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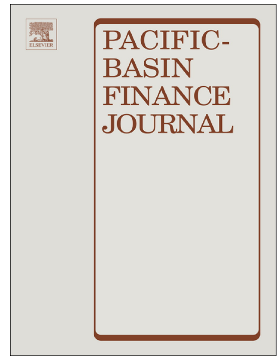

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Opportunistic Behaviors of Credit Rating Agencies and Bond Issuers

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Opportunistic Behaviors of Credit Rating Agencies and Bond Issuers

ABSTRACT

Using credit rating data from the three credit rating agencies (CRAs) in Korea, we examine whether bond issuers and CRAs engage in rating shopping and catering. First, we find that Korean bond issuers, who are required by law to receive two or more ratings, tend to fire or switch from CRAs that assign lower ratings than other CRAs. Second, when a bond issuer hires an additional CRA, the new CRA assigns a higher rating than incumbent CRAs. Lastly, we see that increased competition, which is measured by the number of CRAs hired by a given bond issuer, affects the likelihood of an upgrade occurring. Although CRAs often upgrade ratings when their rivals assign higher ratings, our findings show that higher competition further increases the likelihood that CRAs will upgrade ratings when there are rating disagreements. These results imply that bond issuers and CRAs engage in opportunistic behaviors that undermine the quality of credit ratings.

Keywords: rating shopping, rating catering, credit rating agency, competition
JEL: G24, G30, G34, M40

Opportunistic Behaviors of Credit Rating Agencies and Bond Issuers

I. Introduction

Credit rating information helps creditors make lending decisions by reducing information asymmetry about debtors' ability to pay back (Camanho et al. 2012; White 2010). However, information users may not be able to make effective decisions if the information is not reliable (Akerlof 1995). When this happens, some potential creditors may give up on a lending decision or increase risk premiums due to the adverse selection problem. In the lending process, credit rating agencies (CRAs, hereafter) play a key role in monitoring bond issuers by providing high-quality credit rating information. Bond issuers and CRAs, however, have incentives to engage in opportunistic behaviors that undermine rating quality. Bond issuers want to obtain higher ratings, as credit ratings have significant influences not only on the cost of debt but also on capital structures and stock prices (Hand et al. 1992; Kisgen 2006; Tang 2009; Kraft 2015). Given that bond issuers prefer higher ratings, CRAs may want to maintain their business or increase their market share by giving favorable ratings to bond issuers, who pay rating fees (Skreta and Veldkamp 2009; Mathis et al. 2009; Bar-Isaac and Shapiro 2010; Bolton et al. 2012; Griffin et al. 2013).

Although several researchers have studied rating shopping and catering, it is worth investigating opportunistic behaviors using Korean credit rating data because the Korean market provides a unique environment different from that of other countries. In Korea, bond issuers are required by law to acquire two or more ratings for their corporate bonds.[1] This requirement provides researchers with a sufficient number of observations to compare ratings

[1] Article 4-63 of the Regulation on Financial Investment Business in Korea prohibits issuing unsecured corporate bonds that have not been assessed by two or more credit rating agencies. Thus, bond issuers in Korea must choose at least two CRAs among the following three possible CRAs: the Korea Investors Service, Inc., NICE Investors Service, Co., and Korea Ratings, Inc.

and prevents the self-selection problem when multiple ratings are not required.[2] Just as studies of auditor switching show that companies change auditors for opinion shopping (Chow and Rice 1982; Simon and Francis 1988; Krishinan 1994; Lennox 2002), we demonstrate that bond issuers fire CRAs that give lower ratings than other CRAs for rating shopping. Conversely, CRAs are less likely to be fired when they give better ratings than other CRAs.

This firing behavior may result in competition in the credit rating market, inducing CRAs to cater to their clients to increase the market share or maintain business. For instance, when a bond issuer hires an additional CRA, the issuer may put pressure on the new CRA to give higher ratings than those given by the incumbent CRAs. Alternatively, if the new CRA wants to increase the market share, the CRA may initiate contracts and provide higher ratings to attract clients. We therefore also investigate whether new CRAs cater to bond issuers. Our results show that new CRAs assign higher ratings than incumbent CRAs. Lastly, we show that increased competition, which is measured by the number of CRAs hired by a given bond issuer at, affects the likelihood of an upgrade occurring. Consistent with the results of studies on the convergence of credit ratings (Güttler 2011; Lugo et al. 2015), we find that a CRA is likely to upgrade a rating when its rival is giving a higher rating; conversely, the CRA is less

[2] In circumstances where double ratings are not required, companies engage in rating shopping, choosing the highest rating among multiple ratings. As this paper requires companies to have at least two ratings for comparison purposes, issuers that receive only one rating are not included in the sample. This is problematic because companies engaging in rating shopping would obviously hire the CRA that gives the best rating (Benmelech and Dlugosz 2010). In such cases, issuers that self-select to receive multiple ratings are less likely to fire a CRA for rating shopping. Therefore, the norm of double ratings solves the self-selection problem, as companies engaging in rating shopping must, by law, receive two ratings; these have been included in the sample. Although U.S. companies are not required to receive two or more credit ratings, according to Mählmann (2009), most U.S. companies receive double ratings from Moody’s and S&P. Because the double rating is a norm in the U.S. as well, U.S. companies engaging in rating shopping may also decide to receive double ratings because deviation from the norm would be noticed by investors. In such cases, the self-selection problem mentioned above may be minimal. However, issues related to switching and firing do not occur in the U.S. because U.S. companies usually choose to receive a third rating from Fitch in addition to the double ratings from Moody’s and S&P. They are not likely to replace S&P with Fitch or other CRAs, although Fitch also has a substantial market share, which ranges from 10.9 to 25 percent across rating categories as of 2015 according to the SEC (2016). Therefore, the Korean rating market provides an appropriate environment to investigate the firing and replacing behaviors of bond issuers.

likely to upgrade the rating in the opposite case. Our findings show that higher competition further increases the likelihood of an upgrade when a CRA assigns a lower rating than its rivals. Moreover, the effect of competition persists even when CRAs assign higher ratings than their rivals. These findings are consistent with those of Becker and Milbourn (2011), Camanho et al. (2012), and Griffin et al. (2013).

This paper offers several contributions. First, we provide additional evidence of rating shopping in the form of firing or replacement, as observed in the Korean credit market. To the best of our knowledge, no study has investigated whether bond issuers fire or replace their incumbent CRAs selectively for rating shopping purposes. Second, this paper elucidates the specific circumstances in which CRAs cater to bond issuers: bond issuers hire an additional CRA and the number of rivals increases. Unlike the mixed findings in prior studies using the market share of Fitch as a proxy for market competition (Becker and Milbourn 2011 and Bae et al. 2015), we use a direct proxy for increased competition measured by the number of CRAs that evaluate a given bond issuer. Third, we provide an additional finding to complement the rating convergence literature. When competitive pressure is high, CRAs are likely to upgrade ratings not only when they assign a lower rating, but also when they assign a higher rating than their rivals. Lastly, this paper provides useful information to regulators and investors, as it shows specific circumstances under which bond issuers and CRAs are likely to engage in opportunistic behaviors.[3]

II. Literature Review and Hypothesis Development

2.1 Literature Review

[3] The Financial Supervisory Service, which corresponds to the U.S. Securities and Exchange Commission (SEC), released a plan for the advancement of the credit rating market on September 21, 2016. The plan requires that the Korea Financial Investment Association (KFIA) disclose detailed information on the performance of CRAs, which includes default rates, rating trends of bankrupt companies, and the names of companies that experience rapid changes in ratings.

Researchers have conducted studies on rating shopping and rating catering. Klein and Leffler (1984) provide a theoretical statement that sellers lack the incentive to provide high-quality products when customers do not know their quality before they buy them. However, as the sellers and customers gain experience with each other, customers begin to recognize the quality of the product from previous purchases. Klein and Leffler (1984) conclude that sellers maintain a good reputation by supplying high-quality products to guarantee future income. Most studies on rating inflation develop their logic based on this theory. They find equilibrium between obtaining short-term benefits by inflating ratings and enjoying long-term benefits by maintaining reputation.

Mathis et al. (2009) argue that CRAs are more likely to give favorable ratings to clients with complex bond structures because it is difficult for investors to detect such opportunistic behaviors. Bar-Isaac and Shapiro (2010) show that rating accuracy decreases when a business cycle is in a good state because the probability of a bond defaulting decreases and because of the difficulty of retaining and hiring analysts. Camanho et al. (2012) maintain that CRAs pursue short-term income from rating inflation rather than long-term revenue from maintaining reputation, especially when they experience competitive pressure. Bolton et al. (2012) also show that the reputation incentive fails when there is keen competition and when investors tend to trust ratings. Spatt and Sangiorgi (2011) explain that rating inflation occurs when investors do not know whether a bond issuer received a rating from a credit rating agency. Under these conditions of opacity, the issuer can choose not to publish poor ratings, choosing instead to disclose only satisfactory ratings. Skreta and Veldkamp (2009) find that the complexity of issuers' assets affects the tendency toward rating shopping. For issuers with simple assets structures, the variation of ratings given by CRAs is small. In this case, the issuer has little chance to buy a favorable rating. On the other hand, for issuers with complex assets structures, CRAs' ratings may vary. Skreta and Veldkamp (2009) argue that the issuer has a greater chance to buy a favorable rating under this circumstance. In general, theoretical papers conclude that information asymmetry and competition among CRAs increase rating inflation.

However, empirical studies show mixed results on rating inflation. Bongaerts et al. (2012) find that Fitch acts as a tiebreaker when ratings determined by S&P and Moody's are split into two different categories: investment groups and high-yield groups. They show that the additional rating from Fitch pulls bonds into the investment category.

Benmelech and Dlugosz (2010) show that ratings of structured finance securities determined by only one CRA are more likely to be downgraded than those determined by multiple CRAs. They demonstrate that issuers select the best rating among multiple ratings when only one rating is disclosed. However, Griffin et al. (2013) argue that the default probability of a collateralized debt obligation with multiple ratings is higher than that with one rating and that CRAs use lenient assumptions in their evaluations and give favorable ratings to issuers when other CRAs provide inflated ratings. Griffin et al. (2013) explain that their results are different from the results of Benmelech and Dlugosz (2010) because they test the default probability of structured bonds, while Benmelech and Dlugosz (2010) analyze the performance of the collateral underlying collateralized debt obligations.

