sample firms

The key portion of ratings analysed in this paper refers to unsolicited ratings. Our research is based on Moody's ratings and supplemented by those issued by S&P and Fitch. Therefore, the initial sample (treatment group) consists of firms that do not purchase rating services and receive unsolicited ratings from Moody's. The identification of treatment group firms is based on the reports of unsolicited ratings, which are released quarterly from 2010 (the earliest information available on Moody's website) until 2017. We filter our sample of unsolicited companies by deleting companies not listed on the stock market, companies with a very small (<2 years) age, and companies without fundamental information from Bloomberg.

After these steps, we have 40 companies with unsolicited ratings offered by Moody's: 26 of the sample firms are located in Europe with the remaining firms in Asia. The majority of the 40 firms (31) are in the banking sector.

The supplemental sample (control group) consists of firms that purchase rating services and receive solicited ratings from Moody's. In order to only consider the factor of solicitation status and avoid the contamination of firms' fundamental factors (region, sector and size), we adopt an initial criterion to select control firms for each of the 40 treatment group firms. These criteria are as follows: (i) the control firms receive ratings from Moody's with their solicitations; (ii) the control firms are listed on the stock market and have valid historical stock prices in the sample period; (iii) the control firms are classified in the same category (sector) as the treatment firm; (iv) the control firms are located in the same region (Europe or Asia) as the treatment firm; and (v) the market capitalisation (size) ranking of the control firm in the corresponding region is close to that of the treatment firm (the ranking difference is not larger than 20 positions).

Using the criteria above, a total of 167 control firms are selected.⁸ The sector and region distributions of the treatment group and the control group are shown in Table 1.

[Insert Table 1 here]

The number of selected firms in the control group is higher than that of firms in the treatment group. This is consistent with the fact that Moody's only issues a very small number of unsolicited ratings. The region and sector distributions of control group firms are more balanced than those of treatment group firms (treatment group firms are concentrated in the European region and in the banking/finance sector).

Even though we use the criteria based on region, sector and firm size to initially filter the control group firms, such filter procedure does not capture the factors of other accounting-based fundamentals, such as leverage, profitability, etc. The comparison of rating levels without controlling for these factors may lead to biased results. Therefore, matching procedures based on the fundamental variables are conducted before the comparison of rating levels.

4.2 Fundamentals

Accounting-based fundamental information of the treatment and the control group firms is collected and applied in the procedure of matching and regressions in order to compare the levels of unsolicited and solicited ratings issued for firms with similar characteristics.

Considering the data available from Bloomberg and the categories of information (size, leverage, profitability), which is generally considered by the market to assess the quality of firms (Ham and Koharki, 2016), we employ eight accounting indicators (shown in Table 2) as our control fundamentals.

[Insert Table 2 here]

⁸ Some of the firms play the role as the control firm for more than one treatment firm.

All accounting data are collected on a quarterly basis. Excluding the missing values, we obtain 2,315 observations of the firm-quarter pair of fundamental variables for unsolicited rating recipients (treatment group) and 7,830 observations for the solicited rating recipients (control group). The descriptive statistics of these variables is shown in Appendix C.

4.3 Matching Scheme (Propensity Score Matching)

Due to the imbalanced data between the treatment group (40 firms) and the control group (167 firms), as well as the fact that the initial filter of the control group firms does not consider other accounting-based variables besides firm size, we apply the method of Propensity Score Matching (PSM) for each of the treatment group firms in order to select its ‘matched control firms’ from the control group. For matching algorithms, there are normally two methods: caliper matching (a maximum allowable distance between propensity scores is specified) and nearest neighbour matching (matches each treatment group participant with the closest possible untreated group participant). The matching mechanism used in this paper is the ‘nearest neighbour with replacement’. The reason we do not use another matching method is that the objective is to match each of the banks in the treatment group with a fixed number of banks (2, 3 and 4) from the control group. Therefore, using caliper matching may cause a problem whereby different treatment group banks would have different numbers of control group counterparties.

This procedure has two steps. First, we run a logit regression for all firms by regressing the dummy variable indicating whether the firm’s rating by Moody’s is unsolicited (=1) or solicited (=0), on fundamental variables and region and sector dummies. Using the estimated coefficients and the information of fundamentals, we calculate a score for each of the sample firms. The score indicates the probability of the firm to be categorised as ‘unsolicited’.

Second, for each firm in the treatment group, we select N firms from the control group that have the closest scores to it. Each control group firm is allowed to be picked more than once for more than one treatment group. N is set as 2, 3 and 4, respectively, in order to have the flexible ratios between the treatment group sample and the matched control sample. The distance of fundamental characteristics between treatment firms and selected control firms is larger if the selection of N is larger, because by taking a larger N, we allow more control firms to be selected for each of the treatment firms. The numbers of firms and firm-quarter observations of the treatment group and the control group for different N are shown in Table 3. In all of the further analysis shown in Section 5, we use four matching schemes to compare the situation for unsolicited and solicited cases: three schemes use N from 2 to 4 to select control firms, respectively, and the fourth scheme use all control firms as members in the control group.

[Insert Table 3 here]

4.4 Distance to default

To measure the default risk predictability of Moody's ratings, we estimate the default risks of firms in the treatment and control groups. Some previous studies use the actual default events of firms and the relationship between default events and credit ratings to reflect the predictability (Becker and Milbourn, 2011; Baghai and Becker, 2018). However, the actual rating events in our sample are rare. Therefore, we use an indicator of Distance to Default (DTD) (Merton, 1974) to measure the default risk of sample firms on a quarterly basis. In empirical tests, DTD is a very commonly-used tool to proxy the credit risk (i.e., probability of default) of firms (Yu, 2005; Blundell-Wignall and Roulet, 2013; Milne, 2014).

DTD is calculated as:

$$\frac{\ln\left(\frac{V}{F}\right) + (r - 0.5\sigma_V^2)/T}{\sigma_V\sqrt{T}} \quad (4.1),$$

where V: market value of the firm asset; F: book value of the firm debt, which is equal to the sum of short-term debt and half of the long-term debt; r: risk-free interest rate; σ_V : volatility of V; and T: time horizon.

$$V \text{ and } \sigma_V \text{ are unobservable and obtained by } s\sigma E = (V/E)N(d_1)\sigma V \quad (4.3),$$

$$\text{where } d_1 = \frac{\ln\left(\frac{V}{F}\right) + (r + 0.5\sigma_V^2)/T}{\sigma_V\sqrt{T}} \text{ and } d_2 = d_1 - \sigma_V\sqrt{T}.$$

In Equation (4.3), E is the market value of the firm equity; σ_E is the volatility of E ; $N()$ indicates the normal distribution function. Other components are observable: E =stock price \times outstanding share (daily); F =current debt+0.5 \times long-term debt (quarterly); σ_E =yearly standard deviation of E ; r =3-month treasury bill rate (collected from Bloomberg) and $T=0.25$ (i.e., a quarter).

To find V and σ_V , we use the iterated estimation method by repeatedly setting estimates as new observations and solving the equations until the differences between newly-solved estimates and previously-solved estimates are lower than 0.001.

A higher DTD indicates a lower risk of default. According to Formula (4.1), the higher DTD (lower risk) may be derived from one or more factors as follows: a higher entity value (V), a lower debt value (F), a higher risk-free rate in the market (r), or a lower volatility of entity value (σ_V).

5. Methodology and results

Our empirical analysis is conducted in two stages in order to test the conditions for the two parts of the self-selection hypothesis. One part is aimed at examining Hypothesis 1; that is, unsolicited ratings

issued are more conservative than solicited ones issued by the same CRA. The other part is aimed at testing Hypothesis 2 by comparing the rating quality between unsolicited and solicited ratings.

5.1 Test of Rating Levels Between Moody's Unsolicited and Solicited Ratings

To test whether unsolicited ratings are systemically more conservative than solicited ones, we conduct the comparison in two streams: single-agency comparison and multi-agency comparison. For the single-agency test, unsolicited and solicited ratings issued by Moody's are considered and the average rating-level gaps between those two types of ratings are identified and tested. Such single-agency tests are widely conducted in the literature (for example, Byoun and Shin, 2002; Poon et al., 2009) to demonstrate the rating gaps of unsolicited and solicited ratings. To exclude the possibility that the seemingly lower levels of unsolicited ratings are due to the systematically weaker observable characteristics of unsolicited rating recipients but not the reaction of Moody's to self-selection behaviour (unobservable factor) of rated firms, we use logit regressions to control for the fundamentals. To further improve the feasibility of our results, we supplement the single-agency test by conducting a multi-agency test. The gap of ratings among different big CRAs have been widely used to study the rating industry. For example, Livingston et al. (2008) apply the rating gaps as an indicator of rating migration. Alsakka and ap Gwilym (2010b) extend the study to the sovereign rating area and study the split sovereign ratings as a factor of future rating variations. Vu et al. (2017) use the sovereign rating splits to reflect the political risks and the transparency of the sovereigns. In this paper, we consider the relative rating gap between Moody's and the two other agencies (S&P and Fitch) in order to test whether or not the gap varies conditional on the Moody's rating being unsolicited. The inherent assumption is that: first, we allow the possible *difference of absolute rating level* between Moody's and another CRA due to the different benchmark rating criteria for different CRAs; and second, we regard the *difference*

of rating gaps for the solicited rating cases and the unsolicited rating cases as the indicator for the effect of solicitation status on the rating conservatism.

5.1.1 Numeric transformation of rating notches

In order to quantitatively analyse the ratings, we follow the rule used by Ashcraft et al. (2011) and transform the original letter-format rating indicators into numerical indicators from 1, which indicates the highest rating level, to 21, which indicates the lowest rating level. Details of the transformation are shown in Table 4.

[Insert Table 4 here]

The letter-format rating indicator system used by Moody's is different from that used by S&P and Fitch but the total number of rating notches (21) are the same among the three agencies. After this transformation, we can not only perform the mathematical calculation (t-test and logit regression) on Moody's rating levels but also quantitatively compare the rating levels of different rating indicating systems used by different rating agencies. The frequency distribution of quarterly rating indicators of all the sample firms is shown in Figure 1.

[Insert Figure 1 here]

The shape of the figure indicates that the distribution of rating levels is positively skewed. The majority of the historical ratings concentrate within the range of [5,10], which represents the range between Aa1 and Baa3. This is reasonable because the firms with ratings higher than Aa1 are regarded as the 'top-rated' ones with superior features, while firms with ratings lower than Baa3 are regarded as 'non-investment grade' ones that may encounter regulatory restrictions by regulators. The firms rated between these two ranges have moderate risk and represent most of the population.