Becker and Milbourn (2011) show that the increase in the market share of Fitch induces S&P and Moody's to give favorable ratings to issuers. However, Bae et al. (2015) argue that CRAs are unlikely to assign higher ratings when industry effects are considered; they use the model of Becker and Milbourn (2011). We also investigate the effect of competition in the credit rating market. However, we utilize a direct proxy for increased competition by focusing on cases in which bond issuers hire more CRAs than required. Our test results show that the probability that CRAs upgrade ratings when there are rating disagreements increases with the competition. Thus, our results counter those of Bae et al.

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(2015), partly supporting the argument of Becker and Milbourn (2011).

Güttler (2011) shows that Moody's are more likely than S&P to adjust ratings to converge when S&P changes ratings. Lugo et al. (2015) show that rating updates of Moody's and S&P affect the timing of Fitch rating updates, while a downgrade on Fitch does not affect ratings on Moody's and S&P. Although our results on the likelihood of an upgrade are related to the findings of Güttler (2011) and Lugo et al. (2015), they are new in that we show the effect of competition measured by the number of CRAs providing rating service to a given bond issuer.

2.2 Hypothesis Development

Bond issuers prefer higher ratings because of their positive effects not only on the cost of debt but also on capital structures and stock prices (Hand et al. 1992; Kisgen 2006; Tang 2009). Hand et al. (1992) show that unexpected upgrades and downgrades of credit ratings affect stock prices as well as bond prices. Kisgen (2006) argues that ratings determine the capital structures of companies, as institutional investors are usually restricted from investing in bonds with speculative grades. These effects provide bond issuers with an incentive to shop for ratings under the current rating system, under which bond issuers select CRAs and pay rating fees (Skreta and Veldkamp 2009; Mathis et al. 2009; Bar-Isaac and Shapiro 2010; Bolton et al. 2012).

Studies on audit opinion shopping provide insights into the issue of rating shopping because the credit rating market and audit market are similar in structure. Like a bond issuer, an audit client chooses an auditor and pays audit fees to that auditor. Although auditors must be impartial and objective, auditor independence can be impaired under this system, as clients have the freedom to switch auditors (Chow and Rice 1982; Simon and Francis 1988; Krishinan 1994; Lennox 2002). Chow and Rice (1982) show that the probability of switching auditors increases when a firm receives a qualified opinion. Consistent with this finding, Lennox (2002) shows that companies make switching decisions that minimize the likelihood of obtaining unfavorable audit reports by predicting audit opinions that firms would have received if they had made other decisions. These results imply that firms switch auditors for opinion shopping purposes. We argue that bond issuers behave similarly to audit clients because bond issuers select CRAs and pay fees like audit clients.

Unlike Lennox (2002), we directly test whether issuers fire or switch CRAs by comparing actual ratings given by multiple CRAs without estimating the probability of obtaining unfavorable ratings from each CRA. If an issuer fires a CRA with the intention of rating shopping, it follows that the issuer fires an incumbent CRA that gives lower ratings than other CRAs. Hypothesis 1 is therefore stated as follows:

Hypothesis 1: *A CRA's probability of getting fired is higher than that of other CRAs when the CRA gives lower ratings than other CRAs.*

As bond issuers prefer to receive higher ratings, CRAs may cater to them by providing a higher rating than their rivals to maintain business or increase their market share (Griffin et al. 2013). In addition, prior studies argue that reputation incentive fails to prevent CRAs from catering to issuers due to various factors such as the business cycle, competition, complexity of the assets structure, and lack of investor savvy (Skreta and Veldkamp 2009; Mathis et al. 2009; Camanho et al. 2012; Bar-Isaac and Shapiro 2010; Bolton et al. 2012). To find additional evidence of catering to bond issuers, we observe a specific circumstance in which bond issuers hire an additional CRA.

Under this circumstance, the new CRA may provide a higher rating than incumbent CRAs for two reasons. First, it is possible that the issuer may pressure the new CRA to give higher ratings than those given by incumbent CRAs. Second, if a new CRA initiates the contract to increase the market share, it follows that the new CRA would suggest a higher rating than that of incumbent CRAs. By doing so, the CRA gives the issuer an incentive to sign an additional contract. Hypothesis 2 is therefore stated as follows:

Hypothesis 2: *When a bond issuer hires an additional CRA, the latter gives a higher rating than that given by incumbent CRAs.*

CRAs are more likely to cater to bond issuers as competitive pressure increases (Camanho et al. 2012; Griffin et al. 2013; Becker and Milbourn 2009). Although Bae et al. (2015) argue that there is no association between increased competition and rating inflation, they utilize the market share of Fitch as a proxy for competition, which is an indirect measure.

In this paper, we use a direct proxy for competition measured by counting the number of CRAs providing rating service to the bond issuer. Although bond issuers are not required to receive triple ratings, some bond issuers voluntarily choose to receive a third rating. Mählmann (2009) provides a rationale behind this decision that some bond issuers can reduce credit spread by receiving more ratings. However, it is possible that bond issuers fire CRAs that assign a poor rating when the benefits of receiving a third rating are minimal or the costs of doing so are too high.

Under this circumstance, the firing decision may be more attractive to issuers receiving triple ratings than the switching decision is to issuers receiving double ratings. While switching from one CRA to another CRA involves switching costs, such as the cost of negotiation with another CRA and writing off the cost of the initial rating, firing one CRA does not incur such costs. Therefore, CRAs feel greater competitive pressure when bond issuers hire more CRAs than required.

According to convergence theory, CRAs upgrade or downgrade ratings when there are rating disagreements, although there are differences in the likelihood of doing so across CRAs (Güttler 2011; Lugo et al. 2015). Although CRAs tend to upgrade (downgrade) ratings when they issue a lower (higher) rating than their rivals, we posit that competitive pressure affects the likelihood of upgrade rating due to the reasons mentioned above. Hypothesis 3 is therefore stated as follows:

Hypothesis 3: *The greater the number of rivals is, the greater the probability of a rating upgrade.*

III. Research Design

3.1 Empirical Models

3.1.1 Measures of Firing

The first hypothesis argues that bond issuers selectively fire CRAs that give lower ratings than other CRAs. We use dummy variables that indicate firing of a CRA as the dependent variable to test Hypothesis 1. The variable takes a value of one if CRA *i* (Korea Ratings, or KR, NICE Investors Service, or NICE, or the Korea Investors Service, or KIS) evaluates firm *j* at period *t*, but does not do so at period *t*+1. Otherwise, the variable takes a value of zero ($KRFire_{jt}$, $NICEFire_{jt}$, and $KISFire_{jt}$). We exclude cases in which bond issuer *j*'s contracts with all CRAs expire.[4]

To check whether bond issuers selectively fire CRAs that give lower ratings than other CRAs, we use differences between ratings provided by CRA *i* and average ratings given by the other CRAs at period t ($CRA^{i}diff1_{jt}$). To obtain these variables, we first quantify credit ratings by assigning the numbers from one to 20 to actual ratings that range from D to AAA ($CRA^{i}rating_{jt}$). To offset the potential bias in $CRA^{i}diff1_{jt}$, which reflects data from only one period, we also use an alternative variable, the difference between the average ratings given by CRA *i* from period *t*-3 to *t* and the average ratings given by the other CRA(s) during the same period ($CRA^{i}diff2_{jt}$). The following probit regression model (1) is used to test Hypothesis 1. The model controls issuers' financial states and performances, which may

[4] Appendix C provides a detailed explanation of our way of measuring firing and hiring.

affect firing decisions. We predict a negative value of β_1 under Hypothesis 1.

$$CRA^{i}fire_{jt} = \beta_0 + \beta_1\,CRA^{i}diff1_{jt} + \beta_2\,SIZE_{jt} + \beta_3\,LEV_{jt} + \beta_4\,CF_{jt} + \beta_5\,PROF_{jt} + \beta_6\,Tangible_{jt} + \beta_7\,AGE_{jt} + \beta_8\,NoR_{jt} + \Sigma YEAR + \Sigma IND + \varepsilon^{i}_{jt} \quad (1)$$

Definitions of variables

$CRA^{i}fire_{jt}$	=	takes a value of one if CRA *i* (KR, NICE, or KIS) gives a rating to firm *j* at period t, but does not do so at period *t*+1, while at least one CRA assesses firm *j* at period *t*+1, and zero, otherwise;
$CRA^{i}diff1_{jt}$	=	the difference between $CRA^{i}rating_{jt}$ and the average rating of the other CRA(s) at period t;
$SIZE_{jt}$	=	natural logarithm of total assets of firm *j* at period *t*;
LEV_{jt}	=	total debt divided by total assets of firm *j* at period *t*;
CF_{jt}	=	EBITDA divided by total assets of firm *j* at period *t*;
$PROF_{jt}$	=	return on assets of firm *j* at period *t*;
$Tangible_{jt}$	=	property, plant, and equipment divided by assets of firm *j* at period *t*;
AGE_{jt}	=	elapsed years from the foundation date of firm *j* at period *t;*
NoR_{jt}	=	the number of CRAs evaluating firm *j* at period *t*;
$\Sigma YEAR$	=	year dummy variable; and
ΣIND	=	industry dummy variable.

3.1.2 Measures of Hiring

To test Hypothesis 2, $CRA^{i}diff1_{jt}$ is used as a dependent variable to observe whether CRA *i* as an additional CRA assigns a higher rating than incumbent CRAs. The dummy variable takes a value of one if firm *j* has incumbent CRAs and additionally signs a contract with CRA *i* at period *t*, and zero otherwise ($CRA^{i}hire_{jt}$). The following equation (2) is used to test Hypothesis 2. We predict a positive value of β_1 under Hypothesis 2.

$$CRA^{i}diff1_{jt} = \beta_0 + \beta_1\,CRA^{i}hire_{jt} + \beta_2\,SIZE_{jt} + \beta_3\,LEV_{jt} + \beta_4\,CF_{jt} + \beta_5\,PROF_{jt} + \beta_6\,Tangible_{jt} + \beta_7\,AGE_{jt} + \beta_8\,NoR_{jt} + \Sigma YEAR + \Sigma IND + \varepsilon^{i}_{jt} \quad (2)$$

Definitions of variables

$CRA^{i}diff1_{jt}$	=	the difference between $CRA^{i}rating_{jt}$ and the average rating of the other CRA(s) at period *t*;
$CRA^{i}hire_{jt}$	=	takes a value of one if firm *j*, which does not obtain a rating from CRA *i* but does so from other CRAs at period *t*-1, obtains a rating from CRA *i* at period *t*, and zero otherwise;
$SIZE_{jt}$	=	natural logarithm of total assets of firm *j* at period *t*;
LEV_{jt}	=	total debt divided by total assets of firm *j* at period *t*;

CF_{jt}	=	EBITDA divided by total assets of firm *j* at period *t*;
$PROF_{jt}$	=	return on assets of firm *j* at period *t*;
$Tangible_{jt}$	=	property, plant, and equipment divided by assets of firm *j* at period *t*;
AGE_{jt}	=	elapsed years from the foundation date of firm *j* at period *t*;
NoR_{jt}	=	number of CRAs evaluating firm *j* at period *t*;
$\Sigma YEAR$	=	year dummy variable; and
ΣIND	=	industry dummy variable.