5.1.2 Single-Agency Comparison

The single-agency comparison is only focused on the ratings of sample firms issued by Moody's. A univariate test (discussed later) directly compares the numerically transformed rating indicators of the treatment group firms (unsolicited) with those of control group (solicited), and a trend of lower ratings (reflected by a higher value of transformed rating indicators) of treatment group firms are observed. However, this finding is not conclusive because it does not take the current fundamentals of the sample firms into account. The lower ratings of the treatment firms may reflect a weaker current fundamental of those firms but not the self-selection behaviour of Moody's, that forecasts that the selected unsolicited firms have weaker future performances. Therefore, a multi-variate test should be conducted as an essential supplement. Specifically, we run logit regressions of the rating indicators on the key variable of solicitation status along with fundamental variables and find a significant estimate for the solicitation status variable, which indicates that after controlling for relevant fundamentals, the solicitation status of Moody's ratings is associated with the level of ratings given by it.

5.1.2.1 Univariate test

The univariate test is the most intuitive way to compare the rating levels between unsolicited and solicited ratings by Moody's, without considering any other fundamental information of sample firms but ratings. The principle is to directly compare the average levels of these two types of ratings and calculate the mean and standard deviations of the level gap to obtain the t-statistics of the gap. In this analysis, we use the logarithm of the numerical rating indicator so as to replace the original integer-format and eliminate the potential negative impact of the distribution's skewness on the feasibility of the t-test. We use the quarterly firm-rating pairs to construct the dataset for the univariate test. Firms in

both the treatment group (unsolicited) and the control group (solicited) are selected and the different matching schemes based on the PSM method are applied respectively to compare the average value of numerically transformed rating indicators. The matching schemes vary according to the selection of N (N=2,3, and 4), which is the number of nearest neighbours selected from the control group for each of the treatment firms. The t-test results are shown in Table 5.

[Insert Table 5 here]

In all of the four matching schemes, we find a larger average value of the logarithm of rating indicators of unsolicited ratings than solicited ratings. Since a higher value of rating indicators is equivalent to a lower rating level, the average unsolicited ratings issued by Moody's are lower than solicited ratings. After taking the exponent (the reverse of the logarithm) of the figures in the table, we find that the average level of unsolicited ratings ($\exp\{2.149\}=8.576$) is equivalent to the middle point between Baa1 (8) and Baa2 (9). The average level of solicited ratings depends on the selection of matching schemes but all of the four figures are close to $\exp\{2.05\}=7.768$ (equivalent to the middle point between A3 (7) and Baa1 (8)). From an intuitive perspective, the average level of unsolicited ratings is one notch lower than solicited ratings. The t-test result shows that the rating difference between the two unsolicited ratings is statistically significant at the 1% significance level.

Furthermore, the different PSM matching criteria show that when the PSM matching the level of difference is lower than that without matching and with the rise of the number of matched counterparties (i.e., increasing N, the number of nearest neighbours), the difference gets bigger. This suggests that the use of PSM matching is associated with a reduction in bias.

Tables 4 and 5 together provide preliminary evidence that unsolicited rating tends to be lower than solicited ones. However, fundamental variables and other fixed effects (year, quarter, country, and

sector) are not considered in this analysis. Therefore, we run the ordered logit regression to control for those factors.

5.1.2.2 Regression Test

We use ordered logit regression to compare the rating levels between unsolicited and solicited ratings controlling for the fundamental factors of the firms:

$$R^*_i = \beta_{1,1}Unsolicited_Dummy_i + \mathbf{X}'\boldsymbol{\gamma}_1 + \varepsilon_i \quad (5.1)$$

The regression is run on the basis of quarterly firm-rating pairs and each i represents a pair of firms. The dependent variable, R^*_i represents the unobservable latent variable, which defines the thresholds of various alternatives of credit rating levels R_i , described in Table 4. A higher R_i represents a lower rating. The key independent variable in Equation (5.1) is *Unsolicited_Dummy_i*, which is equal to 1 if the rating of pair i is unsolicited and 0 if the rating is solicited.

$\beta_{1,1}$, the corresponding estimate of the dummy variable, captures the impact of the solicitation status on the rating level. To fit the hypothesis of self-selection, we expect a significant positive $\beta_{1,1}$ which means that if the ratings are unsolicited (*Unsolicited_Dummy_i* = 1), the rating level should be lower (a higher R_i and a higher R^*_i). \mathbf{X}' represents a vector containing eight fundamental variables shown in Table 2, as well as the dummy variables defining the year, quarter, country, and sector of pair i . $\boldsymbol{\gamma}$ is the corresponding estimate on the sector \mathbf{X}' .

The variables contained in the vector \mathbf{X}' help the model (5.1) to eliminate the fundamental variables and other fixed effects in the analysis of the impact of the solicitation status on the rating levels. $\beta_{1,1}$ captures the association between solicitation status and rating levels—assuming that the firms that receive corresponding ratings issued by Moody's have the same level of fundamentals issued in the same year and same quarter—are located in the same country and are run in the same sector.

We assume that the decision to provide unsolicited ratings for selected firms made by CRAs is not related to the current status of control variables in \mathbf{X}' but are only based on the forecast of the firms' quality. We acknowledge that this is a very strong assumption and the violation of this assumption may cause an endogeneity problem. To tackle this problem, we use the multi-agency comparison (difference-in-difference method) to eliminate the possibility of biased selection in the assignment of unsolicited ratings (see 5.1.3).

The empirical result of Equation (5.1) is shown in Table 6. As expected, regardless of the matching schemes, the estimates on unsolicited dummy $\beta_{1,1}$ are always significantly positive. The mathematical intuition is that after controlling for the fundamentals and other fixed effects, if the rating is unsolicited, the rating notch has a higher probability of being mapped to a high value of R^*_i , which is defined as the threshold of lower rating levels. In other words, the status of unsolicited ratings is associated with a lower rating level.

[Insert Table 6 here]

This finding enhances the result of the univariate test by controlling for other fundamental factors (\mathbf{X}'). We find that the selected accounting-based fundamentals have a significant association with the rating levels issued by Moody's. This suggests that Moody's may consider those factors when determining which rating notches it would give to the rated firms. Specifically, estimates on *Total_Debt_to_Total_Asset* and *Degree_of_Financial_Leverage* are positive, which indicates that Moody's might see debt ratio as a negative factor for the firm. This is natural and reasonable because a higher level of debt ratio (or leverage) is associated with a higher risk of the firms to default on the debt. Estimates on *Total_Investment_to_Total_Assets* are also positive, which indicates that Moody's has conservative attitudes to the expansion of firms' investment scale and regard it as a negative indicator

of the future default risk. Estimates on *Sales_to_Assets*, *Return_on_Assets* and *Asset_Growth_Rate* are negative, which means that those factors may be viewed by Moody's as positive indicators of the firm's default risk. Moody's ratings are higher if the rated firm has a larger current value of sales ratio, ROA and asset growth ratio. Besides that, Moody's rating is not associated with the size of the firms (insignificant estimates on *Total_Asset*). Rather, it reflects the effect of the initial filter of the control sample firms, with the criterion 'the market capitalization (size) ranking of the control firm in the corresponding region is close to that of the treatment firm (the ranking difference is not larger than 20)'. Therefore, the treatment (unsolicited) group and control (solicited) group should contain firms with similar sizes so the statistical estimates of the firm size are not significant. These results capture an asymmetric relationship between CRAs' external opinions (i.e., credit ratings) and firms' solicitation strategy. Gkillas et al. (2020) find that the information reflected by news has an asymmetric impact on firm risks (i.e., different impact according to the risk quantile). Our results reveal another perspective of asymmetry referring to the interaction between entities who receive the external opinions (i.e., rated firms) and entities who release those opinions (i.e., CRAs). We find that the asymmetric impact firstly observed by Gkillas et al. may also be related to how the external opinions are created (i.e., whether the ratings are solicited or not).

5.1.2.3 Supplemental test: rating stability

So far we have shown evidence of the lower rating levels of unsolicited ratings. However, whether the rating levels of unsolicited and solicited ratings have a different pattern of rating changes or not is not yet studied. In this section, we investigate whether or not the gap between the two types of ratings is stable over time and whether one type of rating is more likely to be changed by Moody's in relation to

another type. The regression model is shown in Equation (5.2). What distinguishes the test in this equation from that in Equation (5.1) is the set of dependent variables. In Equation (5.1) R^*_i refers to the latent variable linked to the level of ratings, while in Equation (5.2), RC^*_i refers to the latent variable linked to the quarterly change of rating levels (RC is short for ‘rating change’). The change of rating level is measured as the absolute value of the gap between the numerically-transformed rating level in the current quarter minus that in the previous quarter. Correspondingly, fundamental variables in the vector \mathbf{X}' are adjusted to the format of quarterly change rather than the absolute values. In addition, we split the cases of rating change into ‘upgrade’ cases and ‘downgrade’ cases and regressions are run separately for each of the two cases.

$$RC^*_i = \beta_{2,1}Unsolicited_Dummy_i + \mathbf{X}'\boldsymbol{\gamma}_2 + \varepsilon_i \quad (5.2)$$

Regression results are shown in Table 7. Estimates of the unsolicited dummy are insignificant in all cases. This implies that the solicitation status does not impact the probability of the firms being upgraded or downgraded. Combining this finding with the result obtained for Equation (5.1), we conclude that the rating levels of unsolicited ratings are significantly lower than solicited ones and the degrees of variation patterns for both types of ratings are statistically the same in terms of the frequency and probability of rating changes. In summary, the lower level of unsolicited ratings is persistent and unlikely to be reversed because the upgrade and downgrade probabilities do not differ for different solicitation status.

[Insert Table 7 here]

5.1.3 Multi-Agency Comparison

In the logit regression analysis, we try to control for the fundamental factors. This is to exclude the possibility that the finding that unsolicited ratings are lower is derived from a systematically weaker firm's characteristics of unsolicited rating recipients. In order to exclude all fundamental variables and only consider rating levels, we introduce the ratings given to the sample firms but issued by the other two big agencies, S&P and Fitch, in order to compare the relative level gap between Moody's and the other two agencies' ratings. In principle, the variation of the rating level gap is not related to any fundamental information of rated firms but only related to the rating agency and the solicitation status. In this analysis, Moody's is regarded as the 'treatment agency', while either S&P or Fitch is selected as the 'control agency'. Those firms that receive ratings by both the treatment agency and the control agency are kept in the sample. After that, we filter out the firms that receive unsolicited ratings by the control agency, in order to ensure that all of the sample firms have only solicited ratings by the control agency and either solicited or unsolicited ratings by the treatment agency.

We acknowledge the possibility of endogeneity in this analysis, which would indicate that the fundamentals of firms in treatment and control groups are significantly different. To deal with this issue, we use PSM method to match each treatment firm with a couple of control firms (1, 2, 3, and 4 control firms are matched respectively), which are 'nearest' to the treatment firm in terms of fundamentals (details are described in Section 4.3). The results of the multi-agency test are shown in Table 8.

There are two layers of difference. The first layer is the average gap between numerically-transformed rating levels issued by the treatment and those issued by the control agency. This indicator reflects the gap of rating criterion applied by different rating agencies. The second layer of difference is the gap of the first-layer difference between the firms that receive unsolicited Moody's ratings (treatment firms)

and those that receive solicited Moody's ratings (control firms). The D-i-D estimator shows whether or not the rating criterion gap between Moody's and the other two agencies is associated with the solicitation status (Moody's) of the rated firms. A positive D-i-D estimator is expected to enhance the hypothesis of self-selection, as it would show that compared to the control agency, Moody's issues lower ratings (reflected by a higher value of the transformed rating indicator) for unsolicited rating recipients.

Figure 2 shows the two layers of difference more clearly. A higher position of line indicates a higher rating level (i.e., a more 'positive' one). This figure shows a stylised situation in which the other CRA (either S&P or Fitch) rates firms higher than Moody's for both the control group and the treatment group but the rating gap for the treatment group (the length of B) is bigger than that for the control group (the length of A). In this situation, we posture that Moody's rates unsolicited recipients systemically lower in the cross-agency test.

[Insert Table 8 here]

[Insert Figure 2 here]

For both the Moody's-S&P pair analysis and the Moody's-Fitch pair analysis, we find significant evidence that Moody's issues more conservative ratings for its unsolicited rating recipients. The D-i-D estimators are significantly positive, which fits our expectation: compared to the control agency, Moody's issues more conservative ratings (reflected by a higher value of the transformed rating indicator) for unsolicited rating recipients.

Exploring the details of the D-i-D components, we find additional significant evidence. The treatment group firms have Moody's ratings at a lower level than the S&P/Fitch ratings (reflected by positive

values of the gap between Moody's ratings and S&P/Fitch ratings for the treatment group). However, the control group firms have Moody's ratings at a higher level than the S&P/Fitch ratings (reflected by negative values of the gap between Moody's ratings and S&P/Fitch ratings for the treatment group). This means that the solicitation status reverses the sign of the relative gap between Moody's ratings and S&P/Fitch's ratings: if the firm solicits the rating service from Moody's, Moody's then offer ratings at an average level higher than S&P/Fitch, but if the firm does not solicit the rating service, Moody's offers ratings at a lower level compared to S&P/Fitch. This provides evidence that Moody's ratings for unsolicited rating recipients are more conservative.

5.2 Rating quality of unsolicited and solicited ratings issued by Moody's

Hypothesis 2 states that the quality of unsolicited and solicited ratings is not different. We measure the quality of Moody's ratings in two dimensions: rating predictability and timeliness.

The rating predictability of unsolicited and solicited ratings is measured by the panel regression of DTD indicator on an unsolicited dummy, along with other control variables. We also supplement this test by using a predicting model of DTD to test the relative rating accuracy between solicited and unsolicited ratings.

Rating timeliness is measured by a multi-agency comparison of the rating change speed. Moody's rating change announcements are compared with those of S&P or Fitch in order to test which agency leads/lags another CRA. A higher probability of leading another agency and a lower probability of lagging another agency indicates a higher rating quality.

The empirical analysis in this section is aligned with the conclusion drawn in the theoretical analysis, shown in Formula 3.11 and Formula 3.13. Those two inequations show that the unsolicited and solicited ratings provide external investors with the extra information at the same level, and the quality of the

information is not weaker due to the non-solicitation status of the ratings. In this empirical analysis, we assess the concept of 'information' by means of two measures: default-risk predictability (Section 5.2.1) and relative rating-change timeliness (Section 5.2.2).

5.2.1 Rating predictability

The rating predictability reflects the accuracy of information provided by the ratings regarding the default risk variation of the rated firms. A rating with a higher quality should forecast the future variation of the firm's default risk with a higher degree of accuracy. We follow Campbell et al. (2008) and Chava and Purnanandam (2010) and apply DTD in order to measure the firms' default risk. A higher value of DTD is associated with a lower risk of default. To test whether the rating predictability is different for unsolicited and solicited ratings, we run a panel regression model of DTD on rating levels along with the unsolicited dummy. A significant estimation on rating levels means that the rating has the ability to predict DTD. In addition, if the unsolicited dummy is insignificant, it provides evidence that the solicitation status is not associated with the rating predictability.

To enhance the results of panel regressions, we use an alternative measure of rating predictability: the gap between the observed DTD and the predicted DTD of treatment group firms. First, observed rating and DTD information of control group firms are used to build a predicting model. Then the corresponding estimates obtained in the predicting model with the control group data (solicited rating levels) are applied to predict the DTD of the treatment group firms with their actual unsolicited rating levels. If the error (gap between the observed DTD and the predicted DTD of treatment group firms) is not significant, the hypothesis of no difference of rating predictability would not be rejected.

5.2.1.1 Regression Model

We apply the random-effect panel regression of DTD on the lagged terms of rating indicators along with the unsolicited dummy. The reason for using the random-effect model rather than the fixed-effect one is that the random-effect model is able to capture the impact of firms' heterogeneity (solicitation status) on the dependent variable. If using fixed-effect regressions, the effect of the independent variables (ratings and solicitation status) on DTD at the entity level would be eliminated, while such an effect being the objective of our study (the solicitation status is at an entity level).

The length of the lagging time period ranges from one quarter to one year (i.e., four quarters). Estimates on rating indicators demonstrate the link between past rating forecasts and the future DTD variation, a reflection of rating predictability on firm default risk. Estimates on the unsolicited dummy measure the bias of rating predictability due to the solicitation status.

The panel regression is conducted based on the equation:

$$DTD_{i,t+p} = \alpha_3 + \beta_{3,1}LogRating_{i,t} + \beta_{3,2}UnSLDummy_{i,t} + \mathbf{X}'\boldsymbol{\gamma}_3 + U_i + \varepsilon_{i,t} \quad (5.3)$$

where i indicates the sample firms (all treatment firms are included and the selection of control firms depends on the matching schemes described in Section 4.3). $DTD_{i,t+p}$ is the distance to default of firm i at time $(t+p)$, $p=1,2,3,4$. $LogRating_{i,t}$ is the logarithm of numerically-transformed ratings offered by Moody's to firm i at time t . $UnSLDummy_{i,t}$ is a dummy equal to 1 if firm i receives an unsolicited rating by Moody's at time t and 0 if the Moody's rating at time t is solicited. \mathbf{X}' is the vector of control variables and the components are the same as shown in Table 2. U_i is random-effects term. The regression results are shown in Table 9.

[Insert Table 9 here]

The coefficients of $LogRating_{i,t}$ are consistently negative, which provides evidence of a significant Moody's rating predictability. These negative estimates indicate that a firm that receives a higher rating

from Moody's (equivalent to a lower value of $LogRating_{i,t}$) will have a smaller default risk in the next one to four quarters (equivalent to a higher value of DTD). Such an association is significant after controlling for the fundamental variables and indicates that the Moody's ratings provide extra information regarding future DTD variation. These results are consistent with the theoretical model findings shown in Formula 3.13 (credit ratings are informative in terms of the firm default risk).

The coefficients on $UnSLDummy_i$ are insignificant, which indicates that the rating predictability of unsolicited and solicited ratings is not different. The intuition behind this is that after we control for the rating factor, the solicitation factor is not associated with the future DTD variation. In other words, the unsolicited ratings (of treatment group firms) do not over-predict or under-predict the DTD relative to solicited ratings (of control group firms). This finding is consistent with the theoretical model results of Formula 3.11 (unsolicited and solicited ratings are not different in terms of the predictability of the firm actual status).

5.2.1.2 Robustness check: the mutual impact between DTD and ratings

Equation (5.3) only considers the unidirectional impact of current ratings on future DTD. However, it is reasonable to question whether or not there is a mutual impact between them. Although DTD is not directly observable, it can be calculated using information (stock prices, debt amount and risk-free interest rates) collected from open sources. Therefore, past DTD may be considered by Moody's to issue current ratings. From the results of Equation (5.3), we find an association between past ratings and current DTD. Our robustness check tests whether the past DTD is a factor determining the current rating level. Furthermore, we examine whether or not the solicitation status still impacts the rating level (shown in Equation (5.1)) after we add the past DTD as the explanatory variable. The model equation is shown below and solved by the logit regression estimation:

$$R^*_{i,t} = \alpha_4 + \beta_{4,1}DTD_{i,t-p} + \beta_{4,2}UnSLDummy_{i,t-p} + \varepsilon_{i,t} \quad (5.4)$$

The dependent variable, $R^*_{i,t}$ represents the unobservable latent variable, which defines the thresholds of various alternatives of credit rating levels $R_{i,t}$ of firm i at quarter t . The details of the rating indicator transformation are described in Table 4. $DTD_{i,t-p}$ is the distance to default indicator of firm i at the quarter $(t-p)$, where $p=1, 2, 3,$ and $4,$ respectively. $UnSLDummy_{i,t-p}$ indicates the solicitation status of firm i at quarter $(t-p)$ (equal to 1 if the firm i receives unsolicited ratings at quarter $t-p$ and equal to 0 if it receives solicited ratings at quarter $t-p$). The regression results are shown in Table 10.

[Insert Table 10 here]

The significant link between past DTD and current ratings is observed and the solicitation status remains a significant factor in determining the rating levels after controlling for past DTD. This enhances both Hypothesis 1 and Hypothesis 2. Significantly positive estimates of $\beta_{4,2}$ support the same conclusion, as shown in Equation (5.1): more conservative ratings are offered to unsolicited rating recipients by Moody's. This provides additional evidence in favour of Hypothesis 1.

Significantly negative estimates of $\beta_{4,1}$ reflect that a higher past DTD (a lower default risk) is associated with a lower transformed rating indicator (a higher current rating level). It suggests that Moody's may observe the historical DTD and regard it as a factor to determine its rating levels. Combining this with the result of Equation (5.1), we conclude the following: first, that Moody's current ratings contain information of past DTD; second, that Moody's offers more conservative ratings to unsolicited rating recipients after we control for the factor of past DTD; and third, there is no significant DTD gap between two types of rating recipients controlling for the same rating levels. In summary, although ratings are more conservative for unsolicited rating recipients, such conservatism is not biased because it accurately predicts future DTD. This fits the hypothesis of self-selection: firms with potentially bad future

performances do not opt to be rated, and Moody's takes this into consideration when offering more conservative ratings to them.

5.2.1.3 Predicting model method

The panel regression model analyses the treatment group firms and the control group firms in an equation and splits the two types of firms by adding a dummy variable on the right side of the regression equation. To find a more intuitive way to distinguish the unsolicited ratings from solicited ones, we establish a novel method to measure the predictability of ratings. We use a simple regression model of DTD with only the control group firm data to obtain the estimates on rating factors, as done by Switzer et al. (2018), and then apply those estimates to the treatment group ratings to predict the DTD of unsolicited rating recipients. The predicted value is compared with the observed value to confirm whether or not the estimates create a biased predicted DTD.

We use the actual observations of the control group firms to estimate Equation (5.5). The selection of control group firms varies according to the matching schemes (the number of nearest neighbours in the PSM procedure),

$$\text{Control_Group_DTD}_{i,t+p} = \alpha_5 + \beta_{5,1} \text{Control_Group_LogRating}_{i,t} + \mathbf{X}_{\text{controlGroup}}' \boldsymbol{\gamma}_5 + \varepsilon_{i,t} \quad (5.5)$$

where $\text{Control_Group_DTD}_{i,t+p}$ refers to the DTD of the control group firm i at time $(t+p)$, $p=1,2,3,4$.