To test how the number of CRAs affects the probability of an upgrade, we use a dummy variable as a dependent variable that indicates an upgrade of the rating given by CRA *i* one year after quarter t (CRA^iUp_{jt}). We use additional dummy variables that show whether CRA *i* provides a higher rating than its rivals (CRA^idiffP_{jt}) and whether CRA *i* provides a lower rating than its rivals (CRA^idiffN_{jt}). Our model also includes a dummy variable that takes a value of one if the number of CRAs providing ratings is three, and zero otherwise (Com_{jt}), and interaction terms between CRA^idiffP_{jt} and Com_{jt} ($CRA^idiffP*Com_{jt}$) and between CRA^idiffN_{jt} and Com_{jt} ($CRA^idiffN*Com_{jt}$) to test for effects of *Com* on the likelihood of an upgrade.[5] The following equation (3) is used to test Hypothesis 3.

$$CRA^iUp_{jt} = \beta_0 + \beta_1 CRA^idiffP_{jt} + \beta_2 CRA^idiffN_{jt} + \beta_3 CRA^idiffP*Com_{jt} + \beta_4 CRA^idiffN*Com_{jt} + \beta_5 Com_{jt} + \beta_6 SIZEchg_{jt} + \beta_7 LEVchg_{jt} + \beta_8 SIZE_{jt} + \beta_9 LEV_{jt} + \beta_{10} CF_{jt} + \beta_{11} PROF_{jt} + \beta_{12} Tangible_{jt} + \beta_{13} AGE_{jt} + \Sigma YEAR + \Sigma IND + \varepsilon^i_{jt} \quad (3)$$

Definitions of variables

CRA^iUp_{jt}	=	takes a value of one if CRA *i* gives a higher rating to firm *j* at quarter *t*+4 than quarter t, and zero otherwise;
CRA^idiffP_{jt}	=	takes a value of one if CRA *i* gives a higher rating to firm *j* than the average rating of the other CRAs, and zero otherwise;
CRA^idiffN_{jt}	=	takes a value of one if CRA *i* gives a lower rating to firm *j* than the average rating of the other CRAs, and zero otherwise;
Com_{jt}	=	takes a value of one if the number of CRAs providing ratings is three, and zero otherwise;
$CRA^idiffP*Com_{jt}$	=	an interaction term between CRA^idiffP_{jt} and Com_{jt};
$CRA^idiffN*Com_{jt}$	=	an interaction term between CRA^idiffN_{jt} and Com_{jt};
$SIZEchg_{jt}$	=	$(SIZE_{jt+4} - SIZE_{jt}) / SIZE_{jt}$;
$LEVchg_{jt}$	=	$(LEV_{jt+4} - LEV_{jt}) / LEV_{jt}$;
$SIZE_{jt}$	=	natural logarithm of total assets of firm *j* at period *t*;

[5] In our setting, *NoR* can take a value of two or three because double ratings are required and only three CRAs are allowed to rate corporate bonds in Korea. To make our interpretation convenient, we utilize *Com*, which has the same information as *NoR* because it is calculated by subtracting two from *NoR*.

LEV_{jt}	=	total debt divided by total assets of firm *j* at period *t*;
CF_{jt}	=	EBITDA divided by total assets of firm *j* at period *t*;
$PROF_{jt}$	=	return on assets of firm *j* at period *t*;
$Tangible_{jt}$	=	property, plant, and equipment divided by assets of firm *j* at period *t*;
AGE_{jt}	=	elapsed years from the foundation date of firm *j* at period *t;*
$\Sigma YEAR$	=	year dummy variable; and
ΣIND	=	industry dummy variable.

3.2 Sample Selection

This paper uses rating data from Data Guide, which provides detailed financial information on Korean companies.[6] It includes rating evaluation dates and ratings on corporate bonds given by KR, NICE, and KIS. To compare the ratings provided by these different CRAs to a given bond issuer, we use rating data of all CRAs from 2000 to 2015. In addition, firm-quarter data instead of firm-year data is used, which allows us to focus on specific moments of firing or hiring.[7] We utilize the last rating if there are multiple ratings provided by a CRA to a bond issuer within a given quarter. Although no data is collected at the bond level, ratings on secured bonds, subordinated bonds, and structured bonds are not included because these ratings may have different implications from those of ratings on common corporate bonds (uncollateralized public corporate bonds).[8] We exclude withdrawn and unsolicited ratings from our sample as well.[9]

Table 1 provides detailed information on the samples. Panel A shows that the KR, NICE, and KIS samples have data for 10,918, 10,191, and 10,034 firm quarters, respectively.

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[6] As the rating data from Data Guide includes some errors such as typos and issuer credit ratings, and we want to avoid double ratings, we double-checked all data to eliminate error and issuer ratings by comparing our sample data with data from KISLINE, which provides detailed information on companies.

[7] When firm-year data is used, we include in our tests only the last credit ratings of each year, ignoring various ratings given by CRAs at other times of the year. This causes a potential bias for two reasons. First, the ratings from different CRAs may be temporarily equal to or different from each other. Second, the last rating of the year may not reflect the effect of a firing or hiring because of the timing of such events, which may be distant from the moment at which CRAs give the last rating of the year.

[8] Cornaggia et al. (2013) argue that credit ratings have different meanings across asset classes. They also show that different asset classes have different evaluation standards. Therefore, default risks also differ across asset classes, even when two different assets have the same rating grade.

[9] Bannier et al. (2010) show that unsolicited ratings are generally lower than solicited ratings, as CRAs tend to evaluate unsolicited ratings conservatively.

When we combine the samples, there are 12,973 firm quarters, which are composed of 7,776 double-rating quarters and 5,197 triple-rating quarters. The number of bond issuers included in our sample is 571, and the numbers of companies evaluated by KR, NICE, and KIS are 493, 468, and 472, respectively. Panels B and C show that the observations are not concentrated in a specific year or quarter except for 2010 when observations temporarily decreased due to the financial crisis late in the first decade of the new millennium.

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Insert Table 1 about here
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IV. Results of the Empirical Analysis

4.1 Descriptive Statistics

In Table 2, Panels A, B, and C provide descriptive statistics for the KR, NICE, and KIS samples, respectively. *KRrating*, *NICErating*, and *KISrating*, quantified values of credit ratings given by each CRA, have similar values. The median value of *KRrating*, *NICErating*, and *KRrating* is 15, which corresponds to actual rating A. The mean and median values for the $CRA^{i}diff1$ and $CRA^{i}diff2$ are close to zero. These findings indicate that the three CRAs give similar ratings to issuers in general. Likewise, financial data of bond issuers is similar across samples. This result implies that the clients of these three CRAs are similar to each other.

In Panel D, we provide detailed information on firing. The table shows that 205 of 571 bond issuers in our sample have fired a CRA at some point during this study period. As some of them fired a CRA multiple times, we have 288 firing cases in our sample. When examining the cases by CRA, KR, NICE, and KIS were fired 110, 102, and 76 times, respectively. In 15, 10, and 7 cases, respectively, these three Korean CRAs each assigned a better rating than the other CRA(s) before getting fired. On the other hand, in 33, 29, and 24 cases, respectively, the opposite situation occurred in which KR, NICE, and KIS assigned a lower rating before they were fired. In addition, untabulated correlations between $CRA^i diff1$ and $CRA^i fire$ are -0.0374, -0.0590, -0.0734 for KR, NICE, and KIS, respectively with a 1 percent significance level. These statistics provide a hint that bond issuers select CRAs that assign lower ratings than other CRAs when they fire a CRA.

Panel E of Table 2 reports detailed information on the ratings of additional CRAs compared to incumbent CRAs. In the sample, 183 of 571 bond issuers hire an additional CRA; however, 242 additional hiring cases are included in our sample, as some companies hire an additional CRA more than once. KR, NICE, and KIS were each hired 73, 88, and 81 times as an additional CRA, respectively. In 15, 15, and 19 cases, respectively, KR, NICE, and KIS assign a higher rating than that of incumbent CRAs. On the other hand, in 3, 5, and 4 cases, respectively, KR, NICE, and KIS assign a lower rating than that of incumbent CRAs. In addition, untabulated correlations between $CRA^i diff1$ and $CRA^i hire$ are 0.0339, 0.0211, and 0.0417 for KR, NICE, and KIS, respectively with a 1 percent significance level. These findings indicate that new CRAs are more likely to assign a higher rating than to give a lower rating.

Panel F of Table 2 shows cases of rating disagreement when KR, NICE, and KIS each make an upgrade or downgrade decision one year after the disagreement. Although CRAs assigned a higher rating than those of their rivals, KR, NICE, and KIS upgrade ratings 148, 179, and 201 times, respectively. However, KR, NICE, and KIS upgrade ratings 320, 389, and 293 times, respectively when they assigned a lower rating than those given by rivals. In contrast, KR, NICE, and KIS downgrade ratings 113, 100, and 106 times, respectively when they assigned a higher rating than those of their rivals. When they assigned a lower rating than those given by rivals, KR, NICE, and KIS downgrade ratings 16, 41, and 32 times, respectively. This tendency shows that CRAs are likely to upgrade (downgrade) ratings rather than downgrade (upgrade) ratings when they gave a lower (higher) rating than their rivals, which is consistent with the convergence theory.