$\text{Control_Group_LogRating}_{i,t}$ is the logarithm of numerically-transformed ratings offered by Moody's to the control group firm i at time t . \mathbf{X}' is the vector of control variables and the components are the same as shown in Equation (5.1).

The corresponding estimates, $\hat{\alpha}_5$, $\hat{\beta}_{5,1}$ and $\hat{\boldsymbol{\gamma}}_5$ are obtained from Equation (5.5) before those estimates are applied in order to predict the treatment group firms' DTD (\widehat{DTD}) in Equation (5.6).

$$\begin{aligned}
& Treatment_Group_DT\widehat{D}_{i,t+p} \\
& = \hat{\alpha}_5 + \hat{\beta}_{5,1} Treatment_Group_LogRating_{i,t} + X_{treatmentGroup} \hat{\gamma}_5 \quad (5.6)
\end{aligned}$$

In Equation (5.6), $Treatment_Group_LogRating_{i,t}$ and $X_{treatmentGroup}$ are observations in the treatment group dataset. $\hat{\alpha}_5$, $\hat{\beta}_{5,1}$ and $\hat{\gamma}_5$ are obtained by solving Equation (5.5).

The final step is to take the difference between the observed $Treatment_Group_DTD_{i,t+p}$ and the predicted $Treatment_Group_DT\widehat{D}_{i,t+p}$ in order to calculate the relative rating bias between unsolicited and solicited ratings of Moody's.

$$Relative\ Prediction\ Bias = Treatment_Group_DTD_{i,t+p} - Treatment_Group_DT\widehat{D}_{i,t+p} \quad (5.7)$$

A significant positive bias indicates that the actual DTD of unsolicited rating recipients is larger than the predicted DTD using the estimated coefficients derived from solicited rating recipients, along with the actual rating of unsolicited rating recipients. Thus, the unsolicited ratings under-estimate the DTD relative to solicited ones (equivalent to an over-estimation of the default risk). Conversely, a significant negative bias indicates that unsolicited ratings over-estimate the DTD relative to solicited ones and an insignificant bias indicates that unsolicited ratings neither under-estimate nor over-estimate the DTD relative to solicited ones. The results of the calculation of the average 'relative rating bias' are shown in Table 11.

[Insert Table 11 here]

In most of the cases shown in Table 11, the relative prediction bias of DTD between unsolicited and solicited ratings is insignificant, which supports our previous conclusion that the DTD predictability is not different for the two types of ratings by Moody's. In some of the cases, the bias is significantly positive, showing a weak evidence that Moody's may over-estimate the future risk of the default of firms (under-estimate the DTD). This finding also fits the self-selection hypothesis by showing that

Moody's selects those firms that it believes would have a worse future performance and offers unsolicited ratings to them at a more conservative level. The conservative ratings under-estimate the future DTD of the rating recipients compared with the solicited rating recipients.

5.2.2 Rating timeliness

The timeliness of the rating action announcements (downgrades, upgrades, warnings of rating change, and the revision following the warnings) is an alternative indicator of rating quality applied in this paper. A rating agency is thought to be of higher quality if the rating changes announced by that agency are more likely to lead, and less likely to lag, other agencies. The timeliness reflects the information content delivered to the market by the rating action announcements. Assume we have two agencies, A and B. If announcements by A are released a couple of days before B, the information content of B's announcement should be lower than A's, because the market participants have received and responded to the signal of A's announcements and would not obtain new information from B's announcements. In this paper, Moody's rating timeliness is measured by a relative lead-lag relationship of rating action announcements between Moody's and S&P/Fitch. A higher probability of the case that 'Moody's lead S&P/Fitch', or a lower probability of the case that 'Moody's lag S&P/Fitch' indicates a better rating quality of Moody's, and vice versa. If the probability that Moody's unsolicited ratings lag or lead its peers' (S&P and Fitch) ratings is not significantly associated with Moody's solicited ratings, we would find evidence that the relative rating quality of Moody's ratings is not related to the status of solicitation. In summary, we find that Moody's unsolicited rating changes are neither significantly faster nor significantly slower than the solicited rating changes. This demonstrates that the rating quality of unsolicited and solicited ratings by Moody's does not differ significantly between the two types of ratings in terms of rating timeliness.

5.2.2.1 Measurement of rating timeliness: lead-lag relationship between Moody's and the control agency

Rating timeliness is reflected by the sequence of occurrence of Moody's and other two agencies' rating actions. The rating actions of Moody's should be defined first. In this paper, we identify three segments of rating actions: first, negative actions including downgrades and possible downgrade announcements; second, positive actions including upgrades and possible upgrade announcements; and third, revision actions where Moody's excludes the firm from the possible downgrade/upgrade list. From the sample dataset, we identify 1,191 Moody's adjustment actions for 142 sample firms in the sample period (2001Q1-2017Q4). Of these, 927 actions are taken for solicited ratings and 264 actions are for unsolicited ratings.

After identifying Moody's rating actions, we search for the actions of S&P and Fitch for each of Moody's actions, in order to find the cases of 'Moody's lead S&P/Fitch' and 'Moody's lag S&P/Fitch'. For each of the rating actions taken by Moody's, we find the specific actions by S&P and Fitch, which that satisfy the conditions as follows and identify them as the case 'Moody's lead S&P or Fitch': first, they are of the same type of actions by Moody's (negative, positive or revising); and second, they occur no more than 90 days *after* the actions of Moody's were taken. Similarly, for each of the rating actions taken by Moody's, we find the specific actions by S&P and Fitch, which satisfy the following conditions and identify them as the case 'Moody's lag S&P or Fitch': first, they are of the same type of actions by Moody's (negative, positive or revising); and second, they occur no more than 90 days *before* the actions of Moody's were taken.

With a view to present a more intuitive explanation, we describe two actual examples (selected from the dataset) to show how the ‘Moody’s lead S&P/Fitch’ and ‘Moody’s lag S&P/Fitch’ cases are identified. These examples are displayed in Appendix D..

The previous literature in this area overlooks some complex cases of lead-lag relationships where multiple rating actions of different agencies (or by same agency) are taken sequentially at close dates. In these cases, Moody’s actions may be identified as simultaneously ‘leading’ and ‘lagging’ S&P or Fitch, which is unreasonable from a practical perspective. Therefore, some of these complex cases, which are considered in our study, are also presented in Appendix C.

5.2.2.2 Comparison of lead-lag relationships between Moody’s and S&P/Fitch for solicited and unsolicited cases

We analyse the lead-lag relationship for Moody-S&P and Moody-Fitch pairs respectively. For the Moody-S&P pair, 799 out of 1,191 Moody’s rating actions are valid, compared with S&P actions.⁹ Among all the valid actions, 117 actions (14.64% of 799) are identified as ‘leading S&P’ and 154 actions (19.27% of 799) are identified as ‘lagging S&P’.

For the Moody/Fitch pair, 947 out of 1,191 Moody’s rating actions are valid, compared with Fitch actions.¹⁰ Among all of the valid actions, 123 actions (12.99% of 947) are identified as ‘leading Fitch’ and 112 actions (11.83% of 799) are identified as ‘lagging Fitch’. Detailed results are shown in Table 12. Since the total number of ‘revising actions’ is very small, we only keep negative and positive actions in our further analysis.

⁹ The ‘invalid’ actions refer to those Moody’s rating actions occurring at the date when S&P does not rate the corresponding firms, so they are excluded from our analysis.

¹⁰ The ‘invalid’ actions refer to those Moody’s rating actions occurring at the date when Fitch does not rate the corresponding firms, so they are excluded from the analysis.

[Insert Table 12 here]

To measure the relative quality of Moody's ratings, we focus on the ratio of cases when Moody's lead/lag S&P/Fitch. A higher ratio of 'Moody's leading' cases or a lower ratio of 'Moody's lagging' cases indicates a better Moody's rating quality. The comparison between ratios of unsolicited and solicited ratings show us the impact of solicitation status on relative rating qualities.

In Table 12, we can observe some potential evidence of a worse quality of unsolicited ratings than solicited ones for the negative action sample, whereby solicited Moody's ratings have a greater proportion of cases of 'Moody's leads S&P/Fitch' than unsolicited Moody's ratings (15.32%>11.21% for Moody-S&P pairs of 'all types of actions'; 13.46%>11.42% for Moody-Fitch pairs of 'all types of actions'; 17.93%>13.33% for Moody-S&P pairs of 'negative actions'; 16.26%>14.66% for Moody-Fitch pairs of 'negative actions'). This shows that Moody's lead S&P/Fitch negative rating actions with a lower probability if the ratings are unsolicited by firms, which mirrors a worse rating quality. Except for that instance, we do not find a consistent and significant gap between the rating timeliness of unsolicited and solicited ratings by Moody's.

To statistically test the association between the solicitation status and rating timeliness, we use a Chi-square test to examine the significance of the relation between the dummy indicating whether or not Moody's lead/lag S&P/Fitch, and the dummy indicating whether or not Moody's ratings are solicited or unsolicited. The response variable is the lead/lag dummy and the category variable is the solicitation status. The null hypothesis of the Chi-square test is that there is no association between lead/lag dummy variable and the solicitation variable. The tests are taken for each type of rating actions, each PSM scheme and for each pair of rating agencies. The results of the Chi-square test are shown in Table 13.

[Insert Table 13 here]

We do not find a case when the association is significant according to the all Chi-square values, which are not large enough to reject the null hypothesis of no association. The results show evidence that even if we have found some potential evidence of a better quality of solicited ratings in terms of timeliness (shown in Table 12), the association is not statistically significant (Table 13). Therefore, we conclude that rating qualities regarding the rating adjustment action timeliness do not differ between Moody's solicited and unsolicited ratings.

To enhance the results of Chi-square tests, we conduct logit regressions to test the association between the solicitation status of Moody's ratings and its lead-lag relationship with S&P/Fitch's ratings. The dependent variable is a dummy variable indicating whether the rating change of Moody's is followed by/follows the other two agencies (=1) or not (=0), and the key independent variables are dummy variables indicating whether this corresponding firms are unsolicited rated (=1) or solicited rated (=0). Year, sector and region are also included in the independent variables set.

The results of logit regressions are shown in Tables 14 and 15. The situations of Moody's lead and lag the other two CRAs are separately reported in the two tables. In each table, we present the cases of negative and positive rating actions respectively and consider different PSM matching schemes.

[Insert Table 14 here]

[Insert Table 15 here]

Coefficients of the 'unsolicited' dummy in the two tables show similar results, as the Chi-square values do not support a significant association, even if we find some cases with marginally significant estimates. In the table of Moody's lead S&P/Fitch, we find marginally significantly negative estimates in negative action cases for the Moody-S&P pairs. Negative estimates in this case, indicate a worse quality of unsolicited ratings: if the Moody's ratings are unsolicited (dummy = 1), Moody's is less likely to lead

S&P regarding negative rating actions. However, the association only exists for negative actions in Moody-S&P pairs and is not persistent in other cases.

5.3 Summary of the empirical results

We validate Hypothesis 1 by providing evidence that Moody's issues ratings with more conservative levels to unsolicited rating recipients. Our tests are run in two parts: the single-agency test and the multi-agency test. The single-agency test focuses on the ratings of Moody's and finds that the unsolicited ratings of Moody's are lower than the solicited ratings, controlling for fundamental factors as well as other basic variables. The multi-agency test supplements the single-agency test result by introducing the ratings issued by S&P and Fitch and applying the concepts of 'relative rating gap' between Moody's and S&P/Fitch in order to measure the conservatism of ratings. We find that for those firms that receive Moody's unsolicited ratings and S&P/Fitch's solicited ratings, Moody's ratings (unsolicited) are lower than S&P/Fitch's (solicited), while for those firms that receive Moody's solicited ratings and S&P/Fitch's solicited ratings, Moody's ratings (solicited) are higher than S&P/Fitch's (solicited). This indicates that the unsolicitation status of Moody's is associated with a lower rating level (a higher value of the numerically-transformed rating indicator) than its solicited counterpart. This finding also supports the conclusion based on our theoretical model (see Equation 3.8).

Hypothesis 2 is related to the concept of rating quality. We use two indicators to measure the rating quality: rating predictability and rating action timeliness. For the rating predictability measure, we use DTD and its relation with past ratings so as to test the predictability of Moody's ratings. Both the regression model method and the predicting model method suggest that there is no gap between the predictability of unsolicited and solicited ratings. For the rating action timeliness, we identify Moody's rating actions and match each of these with the actions taken by S&P and Fitch to define the cases of

‘Moody’s lead S&P/Fitch’ or ‘Moody’s lag S&P/Fitch’. We find that the likelihood of either of the two cases is not associated with the solicitation status, which demonstrates that rating timeliness is not a function of solicitation status. The empirical results for Hypothesis 2 also fit the theoretical arguments expressed in Formulas 3.11 and 3.13.

6 Conclusions

This paper studies the association between rating solicitation and rating levels, as well as rating qualities. Our empirical analyses show evidence in favour of the self-selection hypothesis, that is: weak firms tend to opt not to be rated by rating agencies and rating agencies take the solicitation status into account and assign lower ratings to unsolicited recipients.

Our study is designed to identify the phenomenon of more conservative ratings for unsolicited cases than for solicited cases and justify ratings’ behaviour of unsolicited rating conservatism by observing same rating quality for both types of ratings. We propose a theoretical model, according to which, if the self-selection hypothesis holds, we would have two findings: first, ratings offered to firms that do not solicit them should be systemically lower than those offered to soliciting firms; and second, the rating quality (i.e., the information provided by both types of ratings) should be identical, regardless of the solicitation status. These findings are supported by extensive empirical tests.

We find that controlling for key fundamentals, Moody’s unsolicited ratings are significantly lower than solicited ratings. This result is supplemented by a multi-agency comparison which reveals that Moody’s unsolicited ratings are lower than solicited ratings for the same firms offered by S&P and Fitch.

To examine the rating quality, we use two measures, rating predictability and rating action timeliness, to reflect the rating quality and compare the average quality between solicited and unsolicited ratings.

No significant gap of rating quality is found, which demonstrates that unsolicited ratings are not related to a deterioration of rating quality. Both findings support the self-selection hypothesis: ratings are more conservative in solicited rating cases and unsolicited ratings are rational in terms of rating quality.

In conclusion, the findings in this paper justify Moody's behaviour of offering lower ratings for unsolicited rating recipients and show that unsolicited ratings still provide useful information regarding firms' risk of default for market participants, even though rating agencies neither charge fees nor collect internal information from rated firms in unsolicited rating decisions. This is in accordance with the claim made by Moody's and other financial regulators: they believe that unsolicited ratings are not biased and provide transparency to the market.

The evidence of self-selection is favourable for the CRAs' reputation because it fits the aim officially stated by Moody's of issuing unsolicited ratings; namely 'increasing the market transparency'. Hence, rating agencies contribute to a higher transparency in the market by recognizing those weak firms with potential risks that are not yet acknowledged by general investors and issuing ratings on these risky firms to investors, despite the fact that they (CRAs) do not collect any service fees from rated firms. Moreover, the relatively lower ratings provide extra information to the market by releasing a signal to investors that those rated firms are more likely to perform worse than their peers who solicit ratings.

The literature suggests that there widely exists asymmetric impact of external information on firm risk, such as technology shocks (Kogan and Dimitris, 2014), foreign economic news (Gkillas et al. 2020) and industry-level news (Hao et al., 2011). Our findings imply that such impact asymmetry also exists among different micro-entities (firms) and is driven by the payment model of the information providers (CRAs).

Our research sheds new light on the self-selection effect regarding information asymmetry in the credit rating industry. Admittedly, this study has limitations but they can be seen as new pathways for future research. First, we are restricted by data access and do not consider capital market outcomes as an indicator of rating quality. Thus, further research may be conducted to include capital-market indicators, such as stock returns, credit default swap (CDS) spreads and bond spreads in order to better reflect the rating quality. This will reflect higher-frequency risk for firms and is important for short-run analyses. Second, we only consider cross-firm asymmetry but not cross-quantile one (i.e., different quantiles of data such as risk levels) within single firms. This could therefore be done in future studies. In this context, another promising possibility would be the application of other econometric models such as asymmetric slope regression to capture cross-quantile asymmetry. This is important especially for practical reasons: if the rating-risk relationship is different for different risk levels of a firm, investors should adopt different strategies for a same firm in different scenarios.

References

- Alsakka, R., and Ap Gwilym, O. (2010a). Leads and lags in sovereign credit ratings. *Journal of Banking and Finance*, 34(11), 2614-2626.
- Alsakka, R., and ap Gwilym, O. (2010b). Split sovereign ratings and rating migrations in emerging economies. *Emerging Markets Review*, 11(2), 79-97
- Ammer, J., and Packer, F. (2000). How consistent are credit ratings? A geographic and sectoral analysis of default risk. *The Journal of Fixed Income*, 10(3), 24-30.
- Ashcraft, A., Goldsmith-Pinkham, P., Hull, P., and Vickery, J. (2011). Credit ratings and security prices in the subprime MBS market. *American Economic Review*, 101(3), 115-19.
- Baghai, R. P., and Becker, B. (2018). Non-rating revenue and conflicts of interest. *Journal of Financial Economics*, 127(1), 94-112.
- Bannier, C. E., Behr, P., and Güttler, A. (2008). Do unsolicited ratings contain a strategic rating component? Evidence from S&P. *Unpublished Manuscript*.
- Bannier, C. E., Behr, P., and Güttler, A. (2009). Rating opaque borrowers: why are unsolicited ratings lower? *Review of Finance*, 14(2), 263-294.
- Bar-Isaac, H., and Shapiro, J. (2013). Ratings quality over the business cycle. *Journal of Financial Economics*, 108(1), 62-78.
- Becker, B., and Milbourn, T. (2011). How did increased competition affect credit ratings? *Journal of Financial Economics*, 101(3), 493-514.

- Behr, P., and Güttler, A. (2008). The informational content of unsolicited ratings. *Journal of Banking and Finance*, 32(4), 587-599.
- Berwart, E., Guidolin, M., and Milidonis, A. (2016). An empirical analysis of changes in the relative timeliness of issuer-paid vs. investor-paid ratings. *Journal of Corporate Finance*.
- Bhattacharya, U., Wei, K. D., and Xia, H. (2019). Follow the money: Investor trading around investor-paid credit rating changes. *Journal of Corporate Finance*, 58, 68-91.
- Blundell-Wignall, A., and Roulet, C. (2013). Business models of banks, leverage and the distance-to-default. *OECD Journal: Financial Market Trends*, 2012(2), 7-34.
- Bonsall IV, S. B. (2014). The impact of issuer-pay on corporate bond rating properties: Evidence from Moody's and S&P's initial adoptions. *Journal of Accounting and Economics*, 57(2-3), 89-109.
- Bowe, M., and Larik, W. (2014). Split ratings and differences in corporate credit rating policy between Moody's and Standard and Poor's. *Financial Review*, 49(4), 713-734.
- Bruno, V., Cornaggia, J., and Cornaggia, K. J. (2015). Does regulatory certification affect the information content of credit ratings? *Management Science*, 62(6), 1578-1597.
- Byoun, S., and Shin, Y. S. (2002). Unsolicited credit ratings: Theory and empirical analysis. *2002 Proceedings of the Midwest Business Economics Association*, 98-112.
- Byoun, S., Fulkerson, J. A., Han, S. H., and Shin, Y. S. (2014). Are unsolicited ratings biased? Evidence from long-run stock performance. *Journal of Banking and Finance*, 42, 326-338.

Campello, M., & Chen, L. (2010). Are financial constraints priced? Evidence from firm fundamentals and stock returns. *Journal of Money, Credit and Banking*, 42(6), 1185-1198.

Campbell, J. Y., Hilscher, J., and Szilagyi, J. (2008). In search of distress risk. *The Journal of Finance*, 63(6), 2899-2939.

Cantor, R., and Packer, F. (1994). The credit rating industry. *Quarterly Review*, (Sum), 1-26.

Chava, S., and Purnanandam, A. (2010). Is default risk negatively related to stock returns? *The Review of Financial Studies*, 23(6), 2523-2559.

Cheng, M., and Neamtiu, M. (2009). An empirical analysis of changes in credit rating properties: Timeliness, accuracy and volatility. *Journal of Accounting and Economics*, 47(1-2), 108-130.hjk

Cornaggia, J., and Cornaggia, K. J. (2013). Estimating the costs of issuer-paid credit ratings. *The Review of Financial Studies*, 26(9), 2229-2269.

Ferri, G., Liu, L. G., & Stiglitz, J. E. (1999). The procyclical role of rating agencies: Evidence from the East Asian crisis. *Economic Notes*, 28(3), 335-355.

Fulghieri, P., Strobl, G., and Xia, H. (2014). The economics of solicited and unsolicited credit ratings. *The Review of Financial Studies*, 27(2), 484-518.

Gkillas, K., Konstantatos, C., Tsagkanos, A., & Siriopoulos, C. (2020). Do economic news releases affect tail risk? Evidence from an emerging market. *Finance Research Letters*, 101727.

Griffin, J. M., Nickerson, J., and Tang, D. Y. (2013). Rating shopping or catering? An examination of the response to competitive pressure for CDO credit ratings. *The Review of Financial Studies*, 26(9), 2270-2310.