****
Insert Table 2 about here
****

4.2 Regression Results

4.2.1 Effects of Differences in Credit Ratings among CRAs on Firing Decisions

Panel A of Table 3 presents the results of probit regression Model (1). Columns (1), (2), and (3) show the results for each CRA. The coefficients of $CRA^i diff1$ have negative values ranging from -0.4063 to -0.5463 with a 1 percent significance level. We estimate probabilities that KR, NICE, and KIS are fired given that all explanatory variables are set to their mean values except for $CRA^i diff1$. When $CRA^i diff1$ is zero, the probabilities that KR, NICE and KIS are fired are 0.0029, 0.0025, and 0.0014, respectively. When $CRA^i diff1$ is one (i.e., CRA *i* gives a rating one grade higher than that of other CRAs), the probabilities that KR, NICE, and KIS are fired are 0.0006, 0.0006, and 0.0002, respectively.[10] We investigate whether these results are robust by testing using a random effects model in Columns (4) – (6) of Panel A. The coefficients of $CRA^i diff1$ are similar to those of the non-random effects model. These results reveal that CRAs are less likely to be fired by clients when they assign higher ratings than their rivals.

In Panel B of Table 3, we use an alternative measure for rating differences among CRAs because $CRA^i diff1$ may capture only temporary differences or because bond issuers may make

[10] Although the estimated probabilities are small, they are natural results because the number of firing cases is relatively small to that of non-firing cases. Moreover, the proportion of the firing case becomes smaller as we utilize quarter observations. However, 205 of 571 bond issuers in our sample have experience of firing a CRA at some point during the study period of 2000-2015. To show the significance of the rating difference effects on the firing clear, we repeated the same procedure using a subsample where at least one CRA is fired. The results are discussed in section 4.3.1.

firing decisions a few quarters before a CRA is fired. Thus, we compare averages of ratings for the past year (*CRA*^{i}*diff2*). In Columns (1) – (3), the coefficients of *CRA*^{i}*diff2* are similar to those in Panel A because CRAs do not usually upgrade or downgrade ratings quickly. The results are similar when the results of the random effects model are considered. In Columns (4) – (6), all coefficients of *CRA*^{i}*diff2* are negative at a 1 percent significance level. The results discussed above generally support Hypothesis 1.

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Insert Table 3 about here
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4.2.2 Effects of Hiring an Additional CRA on Credit Ratings

Table 4 shows the results of the regression analysis testing whether additionally hired CRAs assign higher ratings than those given by incumbent CRAs. In Columns (1), (2), and (3), the coefficients of *CRA*^{i}*hire* range from 0.0706 to 0.1274, which are significant and positive at the 1 or 5 percent levels. When we consider the fact that mean and median values of rating difference variables are zero with small variance, the coefficients are significant. Although this test does not detect whether the additional CRA or the bond issuer initiates rating inflation, the result shows that new CRAs tend to offer higher ratings compared to those of incumbent CRAs. The results presented in Table 4 support Hypothesis 2.

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Insert Table 4 about here
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Table 5 presents the results for the last regression model. Columns (1), (3), and (5) show how disagreements in ratings affect the likelihood of an upgrade. For the coefficient of *CRA*^{i}*diffP*, KR and NICE have negative values of -0.6155 and -0.2793, respectively at the significance levels of 1 and 5 percent, respectively, whereas KIS shows a non-significant figure of -0.1651, which is still negative. Conversely, KR, NICE, and KIS show positive coefficients of *CRA*^{i}*diffN* ranging from 0.6791 to 1.1245, which are significant at the 1 percent level. These coefficients suggest that CRAs are less likely to upgrade ratings when they assign a lower rating than their rivals and more likely to upgrade ratings in the opposite case, which is consistent with the results of previous studies on convergence theory (Güttler 2011; Lugo et al. 2015).

In Columns (2), (4), and (6), Table 5, we additionally include the proxy for competition (*Com*) and the interaction terms with rating disagreements (*CRA*^{i}*diffP*Com* and *CRA*^{i}*diffN*Com*) to test whether competition has any effect on the probability of an upgrade. Although the coefficients of *Com* for KR, NICE, and KIS are not significant, KR and NICE have a positive coefficient for *CRA*^{i}*diffP*Com* with values of 0.9171 and 0.4901, respectively at significance levels of 1 and 5 percent, respectively. Moreover, KR and KIS show significantly positive values of 0.5390 and 0.6893 for *CRA*^{i}*diffN*Com* at the 1 percent level. These values indicate that CRAs with more rivals are more likely than CRAs with fewer rivals to upgrade ratings when their rating was lower than that of their rivals, although a higher number of rivals itself does not induce CRAs to upgrade ratings. In addition, KR and NICE with more rivals are likely to upgrade ratings even when they have already assigned a higher rating than that given by their rivals.

Like the analysis we conducted for Hypothesis 1, we estimated probabilities that KR, NICE, and KIS upgrade ratings conditional on the number of rivals and the assignment of a higher or lower rating than rival(s) while other explanatory variables are set to their mean values. Given that KR, NICE, and KIS assigned a higher rating than their rival(s), the estimated likelihood of upgrade is 0.0110, 0.0474, and 0.0808, respectively, when *Com* is 0, and 0.0801, 0.1140, and 0.1266, respectively, when *Com* is 1. Similarly, given that KR, NICE, and KIS assigned a lower rating than their rival(s), the estimated likelihood of upgrade is 0.4197, 0.4970, and 0.2298, respectively when *Com* is 0, and 0.6205, 0.5447, and 0.4965, respectively when *Com* is 1. Regardless of whether a CRA assigned a higher or lower rating than rivals, the probability of an upgrade increases with the number of competitors. The finding generally supports that CRAs tend to cater more under competitive pressure.

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Insert Table 5 about here
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4.3 Robustness Tests

4.3.1 Effects of Differences in Credit Ratings among CRAs on Firing Decisions

For Equation (1) used to test Hypothesis 1, we run logit regression models to check if there is any difference between the results of the probit and logit models. Panel A of Table 6 presents the results of the logit regression models. The coefficients of $CRA^i diff1$ have negative values ranging from -0.8578 to -1.4756 with a 1 percent significance level. Using the results of Columns (1) – (3) in Panel A, we estimate the probabilities that KR, NICE, and KIS are fired given that all explanatory variables are set to their mean values except for $CRA^i diff1$. When $CRA^i diff1$ is zero, the probabilities that KR, NICE, and KIS are fired are 0.3895, 0.3559, and 0.2761, respectively. When $CRA^i diff1$ is one, the probabilities that KR, NICE, and KIS are fired are 0.0381, 0.0590, and 0.0397, respectively. The difference shows a significant effect of $CRA^i diff1$ on $CRA^i fire$. The coefficients of $CRA^i diff2$ in Panel B are similar to those in Panel A. In Columns (1) – (6), all coefficients of $CRA^i diff2$ are negative at a 1 percent significance level. These results indicate that the results of the probit and logit models are qualitatively the same.

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Insert Table 6 about here
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As $CRA^i fire$ takes a value of one in a small number of cases, the variation of the predictor is low, which may mean that our estimated coefficients for Equation (1) are imprecise. Thus, we conduct additional tests using a subsample. We choose cases in which at least one of the three CRAs is fired. Table 7 presents the results of the probit regression model using the subsample. In Columns (1) – (6) of Panel A, the coefficients of $CRA^{i}diff1$ have negative values with a 1 percent significance level. In Panel B, the coefficients of $CRA^{i}diff2$ have negative values with a 1 or 5 percent significance level as well. The additional test shows that the results of the full sample presented in Table 3 and the subsample test are qualitatively the same.

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Insert Table 7 about here
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4.3.2 Effects of Hiring an Additional CRA on Credit Ratings

As $CRA^{i}hire$ takes a value of one in a small number of cases, the variation of the predictor is low. Thus, we investigate whether these results are robust by testing Hypothesis 2 in a subsample. The variance of $CRA^{i}hire$ is sufficient in the subsample under which at least one of the three CRAs is hired as an additional CRA (i.e., either *KRhire*, *NICEhire*, or *KIShire* takes a value of one). Table 8 presents the results of the subsample test. In Columns (1) – (3), the coefficients of $CRA^{i}hire$ are positive with a 1 or 5 percent significance level. While the results of Table 4 and Table 8 are qualitatively the same, the magnitude of the coefficients increases significantly from 0.1274, 0.0706, and 0.0885 in Table 4 to 0.2719, 0.3156, and 0.2245 in Table 8.

****
Insert Table 8 about here
****

V. Conclusion

In this study, we observe periods of firing and hiring that are probably associated with rating shopping or rating catering. We find evidence that rating shopping and catering occur in the Korean rating market. The test results show that bond issuers tend to fire CRAs that give lower ratings than other CRAs. In addition, when an issuer with incumbent CRAs hires an additional CRA, the newly hired CRA tends to assign higher ratings than those given by incumbent CRAs. We also find evidence that competition affects the probability that CRAs upgrade ratings when there are rating disagreements. These results are consistent with the results of prior theoretical and empirical studies, which demonstrate that competition among CRAs reduces rating quality (Becker and Milbourn 2011; Camanho et al. 2012; Griffin et al. 2013).

This paper offers several contributions. First, it provides additional evidence of rating shopping in the form of selective firing. To the best of our knowledge, no study has investigated whether bond issuers fire their incumbent CRAs selectively for rating shopping purposes. Second, this paper provides additional evidence that increased competition in the rating market reduces credit quality in some cases. Unlike prior studies that provide mixed results using the market share of Fitch as a proxy for market competition (Becker and Milbourn 2011 and Bae et al. 2015), we use the number of rivals as a proxy for competition among CRAs. Using this proxy, we find that greater competition leads to higher ratings, which is consistent with the findings of Becker and Milbourn (2011), Camanho et al. (2012), and Griffin et al. (2013). Third, we add a finding to the literature on rating convergence. Unlike Güttler (2011) and Lugo et al. (2015), our finding suggests that competitive pressure has an additional effect on the likelihood that CRAs upgrade ratings when they assigned lower ratings than those of their rivals. Moreover, this competitive pressure also increases the probability that CRAs upgrade their ratings even when they assigned a higher rating than that of their rivals. These results provide useful information for regulators, justifying their regulations by providing empirical evidence. For instance, the FSS has released a plan for the advancement of the credit rating market which outlines regulations for CRAs and a new CRA selection method under which a third party requests rating services instead of a bond issuer.

The findings of this study suggest that these regulations are justified, as is the decision to defer the introduction of a fourth CRA in Korea, which may increase both competition among CRAs and rating catering. In addition, our results inform investors of possible risks when they utilize rating information that may or may not reflect true default risk.