- Ham, C., and Koharki, K. (2016). The association between corporate general counsel and firm credit risk. *Journal of Accounting and Economics*, 61(2-3), 274-293.
- Han, S. H., Moore, W. T., Shin, Y. S., and Yi, S. (2013). Unsolicited versus solicited: Credit ratings and bond yields. *Journal of Financial Services Research*, 43(3), 293-319.
- Hao, S., Jin, Q., & Zhang, G. (2011). Relative firm profitability and stock return sensitivity to industry-level news. *The Accounting Review*, 86(4), 1321-1347.
- Hilscher, J., and Wilson, M. (2016). Credit ratings and credit risk: Is one measure enough? *Management Science*, 63(10), 3414-3437.
- Jiang, J. X., Stanford, M. H., and Xie, Y. (2012). Does it matter who pays for bond ratings? Historical evidence. *Journal of Financial Economics*, 105(3), 607-621.
- Kashyap, A. K., and Kovrijnykh, N. (2015). Who should pay for credit ratings and how? *The Review of Financial Studies*, 29(2), 420-456.
- Kedia, S., Rajgopal, S., and Zhou, X. A. (2017). Large shareholders and credit ratings. *Journal of Financial Economics*, 124(3), 632-653.
- Klusak, P., Alsakka, R., and ap Gwilym, O. (2017). Does the disclosure of unsolicited sovereign rating status affect bank ratings? *The British Accounting Review*, 49(2), 194-210.
- Kogan, L., & Papanikolaou, D. (2014). Growth opportunities, technology shocks, and asset prices. *The Journal of Finance*, 69(2), 675-718.

Livingston, M., Naranjo, A., and Zhou, L. (2008). Split bond ratings and rating migration. *Journal of Banking and Finance*, 32(8), 1613-1624.

Merton, R. C. (1974). On the pricing of corporate debt: The risk structure of interest rates. *The Journal of Finance*, 29(2), 449-470.

Milne, A. (2014). Distance to default and the financial crisis. *Journal of financial stability*, 12, 26-36.

Moody's (2018). Policy for Designating and Assigning Unsolicited Credit Ratings in the European Union, Available at

https://www.moody's.com/uploadpage/Mco%20Documents/Policy_Designating_UCRs_EU.pdf

Poon, W. P. (2003). Are unsolicited credit ratings biased downward? *Journal of Banking and Finance*, 27(4), 593-614.

Poon, W. P., and Firth, M. (2005). Are unsolicited credit ratings lower? International evidence from bank ratings. *Journal of Business Finance and Accounting*, 32(9-10), 1741-1771.

Poon, W. P., Lee, J., and Gup, B. E. (2009). Do solicitations matter in bank credit ratings? Results from a study of 72 countries. *Journal of Money, Credit and Banking*, 41(2-3), 285-314.

Sangiorgi, F., and Spatt, C. (2017). Opacity, credit rating shopping, and bias. *Management Science*, 63(12), 4016-4036.

Switzer, L. N., Tu, Q., and Wang, J. (2018). Corporate governance and default risk in financial firms over the post-financial crisis period: International evidence. *Journal of International Financial Markets, Institutions and Money*, 52, 196-210.

Vu, H., Alsakka, R., and ap Gwilym, O. (2017). What drives differences of opinion in sovereign ratings?

The roles of information disclosure and political risk. *International Journal of Finance and Economics*, 22(3), 216-233.

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

Yu, F. (2005). Accounting transparency and the term structure of credit spreads. *Journal of Financial Economics*, 75(1), 53-84.

Tables

Table 1 Region distribution and sector distribution of treatment and control groups

This table shows the percentages of firms included in treatment/control group and the geographical distribution of sample firms.

	Treatment Group	Control Group
Region		
Europe	26	128
Non-Europe	14	40
Sector		
Banking/Finance Sector	31	102
Others	9	64

Table 2 Description of fundamental accounting-based variables

This table shows the definition and description of accounting indicators applied in the PSM method.

Category	Variable	Description
Size	Total Assets	Total amount of the firm's assets, by USD
	Total Debt to Total Asset	Total amount of debt relative to assets: The higher the ratio, the higher the degree of leverage and corresponding financial risks.
Leverage	Degree of Financial Leverage	Percentage change in earnings per share over the percentage change in EBIT
	Return on Assets	Net Income / Total Assets
Profitability	Growth Rate of Assets (Quarterly)	The ratio between assets in the current quarter and Assets in the previous quarter minus 1
	Total Investment to Total Assets	The ratio between total investment assets and total assets
	Asset Turnover	The ratio between net sales revenues and average total assets
	Ratio: Sales to Total Assets	The ratio between the sales to the total assets

Table 3 Numbers of firms and firm-quarter observations for different PSM matching schemes

This table shows the number of firms and number of firm-quarter pairs in treatment group and control group which are selected by PSM method. The matching conducted with nearest-neighbor method. Two, three and four nearest neighbors are selected respectively.

N (the number of nearest neighbors in the PSM matching)	No. of Firms		No. of Firm-Quarter Obs	
	Treatment Group	Control Group	Treatment Group	Control Group
2	40	58	2315	2811
3	40	72	2315	3521
4	40	87	2315	4712

Table 4 Rating indicator transformation

This table shows the transformation scheme of credit rating indicators applied in this paper. For regression aim, letter-format credit ratings applied in the industry are transformed into numeric indicators from 1 to 21. A larger number means

Rating notch (Moody's)	Rating notch (S&P and Fitch)	Value of number-format variable
Aaa	AAA	1
Aa1	AA+	2
Aa2	AA	3
Aa3	AA-	4
A1	A+	5
A2	A	6
A3	A-	7
Baa1	BBB+	8
Baa2	BBB	9
Baa3	BBB-	10
Ba1	BB+	11
Ba2	BB	12
Ba3	BB-	13
B1	B+	14
B2	B	15
B3	B-	16
Caa1	CCC+	17
Caa2	CCC	18
Caa3	CCC-	19
Ca	CC	20
C	C	21

Table 5 T-test of the difference of average logarithm of ratings between treatment group (unsolicited ratings) and control group (solicited ratings)

This table shows the result of the t-test of the rating gaps between unsolicited ratings and solicited ratings. The rating notches are numerically transformed according to Table 4 and taken the format of logarithm. Four Propensity Score Matching (PSM) schemes are applied according to different numbers of nearest neighbors. Figures in brackets are the t-statistics.

N (Number of nearest neighbors in the PSM matching)	2	3	4	All
No. of Observations in treatment/control groups	2315/2811	2315/3521	2315/4712	2315/7830
Average log rating of Treatment Group (Unsolicited)	2.149	2.149	2.149	2.149
Average log rating of Control Group (Solicited)	2.062	2.053	2.055	2.032
	0.087***	0.096***	0.093***	0.116***
Difference (treatment - control)	(6.79)	(7.73)	(7.90)	(10.77)

*** 1% significance level; ** 5% significance level; *10% significance level

Table 6 Ordered Logistics Regression of rating notches on unsolicited rating dummy

This table shows the result of ordered logit regression. The regression is run on the basis of quarterly firm-rating pairs. Sample firms are the recipients of both unsolicited and solicited firms. Four matching schemes are applied to select the control group firms with different number of nearest neighbors. The dependent variable is the unobservable variable defining the thresholds of numerically transformed rating-notch indicators. A higher value of the dependent variable is equivalent to a lower (more negative) actual rating (details of the transformation are shown in Table 4). The key independent variable is the unsolicited dummy which is equal to 1 if the corresponding rating is unsolicited and 0 if it is solicited. Fundamental variables are described in Table 2. Year, quarter, country and sector are controlled. The estimation is by MLE method. Figures in the brackets are corresponding Wald-statistics.

*** 1% significance level; ** 5% significance level; * 10% significance level

Number of nearest neighbors in the PSM matching Estimates	Matching Scheme			
	2	3	4	All
Unsolicited Dummy	0.162*** (7.57)	0.209*** (13.52)	0.377*** (47.50)	0.215*** (18.21)
Total Asset ^a	4.97 (0.51)	6.68 (1.01)	11.31** (4.65)	-14.8 (116.14)
Total Debt to Total Asset	0.021*** (86.85)	0.021*** (94.76)	0.020*** (101.20)	0.020*** (199.16)
Degree of Financial Leverage	0.019*** (20.48)	0.018*** (21.12)	-0.00005 (0.012)	-0.00002 (0.016)
Return on Assets	-0.032*** (9.01)	-0.031*** (11.50)	-0.029*** (11.84)	-0.0352*** (35.38)
Growth Rate of Assets (Quarterly)	-0.0014 (0.84)	-0.0027* (3.68)	-0.0033*** (11.89)	-0.0033*** (21.14)
Total Investment to Total Assets	0.0040*** (10.93)	0.0068*** (32.82)	0.00084*** (67.29)	0.0075*** (94.11)
Asset Turnover	1.118** (4.43)	1.400*** (7.78)	0.605 (1.88)	1.122*** (20.51)
Ratio: Sales to Total Assets	-1.719 (0.67)	-2.03 (0.27)	0.396 (0.051)	-1.578* (2.82)
Year Control	Yes	Yes	Yes	Yes
Quarter Control	Yes	Yes	Yes	Yes
Country Control	Yes	Yes	Yes	Yes
Sector Control	Yes	Yes	Yes	Yes
N	3912	4443	5131	8595
AIC	20285.446	22892.729	26201.431	44150.040
SIC	20599.036	23212.684	26528.584	44502.987
-2Log	20185.446	22792.729	26101.431	44050.040

a: the unit of the estimates is $\times 10^{-6}$

Table 7 Ordered Logistics Regression of rating changes on unsolicited rating dummy

This table shows the result of ordered logit regression. The regression is run on the basis of quarterly firm-rating pairs. Sample firms are the recipients of both unsolicited and solicited firms. Four matching schemes are applied to select the control group firms with different number of nearest neighbors. The dependent variable is the unobservable variable defining the thresholds of quarterly change degree of numerically transformed rating-notch indicators. Numerical transformation detail is shown in Table 4. The quarterly change degree is measured by the absolute value of the gap between the rating in the current quarter minus the rating in the previous quarter. The key independent variable is the unsolicited dummy which is equal to 1 if the corresponding rating is unsolicited and 0 if it is solicited. Control variables are the quarterly change of fundamental variables described in Table 2. Year, quarter, country and sector are controlled. Upgrade and downgrade cases are analyzed separately. The estimation is by MLE method. Figures in the brackets are corresponding Wald-statistics.

Number of nearest neighbors in the PSM matching	Matching Scheme							
	2		3		4		All	
	U	D	U	D	U	D	U	D
Up or Down								
Estimates on Unsolicited Dummy	-0.05 (0.057)	-0.16 (0.839)	0.01 (0.004)	-0.07 (0.189)	0.03 (0.021)	-0.06 (0.141)	-0.02 (0.020)	0.01 (0.005)
Fundamental Control	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Control	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Quarter Control	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country Control	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sector Control	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	3260		3686		4212		6822	
AIC	929.553	1204.993	998.608	1326.882	1129.466	1531.626	1778.86	2453.40
SIC	1112.237	1387.677	1184.977	1513.251	1319.837	1721.996	1983.70	2658.24
-2Log	869.553	1144.993	938.608	1266.882	1069.466	1471.626	1718.86	2393.34

Table 8 Multi-agency test of rating levels

This table shows the result of multi-agency test. S&P and Fitch are respectively set as the control agency to compare the rating levels with Moody's. Treatment group firms are those who receive unsolicited ratings by Moody's but solicited ratings by the control agency. Control group firms are those who receive solicited ratings by both Moody's and the control agency. The selection of control group firms depends on the selection of matching scheme which requires different number of nearest neighbors to be collected in the PSM matching procedure. Average rating (numerical transformation details are shown in Table 4) of Moody's, the control agency and their differences are calculated to show the relative rating criterion gap between Moody's and the other agency. D-i-D is calculated by differencing the gap of Moody's and control agency's ratings between the treatment group firms and the control group. T-statistics of the D-i-D estimators are calculated and shown in the brackets.

*** 1% significance level; ** 5% significance level; * 10% significance level

<i>Control Agency: S&P</i>	Treatment Group (Firms receiving unsolicited ratings from Moody's but receiving solicited ratings from S&P)	Control Group (Firms receiving solicited ratings from both Moody's and S&P)			
	(No. of Obs:934)	Matching Scheme 1: (No. of Obs: 1580) Number of nearest neighbors in the PSM matching: 2	Matching Scheme 2: (No. of Obs:2166) Number of nearest neighbors in the PSM matching: 3	Matching Scheme 3: (No. of Obs:2673) Number of nearest neighbors in the PSM matching: 4	Matching Scheme 4: (No. of Obs:5372) Number of nearest neighbors in the PSM matching: All
Average Ratings by Moody's	7.4606	7.8651	8.0078	8.1269	7.7980
Average Ratings by S&P	7.2859	8.4535	8.5090	8.5872	8.2351
Dif of Average Ratings (Moody's – S&P)	+0.1745	-0.5883	-0.5012	-0.4603	-0.4371
DID (Between Dif of Treatment Group and Control Group)	N.A	+0.763*** (3.89)	+0.676*** (3.54)	+0.635*** (3.45)	+0.612*** (3.71)
<i>Control Agency: Fitch</i>	Treatment Group (Firms receiving unsolicited ratings from Moody's but receiving solicited ratings from Fitch)	Control Group (Firms receiving solicited ratings from both Moody's and Fitch)			
	(No. of Obs: 1269)	Matching Scheme 1: (No. of Obs: 1790) Number of nearest neighbors in the PSM matching:	Matching Scheme 2: (No. of Obs:2102) Number of nearest neighbors in the PSM matching:	Matching Scheme 3: (No. of Obs:2528) Number of nearest neighbors in the PSM matching:	Matching Scheme 4: (No. of Obs:4764) Number of nearest neighbors in the PSM matching:
Average Ratings by Moody's	8.8944	8.4830	8.3698	8.4040	8.1383
Average Ratings by Fitch	8.0221	8.6674	8.5535	8.5825	8.3482
Dif of Average Ratings (Moody's – Fitch)	+0.8723	-0.1845	-0.1837	-0.1785	-0.2099
DID (Between Dif of Treatment Group and Control Group)	N.A	+1.057*** (4.81)	+1.056*** (5.80)	+1.051*** (5.95)	+1.082*** (6.63)

Table 9 Rating predictability test (panel regression)

This table shows the panel regression result of Equation (5.3). The panel regression is estimated by random-effect estimation. The sample firms include all unsolicited rating recipients in the dataset and the selection of solicited rating recipients depend on four different matching schemes of different nearest neighbor numbers in the PSM procedure. The dependent variable is the Distance to Default (DTD) of the firms at each quarter. Key independent variables are the lagged terms of logarithm of numerically-transformed rating indicator (the transformation details are shown in Table 4) and the unsolicited dummy. The number of lagging periods range from 1 to 4 quarters. Fundamental variables are controlled (details of fundamental variable setting are shown in Table 2). Region, sector, quarter and year effects are controlled. Figures in the brackets are corresponding t-statistics.

*** 1% significance level; ** 5% significance level; * 10% significance level.

Dependent Var. No. of lag terms Number of nearest neighbors in the PSM matching	DTD (Distance to Default)															
	1				2				3				4			
	2	3	4	All	2	3	4	All	2	3	4	All	2	3	4	All
LogRating	-2.01*** (-7.80)	-1.99*** (-8.04)	-2.40*** (-10.4)	-2.07*** (-11.5)	-1.74*** (-5.74)	-1.67*** (-5.71)	-1.94*** (-6.95)	-1.85*** (-8.44)	-1.56*** (-6.13)	-1.46*** (-5.94)	-1.75*** (-7.60)	-1.63*** (-9.12)	-1.39*** (-5.66)	-1.30*** (-5.49)	-1.55*** (-6.97)	-1.48*** (-8.50)
UnSLDummy	-0.15 (-0.15)	-0.21 (-0.25)	-0.31 (-0.35)	-0.51 (-0.58)	-0.28 (-0.30)	-0.28 (-0.34)	-0.44 (-0.51)	-0.52 (-0.62)	-0.11 (-0.11)	-0.18 (-0.21)	-0.35 (-0.38)	-0.50 (-0.54)	-0.27 (-0.27)	-0.31 (-0.35)	-0.47 (-0.51)	-0.59 (-0.62)
Fundamental Control	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sector Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Quarter Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	79	93	106	174	79	93	106	174	78	91	104	174	75	88	101	169
T	63	63	63	63	62	62	62	62	61	61	61	61	60	60	60	60
R ²	30.9%	31.4%	30.7%	29.3%	18.6%	19.2%	17.9%	16.3%	28.3%	29.2%	28.5%	26.9%	28.5%	29.7%	28.9%	26.8%

Table 10 Logit regression of ratings on past DTD and unsolicited dummy

This table shows the result of ordered logistic regression shown in Equation (5.4). Four matching schemes are applied to select the control group firms with different number of nearest neighbors. The dependent variable is the unobservable variable defining the thresholds of numerically transformed rating-notch indicators (details of the transformation are shown in Table 4). The key independent variables are DTD (t-p) and the unsolicited dummy. DTD (t-p) is the Distance to Default indicator in the quarter t-p where p ranges from 1 to 4. The unsolicited dummy is equal to 1 if the firm receives unsolicited ratings from Moody's and equal to 0 if it receives solicited ratings from Moody's. Year, quarter, country and sector are controlled. The estimation is by MLE method. Figures in the brackets are corresponding Wald-statistics.

*** 1% significance level; ** 5% significance level; * 10% significance level.

Dependent Var. No. of lag terms (p)	Ratings															
	1				2				3				4			
	1:2	1:3	1:4	All	1:2	1:3	1:4	All	1:2	1:3	1:4	All	1:2	1:3	1:4	All
Matching Scheme																
Unsolicited Dummy	0.195*** (11.18)	0.225*** (16.39)	0.240*** (19.62)	0.122** (5.92)	0.175*** (8.88)	0.209*** (13.80)	0.224*** (16.76)	0.103** (4.68)	0.159*** (7.16)	0.193*** (11.52)	0.208*** (14.23)	0.097** (3.61)	0.148** (6.08)	0.179*** (9.71)	0.194*** (12.09)	0.081* (2.97)
DTD (t-p)	-0.031*** (23.14)	-0.036*** (39.51)	-0.028*** (30.95)	-0.012*** (11.86)	-0.032*** (29.43)	-0.038*** (42.79)	-0.030*** (33.23)	-0.013*** (13.17)	-0.031*** (27.20)	-0.038*** (41.69)	-0.030*** (32.38)	-0.012*** (12.43)	-0.032*** (26.54)	-0.039*** (43.04)	-0.031*** (33.65)	-0.013*** (13.25)
Region Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sector Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Quarter Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	3904	4562	5174	8812	3828	4472	5070	8639	3749	4380	4964	8465	3671	4290	4861	8293
AIC	19588.5	22871.2	25782.3	44663.7	19262.2	22469.4	25319.9	43873.0	18897.3	22041.4	24829.8	43055.2	18545.2	21637.0	24372.8	42253.5
SIC	19845.5	23134.6	26050.9	44954.2	19524.7	22738.4	25594.2	44176.8	19158.9	22309.6	25103.2	43351.1	18805.9	21904.3	24651.8	42548.4
-2Log	19506.5	22789.2	25700.3	44581.7	19178.2	22385.4	25235.9	43787.0	18813.3	21957.4	24745.8	42971.2	18461.2	21553.0	24286.8	42169.5

Table 11 Rating predictability test (relative DTD prediction bias)

This table shows the result of the calculation of relative prediction bias of DTD between solicited and unsolicited ratings. The value is calculated by the equation $Treatment_Group_DTD_{i,t+p} - Treatment_Group_DTD_{i,t+p}$. $Treatment_Group_DTD_{i,t+p}$ is the actual observation of DTD of unsolicited rating recipients i (treatment group firms) at a future point $t+p$ ($p=1$ to 4 quarters) and $Treatment_Group_DTD_{i,t+p}$ is calculated in the format of Equation (5.5) using the actual observation of rating at time t along with other fundamental variables at time t , along with the estimates of prediction coefficients derived from Equation (5.4). Figures in the brackets are corresponding t-statistics,
 *** 1% significance level;
 ** 5% significance level;
 * 10% significance level.

No of Lag Terms (p)	Number of nearest neighbors in the PSM matching	No. of Obs in Solicited Rating Dataset	No. of Obs in Unsolicited Rating Dataset	Relative prediction bias of DTD
1	2	1677	1191	0.46* (1.66)
	3	2090	1191	0.12* (1.83)
	4	2591	1191	-0.03 (-0.24)
	All	5139	1191	-0.56 (-1.32)
2	2	1638	1167	0.03 (0.13)
	3	2041	1167	0.13** (2.10)
	4	2532	1167	-2.30 (-1.18)
	All	5033	1157	0.27 (0.58)
3	2	1618	1154	-1.01 (-0.75)
	3	2008	1154	0.05 (0.63)
	4	2491	1154	0.15* (1.64)
	All	4955	1154	-0.02 (-0.14)
4	2	1595	1136	0.39** (2.48)
	3	1973	1136	0.14 (1.22)
	4	2448	1136	-0.18 (-0.81)
	All	4872	1136	0.02 (0.33)

Table 12 The detail of the lead-lag relationship between Moody's and S&P (or Fitch)

Pair	Type of actions	Total		Negative		Positive	
		Un-solicited	Solicited	Un-solicited	Solicited	Un-solicited	Solicited
Moody-S&P	No. of all valid cases of Moody's actions	116	683	60	435	45	169
	Ratio of cases when Moody's leads S&P out of all valid cases	11.21%	15.23%	13.33%	17.93%	11.11%	8.28%
	Ratio of cases when Moody's lags S&P out of all valid cases	19.83%	19.18%	26.67%	23.22%	11.11%	11.24%
Moody-Fitch	No. of all valid cases of Moody's actions	219	728	116	455	87	191
	Ratio of cases when Moody's leads Fitch out of all valid cases	11.42%	13.46%	14.66%	16.26%	9.20%	8.38%
	Ratio of cases when Moody's lags Fitch out of all valid cases	11.87%	11.81%	13.79%	14.07%	11.49%	10.47%

Table 13 Chi Square test of association between rating action timeliness and Moody's solicitation status

This table shows the result of Chi-square test which is conducted to test the association between rating action timeliness, measured by Moody's lead-lag relationship with another rating agency, and the solicitation status. Four cases of Moody's lead-lag relationship (lag S&P, lead S&P, lag Fitch and lead Fitch) are identified. For each of the cases, the association between the dummy indicating the case (equal to 1 if the action fits the condition of lead/lag and 0 else) and solicitation status dummy (equal to 1 if the rating is unsolicited and 0 if it is solicited) is calculated in the format of Chi-square statistics. The null hypothesis of the Chi-square is that there is no association between Moody's and the control agency's lead-lag relationship and Moody's solicitation status. Figures in the cells are corresponding Chi-square statistics and figures in the brackets are p-values.