Lastly, this study has the following limitation: it exclusively refers to unsecured bonds. We do not consider possible effects of ratings on subordinated bonds, secured bonds, and structured bonds. Also, no bond-level data is included; including such data would allow for a more sophisticated analysis of CRA firing. Future research may expand the sample by considering other types of bonds and increase our understanding of rating shopping and catering.

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APPENDIX A
Definitions of Variables

Variable		Definitions
$KRrating_{jt}$	=	a quantified version of an actual credit rating given by Korea Ratings to firm *j* at period *t*. It ranges from 1 to 20, which corresponds to ratings from D to AAA. See Appendix C for the definitions of ratings in Korea;
$NICErating_{jt}$	=	a quantified version of an actual credit rating given by NICE Investors Service to firm *j* at period *t*. It ranges from 1 to 20, which corresponds to ratings from D to AAA. See Appendix C for the definitions of ratings in Korea;
$KISrating_{jt}$	=	a quantified version of an actual credit rating given by the Korea Investors Service to firm *j* at period *t*. It ranges from 1 to 20, which corresponds to ratings from D to AAA. See Appendix C for the definitions of ratings in Korea;
$KRdiff1_{jt}$	=	difference between $KRrating_{jt}$ and the average of $NICErating_{jt}$ and $KISrating_{jt}$;
$KRdiff2_{jt}$	=	difference between the average of $KRrating_j$ from period *t*-4 to *t* and the average of $NICErating_j$ and $KISrating_j$ for the same period;
$NICEdiff1_{jt}$	=	difference between $NICErating_{jt}$ and the average of $KRrating_{jt}$ and $KISrating_{jt}$;
$NICEdiff2_{jt}$	=	difference between the average of $NICErating_j$ from period *t*-4 to *t* and the average of $KRrating_j$ and $KISrating_j$ for the same period;
$KISdiff1_{jt}$	=	difference between $KISrating_{jt}$ and the average of $NICErating_{jt}$ and $KRrating_{jt}$;
$KISdiff2_{jt}$	=	difference between the average of $KISrating_j$ from period *t*-4 to *t* and the average of $NICErating_j$ and $KRrating_j$ for the same period;
$KRfire_{jt}$	=	takes a value of one if KR assigns a rating to firm *j* at period *t*, but not at period *t*+1, while at least one CRA assesses firm *j* at period *t*+1, and zero otherwise;
$NICEfire_{jt}$	=	takes a value of one if NICE assigns a rating to firm *j* at period *t*, but not at period *t*+1, while at least one CRA assesses firm *j* at period *t*+1, and zero otherwise;
$KISfire_{jt}$	=	takes a value of one if KIS assigns a rating to firm *j* at period *t*, but not at period *t*+1, while at least one CRA assesses firm *j* at period *t*+1, and zero otherwise;
$KRhire_{jt}$	=	takes a value of one if firm *j* does not obtain a rating from KR, but obtains ratings from other CRAs at period *t*-1 and a rating from KR at period *t*, and zero otherwise;
$NICEhire_{jt}$	=	takes a value of one if firm *j* does not obtain a rating from NICE, but obtains ratings from other CRAs at period *t*-1 and a rating from NICE at period *t*, and zero otherwise;
$KIShire_{jt}$	=	takes a value of one if firm *j* does not obtain a rating from KIS, but obtains ratings from other CRAs at period *t*-1 and a rating from KIS at period *t*, and zero otherwise;
$KRUp_{jt}$	=	takes a value of one if KR gives a higher rating to firm *j* at quarter *t*+4 than quarter *t*, and zero otherwise;
$NICEUp_{jt}$	=	takes a value of one if NICE gives a higher rating to firm *j* at quarter

		t+4 than quarter t, and zero otherwise;
$KISUp_{jt}$	=	takes a value of one if KIS gives a higher rating to firm j at quarter t+4 than quarter t, and zero otherwise;
$KRdiffP_{jt}$	=	takes a value of one if KR gives a higher rating to firm j than the average rating of the other CRAs at period t, and zero otherwise;
$KRdiffN_{jt}$	=	takes a value of one if KR gives a lower rating to firm j than the average rating of the other CRAs at period t, and zero otherwise;
$NICEdiffP_{jt}$	=	takes a value of one if NICE gives a higher rating to firm j than the average rating of the other CRAs at period t, and zero otherwise;
$NICEdiffN_{jt}$	=	takes a value of one if NICE gives a lower rating to firm j than the average rating of the other CRAs at period t, and zero otherwise;
$KISdiffP_{jt}$	=	takes a value of one if KIS gives a higher rating to firm j than the average rating of the other CRAs at period t, and zero otherwise;
$KISdiffN_{jt}$	=	takes a value of one if KIS gives a lower rating to firm j than the average rating of the other CRAs at period t, and zero otherwise;
Com_{jt}	=	takes a value of one if the number of CRAs providing ratings is three at period t, and zero otherwise;
$KRdiffP*Com_{jt}$	=	an interaction term between $KRdiffP_{jt}$ and Com_{jt};
$KRdiffN*Com_{jt}$	=	an interaction term between $KRdiffN_{jt}$ and Com_{jt};
$NICEdiffP*Com_{jt}$	=	an interaction term between $NICEdiffP_{jt}$ and Com_{jt};
$NICEdiffN*Com_{jt}$	=	an interaction term between $NICEdiffN_{jt}$ and Com_{jt};
$KISdiffP*Com_{jt}$	=	an interaction term between $KISdiffP_{jt}$ and Com_{jt};
$KISdiffN*Com_{jt}$	=	an interaction term between $KISdiffN_{jt}$ and Com_{jt};
$SIZE_{jt}$	=	natural logarithm of total assets of firm j at period t;
$SIZEchg_{jt}$		$(SIZE_{jt+4} - SIZE_{jt}) / SIZE_{jt}$;
LEV_{jt}	=	total debt divided by total assets of firm j at period t;
$LEVchg_{jt}$		$(LEV_{jt+4} - LEV_{jt}) / LEV_{jt}$;
CF_{jt}	=	EBITDA divided by total assets of firm j at period t;
$PROF_{jt}$	=	return on assets of firm j at period t;
$Tangible_{jt}$	=	property, plant, and equipment divided by assets of firm j at period t;
AGE_{jt}	=	elapsed years from the foundation date of firm j at period t;
NoR_{jt}	=	the number of CRAs evaluating firm j at period t;
$\Sigma YEAR$	=	year dummy variable; and
ΣIND	=	industry dummy variable.

APPENDIX B

Measures of Firing and Hiring

Firm *j*		CRA1	CRA2	CRA3
2000	1Q			
	2Q			
	3Q	BBB+ *		BBB+ *
	4Q	BBB+		BBB
2001	1Q	BBB+		BBB
	2Q	BBB+		BBB
	3Q	BBB	BBB**	BBB-
	4Q	BBB	BBB	BBB-
2002	1Q	BBB	BBB	BBB-
	2Q	BBB	BBB	BBB- ***
	3Q	BBB-	BBB	
	4Q	BBB-	BBB-	
2003	1Q	BBB-	BBB-	
	2Q	BBB****	BBB****	
	3Q			
	4Q			

This example shows how we measure firing and hiring in this study. In this example, firm *j* issues 2-year maturity straight bonds (SB1 and SB2) in the third quarters of 2000 and 2001. Firm *j* requests CRA1 and CRA3 to evaluate SB1. The ratings within the squares with the solid line are given to SB1. CRA1 and CRA3 both give BBB+ to SB1 at first. However, in the last quarter of 2000, CRA3 downgrades the rating, while CRA1 gives the same rating. In the third quarter of 2001, firm *j* issues a new bond, SB2, and requests evaluations from CRA1 and CRA2. The ratings within the square with the dotted line are given to SB2. As the maturity date of SB2 is at the end of the second quarter of 2003, there is no rating after this period.

There is a problem from the third quarter of 2001 to the second quarter of 2002 because our data set shows only one rating given by CRA1, although it evaluates SB1 and SB2 at the same time. During this period, it is not clear whether the ratings from CRA1 are given to SB1 or SB2. This problem happens because Data Guide, a financial database in South Korea, provides only the last rating given to a company in each quarter. If CRA1 assigned BBB- to SB1 on September 29 and BBB to SB2 on September 30, the data would show only the rating given to SB2 (BBB). Then, the comparison between the rating given by CRA1 and that given by CRA3 in the third quarter of 2001 would be absurd because the BBB rating in the third quarter of 2001 is not the SB1 rating, which must be compared to a rating given by CRA3 to SB1. We can avoid this problem only when CRA1 assigns the same rating to both SB1 and SB2. Thus, we double-checked all data to eliminate split rating cases. Fortunately, CRAs give the same ratings when they assess multiple bonds of a firm because companies issue bonds with similar contractual terms and because ratings for structured bonds and subordinated bonds, which may have significantly different contractual terms and rating standards, are not included. Thus, multiple ratings from one CRA for firm *j* are almost the same in any given period.

Based on the definitions of the variables in Appendix A, the values for the hiring and firing variables in the above example are shown in the table below. In the third quarter of 2000, firm *j* hires CRA1 and CRA3. However, as we want to observe cases in which the bond issuer hires an additional CRA although it has incumbent CRAs, CRA^1hire and CRA^3hire take values of zero in the third quarter of 2000. In the third quarter of 2001, CRA^2hire takes a value of one as CRA2 is hired as an additional CRA. In the second quarter of 2002, CRA3 gives its last rating and does not evaluate firm *j* in the third quarter of 2002, while other CRAs continue to evaluate firm *j*. Therefore, CRA^3fire takes a value of one in the second quarter of 2002. However, in the second quarter of 2003, CRA^1fire and CRA^2fire take values of zero because firm *j* has no more outstanding bonds.

*	CRA^1hire=0	CRA^2hire=0	CRA^3hire=0
**	CRA^1hire=0	CRA^2hire=1	CRA^3hire=0
***	CRA^1fire=0	CRA^2fire =0	CRA^3fire =1
****	CRA^1fire=0	CRA^2fire =0	CRA^3fire =0.

APPENDIX C

Definitions of Ratings

Rating	Definitions
AAA	Capacity for timely payment is extremely strong;
AA	Capacity for timely payment is very strong but somewhat less than AAA;
A	Capacity for timely payment is strong, but somewhat susceptible to external changes in the future;
BBB	Capacity for timely payment is adequate, but is more likely to be weakened by future market changes;
BB	Capacity for timely payment faces no immediate problems, but is speculative in its future stability;
B	Capacity for timely payment is poor and speculative;
CCC	Contains the possibility of default;
CC	Contains more possibility of default;
C	Highly likely to default; and
D	In default at present.