Chi-Square (p-value)	Type of Actions	All				Negative				Positive			
		1:2	1:3	1:4	All	1:2	1:3	1:4	All	1:2	1:3	1:4	All
Moody-S&P Pair	Matching Scheme												
	Moody's Lag	0.0409 (0.84)	0.0426 (0.84)	0.0016 (0.97)	0.0267 (0.87)	0.0603 (0.81)	0.0534 (0.82)	0.2862 (0.53)	0.3474 (0.56)	0.0203 (0.89)	0.1327 (0.72)	0.2340 (0.63)	0.0057 (0.94)
	Moody's Lead	1.910 (0.17)	0.6830 (0.41)	0.8702 (0.35)	1.2821 (0.26)	1.1463 (0.27)	0.3899 (0.53)	0.5129 (0.47)	0.7764 (0.38)	0.2354 (0.63)	0.4407 (0.51)	1.1329 (0.29)	0.1785 (0.68)
	Moody's Lag	0.3289 (0.57)	0.7395 (0.39)	0.3171 (0.57)	0.0006 (0.98)	0.2075 (0.65)	0.3112 (0.58)	0.1348 (0.71)	0.0006 (0.98)	0.1499 (0.70)	0.4119 (0.52)	0.1669 (0.68)	0.0650 (0.80)
Moody-Fitch Pair	Moody's Lag	1.3257 (0.25)	0.4027 (0.53)	2.0476 (0.15)	0.6236 (0.43)	0.6907 (0.41)	0.2090 (0.65)	1.2046 (0.27)	0.3511 (0.55)	0.0033 (0.95)	0.0860 (0.77)	0.1394 (0.71)	0.0508 (0.82)
	Moody's Lead												

Table 14 Logit regression of ‘Moody’s lead’ indicator on solicitation status dummies

This table reports the results of logistic regressions of ‘Moody’s lead’ dummies on solicitation status dummies. The regressions are run on the basis of Moody’s rating actions. Dependent variable is the dummy equal to 1 if the corresponding rating action is identified as leading S&P or Fitch and to 0 else. The key independent variable, ‘un-solicitation dummy’ is equal to 1 if the corresponding rating action of Moody’s is provided to unsoliciting firms and to 0 if that is provided to soliciting firms. Dummies indicating the year when the actions are taken, the sector of the rated firm, and the region where the firm is registered, are also included in the independent variables. Figures in the brackets are Wald-statistics for the corresponding estimators.

Logistic Regression	Action Type	All				Negative				Positive			
		1:2	1:3	1:4	All	1:2	1:3	1:4	All	1:2	1:3	1:4	All
Dependent Variable (Dummy)		<i>Moody's Lead S&P/Fitch</i>											
Pair													
Moody-S&P	Coefficients on Un-Solicitation Dummy	-0.4516 (1.36)	-0.2978 (0.54)	-0.2953 (0.70)	-0.2821 (0.76)	-0.7744 (2.24)	-0.4264 (0.71)	-0.5293 (1.27)	-0.4321 (1.07)	0.8839 (0.74)	0.7142 (0.65)	1.0398 (1.50)	0.3677 (0.33)
	Year Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
	Sector Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
	Region Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
	N	323	381	471	799	192	227	287	495	94	112	130	214
	AIC	274.670	307.109	391.323	681.750	184.148	202.341	259.638	467.268	72.426	87.754	93.544	142.227
	SC	350.223	385.965	474.420	775.417	249.298	270.840	332.827	551.359	118.205	142.124	150.894	209.547
	-2LogL	234.670	267.109	351.323	641.750	144.148	162.341	219.638	427.268	36.426	47.754	53.544	102.227
Moody-Fitch	Coefficients on Un-Solicitation Dummy	-0.1036 (0.20)	-0.0197 (0.005)	-0.2086 (0.59)	-0.0334 (0.02)	-0.2421 (0.42)	-0.1021 (0.08)	-0.1981 (0.34)	0.0158 (0.002)	-0.0799 (0.02)	0.1670 (0.08)	0.1914 (0.11)	-0.0396 (0.006)
	Year Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
	Sector Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
	Region Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
	N	521	559	643	947	307	327	385	571	161	175	191	214
	AIC	410.437	427.103	529.400	726.154	281.567	289.581	367.732	494.165	119.732	124.130	130.260	184.737
	SC	495.552	513.626	618.723	823.220	356.104	365.380	446.797	581.113	181.360	187.426	195.305	257.289
	-2LogL	370.437	387.103	489.400	686.154	241.567	249.581	327.732	454.165	79.732	84.130	90.260	144.737

Table 15 Logit regression of ‘Moody’s lag’ indicator on solicitation status dummies

This table reports the results of logistic regressions of ‘Moody’s lag’ dummies on solicitation status dummies. The regressions are run on the basis of Moody’s rating actions. Dependent variable is the dummy equal to 1 if the corresponding rating action is identified as lagging S&P or Fitch and to 0 else. The key independent variable, ‘un-solicitation dummy’ is equal to 1 if the corresponding rating action of Moody’s is provided to unsoliciting firms and to 0 if that is provided to soliciting firms. Dummies indicating the year when the actions are taken, the sector of the rated firm, and the region where the firm is registered, are also included in the independent variables. Figures in the brackets are Wald-statistics for the corresponding estimators.

Logistic Regression	Action Type	All				Negative				Positive			
		1:2	1:3	1:4	All	1:2	1:3	1:4	All	1:2	1:3	1:4	All
	Matching Scheme												
	Dependent Variable (Dummy)	<i>Moody's Lag S&P/Fitch</i>											
Pair													
Moody-S&P	Coefficients on Un-Solicitation Dummy	-0.076 (0.06)	0.0068 (0.005)	0.0370 (0.02)	0.1698 (0.42)	0.0425 (0.01)	0.0067 (0.003)	0.0781 (0.05)	0.2193 (0.45)	1.0804 (1.06)	1.3685 (2.04)	0.6015 (0.68)	0.4338 (0.45)
	Year Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
	Sector Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
	Country Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
	N	323	381	471	799	192	227	287	495	94	112	130	214
	AIC	336.508	403.521	492.636	794.575	232.848	281.932	341.031	560.469	79.072	94.101	109.266	150.583
	SC	412.061	482.377	575.733	888.242	297.998	350.431	414.220	644.560	124.851	148.471	166.617	217.903
	-2LogL	296.508	363.521	452.636	754.575	192.848	241.932	301.031	520.469	43.072	54.101	69.266	110.583
Moody-Fitch	Coefficients on Un-Solicitation Dummy	-0.3025 (1.01)	-0.2778 (0.94)	-0.1970 (0.51)	-0.0712 (0.07)	-0.3189 (0.63)	-0.2488 (0.42)	-0.1919 (0.28)	-0.1040 (0.09)	-0.4997 (0.66)	-0.4312 (0.49)	-0.3102 (0.28)	-0.2152 (0.14)
	Year Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
	Sector Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
	Country Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
	N	521	559	643	947	307	327	385	571	161	175	191	278
	AIC	413.259	450.947	513.618	684.106	273.387	290.556	335.920	465.445	126.310	133.797	141.632	162.333
	SC	498.374	537.470	602.941	781.171	347.923	366.355	414.985	552.393	187.938	197.093	206.677	234.885
	-2LogL	373.259	410.947	473.618	644.106	233.387	250.556	295.920	425.445	86.310	93.797	101.632	122.333

Figures

Figure 1 Frequency of Quarterly Rating Notches of the data sample

This figure represents the frequency distribution of quarterly numerical rating indicators of sample firms. The rating notches are numerically transformed into the integral format according to the rule that a higher rating is transformed into a lower value of integral (transformation details are shown in the Table 4).

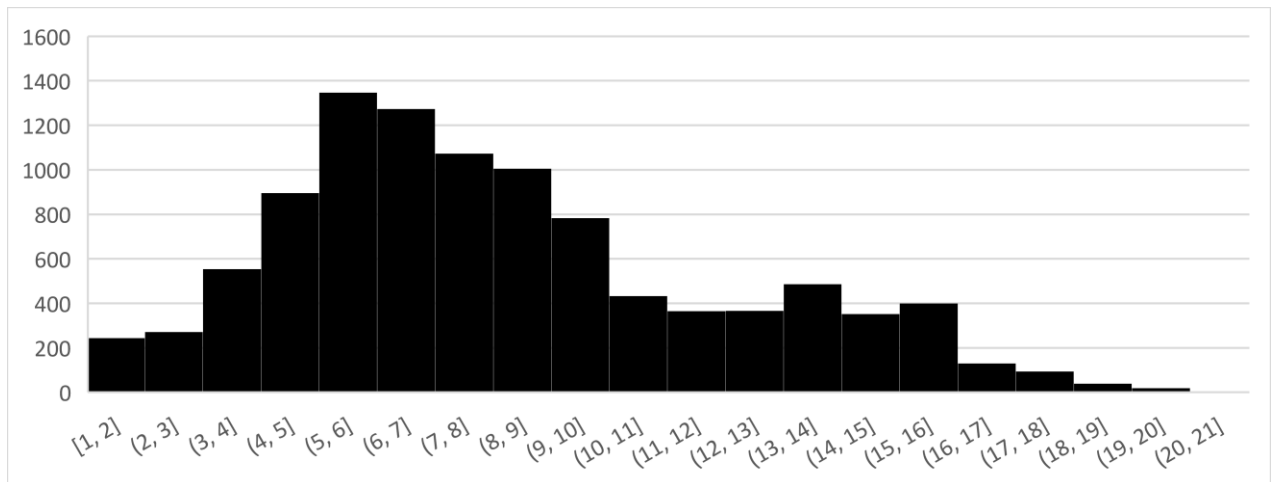


Figure 2 Frequency of Quarterly Rating Notches of the data sample

This figure shows a brief demonstration of how a D-i-D estimator implies a more conservative rating of Moody's for unsolicited rating recipients. A higher position of line indicates a higher rating level (i.e a more "positive" one). This figure shows a stylized situation that the other CRA (either S&P or Fitch) rates firms higher than Moody's for both control group and treatment group but the rating gap for treatment group (the length of B) is bigger than that for control group (the length of A). In the situation of this figure we claim that Moody's rates unsolicited recipients systemically lower in the cross-agency test.