Notes: This list of rating definitions comes from Korea Ratings, one of the three Korean CRAs. Other CRAs have almost the same rating list and use similar phrases. Ratings from AA to B may be modified with a plus (+) or minus (-) sign to show relative standing within the major rating categories. The only difference among CRAs is that the NICE rating system allows CCC to be modified with a plus or minus sign. However, there are very few firm quarters that receive CCC+ or CCC- ratings. This paper regards CCC+ and CCC- as CCC for comparison.

Table 1 Sample Selection and Distribution
This table reports the process of sample selection for KR, NICE, and KIS in Panel A and the distribution by year and quarter in Panel B and Panel C, respectively.

Panel A. Sample Selection Criteria

	KR	NICE	KIS
Total number of firm-quarter entries	14,457	13,651	13,154
(less firms with insufficient financial data)	(3,539)	(3,460)	(3,120)
Size of samples used for testing	**10,918**	**10,191**	**10,034**

Panel B. Sample by Year

Year	KR		NICE		KIS	
	# firms	%	# firms	%	# firms	%
2000	521	4.77	477	4.68	427	4.26
2001	698	6.39	657	6.45	595	5.93
2002	584	5.35	549	5.39	481	4.79
2003	630	5.77	575	5.64	541	5.39
2004	671	6.15	628	6.16	619	6.17
2005	710	6.50	619	6.07	651	6.49
2006	729	6.68	619	6.07	655	6.53
2007	770	7.05	683	6.70	703	7.01
2008	803	7.35	723	7.09	727	7.25
2009	777	7.12	718	7.05	716	7.14
2010	119	1.09	98	0.96	101	1.01
2011	666	6.10	617	6.05	631	6.29
2012	718	6.58	666	6.54	677	6.75
2013	883	8.09	874	8.58	856	8.53
2014	909	8.33	942	9.24	906	9.03
2015	730	6.69	746	7.32	748	7.45
Total	**10,918**	**100**	**10,191**	**100**	**10,034**	**100**

Panel C. Sample by Quarter

Quarter	KR		NICE		KIS	
	# firms	%	# firms	%	# firms	%
1	2,347	21.50	2,176	21.35	2,149	21.42
2	2,906	26.62	2,701	26.50	2,663	26.54
3	2,885	26.42	2,705	26.54	2,656	26.47
4	2,780	25.46	2,609	25.60	2,566	25.57
Total	**10,918**	**100**	**10,191**	**100**	**10,034**	**100**

Table 2 Descriptive Statistics
This table reports the descriptive statistics for firms included in the analysis. Panels A, B, and C provide descriptive statistics for the KR, NICE, and KIS samples, respectively. Each column of Panel D reports the numbers and percentages for each CRA that assigned a higher rating than that of rivals, that assigned the same rating as that of its rivals, and that assigned a lower rating than that of its rivals when the CRA was fired. Panel E and Panel F, respectively, provide information on the numbers and percentages of additional hiring and upgrades and downgrades in the same way as Panel D.

Panel A. Korea Ratings

Variable	N	Mean	S.D.	Min	Median	Max
KRrating	10,918	14.56	3.58	12	15	20
KRfire	10,918	0.01	-	0	0	1
KRdiff1	10,918	0	0.29	0	0	3
KRdiff2	10,918	0.01	0.26	0	0	3
KRhire	10,918	0.01	-	0	0	1
SIZE	10,918	21.41	1.74	20.17	21.35	25.84
LEV	10,918	62.76	18.28	51.08	63.6	96.5
CF	10,918	1.73	1.86	0.56	1.5	7.6
PROF	10,918	2.2	7.87	0.1	2	23.11
Tangible	10,918	0.32	0.25	0.07	0.32	0.87
AGE	10,918	31.41	17.67	17	32	105
NoR	10,918	2.48	0.50	2	2	3

Panel B. NICE Investors Service

Variable	N	Mean	S.D.	Min	Median	Max
NICErating	10,191	14.58	3.6	1	15	20
NICEfire	10,191	0.01	-	0	0	1
NICEdiff1	10,191	-0.01	0.33	-5	0	3
NICEdiff2	10,191	-0.01	0.29	-5	0	3
NICEhire	10,191	0.01	-	0	0	1
SIZE	10,191	21.44	1.75	17.35	21.38	25.84
LEV	10,191	62.95	18.16	19.16	63.35	96.5
CF	10,191	1.69	1.85	-4.22	1.48	7.6
PROF	10,191	2.13	7.9	-37.96	2	23.11
Tangible	10,191	0.31	0.25	0	0.31	0.87
AGE	10,191	32.63	18.55	0	33	94
NoR	10,191	2.51	0.49	2	2	3

Panel C. Korea Investors Service

Variable	N	Mean	S.D.	Min	Median	Max
KISrating	10,034	14.82	3.54	1	15	20
KISfire	10,034	0.01	-	0	0	1
KISdiff1	10,034	0	0.35	-6	0	5
KISdiff2	10,034	0.01	0.32	-4.5	0	5
KIShire	10,034	0.01	-	0	0	1
SIZE	10,034	21.4	1.74	17.35	21.33	25.84
LEV	10,034	62.09	18.74	19.16	62.69	96.5

CF	10,034	1.79	1.87	-4.22	1.55	7.6
PROF	10,034	2.44	7.72	-37.96	2.16	23.11
Tangible	10,034	0.32	0.25	0	0.32	0.87
AGE	10,034	32.09	18.59	0	32	105
NoR	10,034	2.52	0.50	2	3	3

Panel D. Detailed Information on Firing

CRA rating before getting fired	KR		NICE		KIS	
	#	%	#	%	#	%
> Others' ratings	15	13.64	10	9.80	7	9.21
= Others' ratings	62	56.36	63	61.76	45	59.21
< Others' ratings	33	30.00	29	28.43	24	31.58
Total	**110**	**100**	**102**	**100**	**76**	**100**

Panel E. Detailed Information on Additional Hiring

CRA rating when hired	KR		NICE		KIS	
	#	%	#	%	#	%
> Others' ratings	15	20.55	15	17.05	19	23.46
= Others' ratings	55	75.34	68	77.27	58	71.60
< Others' ratings	3	4.11	5	5.68	4	4.94
Total	**73**	**100**	**88**	**100**	**81**	**100**

Panel F. Detailed Information on Upgrades and Downgrades

		KR		NICE		KIS	
		#	%	#	%	#	%
Upgrades	> Others' ratings	148	4.09	179	5.21	201	6.18
	= Others' ratings	3,152	87.07	2,866	83.46	2,758	84.81
	< Others' ratings	320	8.84	389	11.33	293	9.01
	Total	**3,620**	**100.00**	**3,434**	**100**	**3,252**	**100**
Downgrades	> Others' ratings	113	15.21	100	14.08	106	15.47
	= Others' ratings	614	82.64	569	80.14	547	79.85
	< Others' ratings	16	2.15	41	5.77	32	4.67

Total	**743**	**100**	**710**	**100**	**685**	**100**

Table 3 Result of Probit Regression Testing Effects of Differences in Credit Ratings among CRAs on Firing Decisions

This table presents coefficient estimates from the probit regression of equation (1). The dependent variable is $CRA^{i}fire_{jt}$, a dummy variable that indicates whether firm *j* fires CRA *i* after period *t*. In Panel A, the independent variable of interest is $CRA^{i}diff1_{jt}$, the difference between $CRA^{i}rating_{jt}$ and the average rating of a given CRAs' rivals. In Panel B, the independent variable of interest is $CRA^{i}diff2_{jt}$, the difference between the average of $CRA^{i}rating_{jt}$ from period *t*-4 to *t* and the average rating of the rivals for the same period. In each panel, Columns (1), (2), and (3) show the results of the test without random effects at the bond issuer level, while Columns (4), (5), and (6) show those with random effects. *SIZE* is natural logarithm of total assets of firm *j*. *LEV* is total debt divided by total assets of firm *j*. *CF* is EBITDA divided by total assets of firm *j*. *PROF* is return on assets of firm *j*. *Tangible* is property, plant, and equipment divided by assets of firm *j*. *AGE* is elapsed years from the foundation date of firm *j*. *NoR* is the number of CRAs evaluating firm *j*. Z-statistics are in parentheses using robust standard errors clustered by firm for the non-random effects model. ***, ** and * denote significance at the 1 percent, 5 percent, and 10 percent levels, respectively. Pseudo-R^2 and log-likelihood (LL) are reported for the non-random and random effects models, respectively.

$$CRA^{i}fire_{jt} = \beta_0 + \beta_1 CRA^{i}Diff1_{jt} + \beta_2 SIZE_{jt} + \beta_3 LEV_{jt} + \beta_4 CF_{jt} + \beta_5 PROF_{jt} + \beta_6 Tangible_{jt} + \beta_7 AGE_{jt} + \beta_8 NoR_{jt} + \Sigma YEAR + \Sigma IND + \varepsilon^{i}_{jt}$$

Panel A. *CRA^i diff1*

Variables	Pred. Sign	*Dependent Variable*					
		KRfire	*NICEfire*	*KISfire*	*KRfire*	*NICEfire*	*KISfire*
		(1)	(2)	(3)	(4)	(5)	(6)
Intercept		0.0805	-0.8932	-1.3927	0.1113	-0.8934	-1.3927
		(0.11)	(-0.92)	(-1.47)	(0.12)	(-1.03)	(-1.3)
CRAdiff1	-	-0.4648	-0.4063	-0.5463	-0.4960	-0.4064	-0.5465
		(-2.85)***	(-3.87)***	(-4.17)***	(-3.64)***	(-3.94)***	(-4.48)***
SIZE	-	-0.2106	-0.1880	-0.1982	-0.2240	-0.1880	-0.1982
		(-5.74)***	(-3.9)***	(-3.82)***	(-4.59)***	(-4.31)***	(-3.57)***
LEV	+	0.0007	0.0071	0.0060	0.0008	0.0071	0.0060
		(0.22)	(1.99)**	(1.58)	(0.23)	(1.91)*	(1.23)
CF	+	0.0072	0.0520	0.1231	0.0074	0.0520	0.1232
		(0.22)	(1.46)	(2.96)***	(0.19)	(1.38)	(2.79)***
PROF	+	0.0109	-0.0084	-0.0097	0.0112	-0.0084	-0.0097
		(1.14)	(-1.24)	(-1.31)	(1.29)	(-1.03)	(-1.02)
Tangible	-	-0.3716	-0.1846	0.1022	-0.4003	-0.1846	0.1022

		(-1.43)	(-0.61)	(0.35)	(-1.22)	(-0.57)	(0.29)
AGE	-	0.0005	0.0023	0.0013	0.0008	0.0023	0.0013
		(0.17)	(0.67)	(0.36)	(0.22)	(0.65)	(0.31)
NoR	+	0.5356	0.6153	0.8515	0.5775	0.6152	0.8515
		(4.4)***	(4.0)***	(4.46)***	(4.22)***	(4.74)***	(5.16)***
Year Fixed Effects		Y	Y	Y	Y	Y	Y
Industry Fixed Effects		Y	Y	Y	Y	Y	Y
Issuer Random Effects		N	N	N	Y	Y	Y
Model Fit		Pseudo-R^2= 0.1058	Pseudo-R^2=0.1498	Pseudo-R^2=0.2081	LL = -334.2642	LL = -301.4965	LL = -202.71
Sample Size		10,918	10,191	10,034	10,918	10,191	10,034

Panel B. *CRA*

Panel B. ***CRA^idiff2***

$$CRA^i fire_{jt} = \beta_0 + \beta_1 CRA^i Diff2_{jt} + \beta_2 SIZE_{jt} + \beta_3 LEV_{jt} + \beta_4 CF_{jt} + \beta_5 PROF_{jt} + \beta_6 Tangible_{jt} + \beta_7 AGE_{jt} + \beta_8 NoR_{jt} + \Sigma YEAR + \Sigma IND + \varepsilon^i_{jt}$$

Variables	Pred. Sign	*Dependent Variable*					
		KRfire	*NICEfire*	*KISfire*	*KRfire*	*NICEfire*	*KISfire*
		(1)	(2)	(3)	(4)	(5)	(6)
Intercept		0.1176	-0.9199	-1.5903	0.1395	-0.9201	-1.5903
		(0.16)	(-0.94)	(-1.71)*	(0.16)	(-1.06)	(-1.5)
CRAdiff2	-	-0.4703	-0.4060	-0.5107	-0.4913	-0.4060	-0.5106
		(-2.68)***	(-3.65)***	(-3.74)***	(-3.17)***	(-3.73)***	(-3.8)***
SIZE	-	-0.2106	-0.1880	-0.1960	-0.2205	-0.1880	-0.1960
		(-5.76)***	(-3.88)***	(-3.85)***	(-4.66)***	(-4.31)***	(-3.55)***
LEV	+	0.0007	0.0071	0.0076	0.0007	0.0071	0.0076
		(0.19)	(1.96)**	(1.99)**	(0.19)	(1.89)*	(1.57)
CF	+	0.0092	0.0516	0.1268	0.0098	0.0516	0.1268
		(0.29)	(1.46)	(3.08)***	(0.25)	(1.37)	(2.87)***
PROF	+	0.0104	-0.0082	-0.0115	0.0105	-0.0082	-0.0115
		(1.09)	(-1.21)	(-1.6)	(1.22)	(-1)	(-1.2)
Tangible	-	-0.3729	-0.1980	0.1223	-0.3950	-0.1981	0.1223
		(-1.42)	(-0.65)	(0.42)	(-1.22)	(-0.61)	(0.35)

AGE	-	0.0006	0.0023	0.0016	0.0008	0.0023	0.0016
		(0.2)	(0.66)	(0.43)	(0.23)	(0.65)	(0.37)
NoR	+	0.5349	0.6295	0.8552	0.5671	0.6293	0.8551
		(4.42)***	(4.06)***	(4.59)***	(4.25)***	(4.84)***	(5.22)***
Year Fixed Effects		Y	Y	Y	Y	Y	Y
Industry Fixed Effects		Y	Y	Y	Y	Y	Y
Issuer Random Effects		N	N	N	Y	Y	Y
Model Fit		Pseudo-R^2=0.1017	Pseudo-R^2=0.1476	Pseudo-R^2=0.1931	LL = -335.9426	LL = -302.2854	LL = -206.5375
Sample Size		10,918	10,191	10,034	10,918	10,191	10,034

Table 4

Results of Regression Testing Effects of Hiring an Additional CRA on Additional Ratings

This table presents coefficient estimates from the probit regression model (2). The dependent variable is $CRA^i diff1$, the difference between $CRA^i rating_{jt}$ and the average rating of the rivals. The independent variable of interest is $CRA^i hire_{jt}$, a dummy variable indicating whether bond issuer *j* hires an additional CRA at period *t*. *SIZE* is natural logarithm of total assets of firm *j*. *LEV* is total debt divided by total assets of firm *j*. *CF* is EBITDA divided by total assets of firm *j*. *PROF* is return on assets of firm *j*. *Tangible* is property, plant, and equipment divided by assets of firm *j*. *AGE* is elapsed years from the foundation date of firm *j*. *NoR* is the number of CRAs evaluating firm *j*. Z-statistics are in parentheses using robust standard errors clustered by firm. A fixed effects model was chosen following the results of the Hausman test. ***, ** and * denote significance at the 1 percent, 5 percent, and 10 percent levels, respectively.

$$CRA^i diff1_{jt} = \beta_0 + \beta_1 CRA^i hire_{jt} + \beta_2 SIZE_{jt} + \beta_3 LEV_{jt} + \beta_4 CF_{jt} + \beta_5 PROF_{jt} + \beta_6 Tangible_{jt} + \beta_7 AGE_{jt} + \beta_8 NoR_{jt} + \Sigma YEAR + \Sigma IND + \varepsilon^i_{jt}$$

Variables	Pred. Sign	Dependent Variable		
		KRdiff1	*NICEdiff1*	*KISdiff1*
		(1)	(2)	(3)
Intercept		0.4170	-0.0660	0.4280
		(2.64)***	(-0.35)	(2.0)**
CRAhire	+	0.1274	0.0706	0.0885
		(3.62)***	(2.01)**	(2.23)**
SIZE	-	-0.0189	0.0009	-0.0265
		(-2.26)**	(0.09)	(-2.32)**
LEV	+	0.0008	0.0005	-0.0008
		(2.49)**	(1.35)	(-1.93)*
CF	+/-	0.0001	-0.0028	-0.0018
		(0.05)	(-1.03)	(-0.6)
PROF	+/-	-0.0002	-0.0010	0.0021
		(-0.33)	(-1.72)*	(3.38)***
Tangible	-	0.0738	-0.0328	-0.0018
		(1.95)*	(-0.77)	(-0.04)
AGE	-	-0.0035	-0.0012	0.0060
		(-2.67)***	(-0.8)	(3.43)***
NoR	+	0.0192	0.0357	-0.0194
		(2.16)**	(3.38)***	(-1.76)*
Year Fixed Effects		Y	Y	Y
Industry Fixed Effects		Y	Y	Y
Issuer Fixed Effects		Y	Y	Y
Adj-R^2		0.2488	0.2579	0.2386
Sample Size		10,918	10,191	10,034

Table 5 Results of Regression Testing Effects of the Number of Rivals on the Likelihood of Upgrades

Columns (1), (3), and (5) present coefficient estimates from the probit regression model without interaction terms among $CRA^{i}diffP$(or $CRA^{i}diffN$) and *Com* dummy variables; the other columns include the interaction terms. The dependent variable is $CRA^{i}Up$, a dummy variable that indicates an upgrade of the rating in a given year. The independent variables are: $CRA^{i}diffP$ as a dummy for rating disagreements (1 if $CRA^{i}rating$ is higher than the average of the ratings given by the rivals, 0 otherwise), $CRA^{i}diffN$ as another dummy for rating disagreements (1 if $CRA^{i}rating$ is lower than the average of the ratings given by the rivals, 0 otherwise), *Com* as a dummy for competition (1 if the number of CRAs providing ratings is three, 0 otherwise), $CRA^{i}diffP*Com$ as an interaction term between $CRA^{i}diffP$ and *Com*, and $CRA^{i}diffN*Com$ as an interaction term between $CRA^{i}diffN$ and *Com*. *SIZEchg* is the rate of increase in *Size*. *LEVchg* is the rate of increase in *Lev*. *SIZE* is natural logarithm of total assets of firm *j*. *LEV* is total debt divided by total assets of firm *j*. *CF* is EBITDA divided by total assets of firm *j*. *PROF* is return on assets. *Tangible* is property, plant, and equipment divided by assets of firm *j*. *AGE* is elapsed years from the foundation date of firm *j*. Z-statistics are in parentheses using robust standard errors clustered by firm. ***, ** and * denote significance at the 1 percent, 5 percent, and 10 percent levels, respectively.

$$CRA^{i}Up_{jt} = \beta_0 + \beta_1\, CRA^{i}diffP_{jt} + \beta_2\, CRA^{i}diffN_{jt} + \beta_3\, Com_{jt} + \beta_4\, CRA^{i}diffP{*}Com_{jt} + \beta_5\, CRA^{i}diffN{*}Com_{jt} + \beta_6\, SIZEchg_{jt} + \beta_7\, LEVchg_{jt} + \beta_8\, SIZE_{jt} + \beta_9\, LEV_{jt} + \beta_{10}\, CF_{jt} + \beta_{11}\, PROF_{jt} + \beta_{12} Tangible_{jt} + \beta_{13}\, AGE_{jt} + \Sigma YEAR + \Sigma IND + \varepsilon^{i}_{jt}$$

Variables	Pred. Sign	Dependent Variable					
		KRUp	*KRUp*	*NICEUp*	*NICEUp*	*KISUp*	*KISUp*
		(1)	(2)	(3)	(4)	(5)	(6)
Intercept		-1.9974	-1.9348	-1.0519	-1.0406	-0.8900	-0.8346
		(-3.29)***	(-3.22)***	(-1.66)*	(-1.65)*	(-1.42)	(-1.34)
CRAdiffP	-	-0.6155	-1.2244	-0.2793	-0.5943	-0.1651	-0.2914
		(-4.6)***	(-5.79)***	(-2.33)**	(-2.75)***	(-1.35)	(-1.42)
CRAdiffN	+	1.1245	0.8648	1.1403	1.0691	0.6791	0.3687
		(9.42)***	(5.63)***	(10.49)***	(6.68)***	(5.02)***	(1.98)**
Com	+	0.0353	-0.0297	0.0060	-0.0249	0.0981	0.0414
		(0.47)	(-0.39)	(0.08)	(-0.31)	(1.3)	(0.52)
CRAdiffP Com*	+		0.9171		0.4901		0.2159
			(3.64)***		(1.98)**		(0.9)
CRAdiffN Com*	+		0.5390		0.1448		0.6893
			(2.31)**		(0.66)		(2.78)***
SIZEchg	+	0.0028	-0.0096	-0.0601	-0.0646	0.1836	0.1550
		(0.02)	(-0.07)	(-0.49)	(-0.52)	(1.21)	(1.03)

LEVchg	-	-0.0084	-0.0082	-0.0067	-0.0067	-0.0102	-0.0100
		(-2.92)***	(-2.92)***	(-3.8)***	(-3.84)***	(-2.45)**	(-2.4)**
SIZE	-	-0.0048	-0.0049	-0.0159	-0.0160	-0.0238	-0.0242
		(-0.16)	(-0.16)	(-0.51)	(-0.52)	(-0.81)	(-0.82)
LEV	+	0.0087	0.0086	0.0088	0.0090	0.0056	0.0054
		(3.47)***	(3.43)***	(3.35)***	(3.43)***	(2.26)**	(2.2)**
CF	+	0.1196	0.1196	0.1169	0.1176	0.0974	0.0975
		(5.21)***	(5.15)***	(4.96)***	(5)***	(4.15)***	(4.23)***
PROF	+	0.0083	0.0085	0.0085	0.0088	0.0099	0.0101
		(1.92)*	(1.97)**	(1.71)*	(1.79)*	(2.04)**	(2.09)**
Tangible	-	0.3631	0.3370	0.4210	0.4086	0.0527	0.0388
		(1.67)*	(1.55)	(1.99)**	(1.94)*	(0.25)	(0.18)
AGE	-	0.0037	0.0034	0.0028	0.0027	0.0036	0.0034
		(1.52)	(1.4)	(1.19)	(1.16)	(1.62)	(1.55)
Year Fixed Effects		Y	Y	Y	Y	Y	Y
Industry Fixed Effects		Y	Y	Y	Y	Y	Y
Model Fit		Pseudo-R^2=0.1493	Pseudo-R^2=0.1536	Pseudo-R^2=0.1483	Pseudo-R^2=0.1494	Pseudo-R^2=0.1117	Pseudo-R^2=0.1149
Sample Size		8,917	8,917	8,290	8,290	8,204	8,204

Table 6 Robustness Check for Testing of H1 (Logit Model)

This table presents coefficient estimates from the logit regression of equation (1). The dependent variable is $CRA^i fire$, a dummy variable that indicates whether firm *j* fires CRA *i* after quarter *t*. In Panel A, the independent variable of interest is $CRA^i diff1$, the difference between $CRA^i rating$ and the average rating of the rivals. In Panel B, the independent variable of interest is $CRA^i diff2$, the difference between the average of $CRA^i rating$ from period *t*-4 to *t* and the average rating of the rivals for the same period. In each panel, Columns (1), (2), and (3) show the results of the test without random effects at the bond issuer level, while Columns (4), (5), and (6) show those with random effects. *SIZE* is natural logarithm of total assets of firm *j*. *LEV* is total debt divided by total assets of firm *j*. *CF* is EBITDA divided by total assets of firm *j*. *PROF* is return on assets of firm *j*. *Tangible* is property, plant, and equipment divided by assets of firm *j*. *AGE* is elapsed years from the foundation date of firm *j*. *NoR* is the number of CRAs evaluating firm *j*. Z-statistics are in parentheses using robust standard errors clustered by firm for non-random effects model. ***, ** and * denote significance at the 1 percent, 5 percent, and 10 percent levels, respectively. Pseudo-R^2 and log-likelihood (LL) are reported for the non-random and random effects models, respectively.

$$CRA^i fire_{jt} = \beta_0 + \beta_1 CRA^i Diff1_{jt} + \beta_2 SIZE_{jt} + \beta_3 LEV_{jt} + \beta_4 CF_{jt} + \beta_5 PROF_{jt} + \beta_6 Tangible_{jt} + \beta_7 AGE_{jt} + \beta_8 NoR_{jt} + \Sigma YEAR + \Sigma IND + \varepsilon^i_{jt}$$

Panel A. *CRAdiff1*

Variables	Pred. Sign	*Dependent Variable*					
		KRfire	*NICEfire*	*KISfire*	*KRfire*	*NICEfire*	*KISfire*
		(1)	(2)	(3)	(4)	(5)	(6)
Intercept		1.1263	-0.9228	-1.6443	1.1510	-0.9229	-1.6442
		(0.53)	(-0.32)	(-0.63)	(0.48)	(-0.38)	(-0.58)
CRAdiff1	-	-1.2094	-0.8578	-1.4756	-1.2691	-0.8578	-1.4756
		(-3.21)***	(-3.87)***	(-5.39)***	(-3.85)***	(-3.9)***	(-5.17)***
SIZE	-	-0.5490	-0.5324	-0.5862	-0.5805	-0.5324	-0.5862
		(-5.45)***	(-3.9)***	(-3.74)***	(-4.63)***	(-4.46)***	(-3.93)***
LEV	+	0.0028	0.0191	0.0152	0.0034	0.0191	0.0152
		(0.29)	(1.81)*	(1.4)	(0.36)	(1.9)*	(1.2)
CF	+	0.0307	0.1667	0.3121	0.0301	0.1667	0.3121
		(0.35)	(1.76)*	(2.93)***	(0.3)	(1.75)*	(2.95)***
PROF	+	0.0262	-0.0266	-0.0199	0.0270	-0.0266	-0.0199
		(0.93)	(-1.45)	(-1.16)	(1.19)	(-1.31)	(-0.93)
Tangible	-	-0.8945	-0.4310	0.0597	-0.9872	-0.4313	0.0597
		(-1.27)	(-0.54)	(0.08)	(-1.17)	(-0.52)	(0.07)

AGE	-	0.0021	0.0087	0.0047	0.0023	0.0087	0.0047
		(0.23)	(0.9)	(0.44)	(0.24)	(0.92)	(0.41)
NoR	+	1.4819	1.8867	2.4979	1.5614	1.8867	2.4979
		(4.33)***	(4.3)***	(4.54)***	(4.48)***	(5.3)***	(5.65)***
Year Fixed Effects		Y	Y	Y	Y	Y	Y
Industry Fixed Effects		Y	Y	Y	Y	Y	Y
Issuer Random Effects		N	N	N	Y	Y	Y
Model Fit		Pseudo-R^2=0.1017	Pseudo-R^2=0.1476	Pseudo-R^2=0.1931	LL = -335.3848	LL = -299.9311	LL = -199.2618
Sample Size		10,918	10,191	10,034	10,918	10,191	10,034

$$CRA^{i}fire_{jt} = \beta_0 + \beta_1\, CRA^{i}Diff2_{jt} + \beta_2\, SIZE_{jt} + \beta_3\, LEV_{jt} + \beta_4\, CF_{jt} + \beta_5\, PROF_{jt} + \beta_6\, Tangible_{jt} + \beta_7\, AGE_{jt} + \beta_8\, NoR_{jt} + \Sigma YEAR + \Sigma IND + \varepsilon^{i}_{jt}$$

Panel B. *CRAdiff2*

Variables	Pred. Sign	*Dependent Variable*					
		KRfire	*NICEfire*	*KISfire*	*KRfire*	*NICEfire*	*KISfire*
		(1)	(2)	(3)	(4)	(5)	(6)
Intercept		1.3037	-0.9190	-2.4422	1.3210	-0.9191	-2.4425
		(0.63)	(-0.31)	(-0.95)	(0.56)	(-0.38)	(-0.87)
CRAdiff2	-	-1.1711	-0.8170	-1.3389	-1.1829	-0.8169	-1.3389
		(-2.72)***	(-3.68)***	(-4.02)***	(-3.17)***	(-3.65)***	(-4.46)***
SIZE	-	-0.5478	-0.5377	-0.5649	-0.5685	-0.5377	-0.5649
		(-5.46)***	(-3.87)***	(-3.69)***	(-4.68)***	(-4.48)***	(-3.83)***
LEV	+	0.0019	0.0188	0.0208	0.0022	0.0188	0.0208
		(0.21)	(1.76)*	(1.93)*	(0.24)	(1.86)*	(1.66)*
CF	+	0.0358	0.1693	0.3224	0.0379	0.1693	0.3224
		(0.4)	(1.8)*	(3.09)***	(0.38)	(1.78)*	(3.05)***
PROF	+	0.0244	-0.0261	-0.0254	0.0242	-0.0261	-0.0254
		(0.86)	(-1.44)	(-1.54)	(1.07)	(-1.29)	(-1.17)
Tangible	-	-0.8821	-0.4867	0.1775	-0.9364	-0.4869	0.1775
		(-1.23)	(-0.61)	(0.23)	(-1.12)	(-0.59)	(0.21)
AGE	-	0.0025	0.0087	0.0046	0.0026	0.0087	0.0046
		(0.27)	(0.89)	(0.43)	(0.27)	(0.92)	(0.4)

NoR	+	1.4715 (4.37)***	1.9336 (4.33)***	2.4471 (4.57)***	1.5275 (4.5)***	1.9336 (5.4)***	2.4472 (5.61)***
Year Fixed Effects		Y	Y	Y	Y	Y	Y
Industry Fixed Effects		Y	Y	Y	Y	Y	Y
Issuer Random Effects		N	N	N	Y	Y	Y
Model Fit		Pseudo-R^2=0.0975	Pseudo-R^2=0.1516	Pseudo-R^2=0.2015	LL = -337.4613	LL = -300.8593	LL = -204.3895
Sample Size		10,918	10,191	10,034	10,918	10,191	10,034

Table 7 Robustness Check for Testing of H1 (Subsample)

This table presents coefficient estimates from the regression of equation (1) using a subsample in which at least one of the three CRAs is fired. The dependent variable is $CRA^i fire$, a dummy variable that indicates whether firm *j* fires CRA *i* after quarter *t*. In Panel A, the independent variable of interest is $CRA^i diff1$, the difference between $CRA^i rating$ and the average rating of the rivals. In Panel B, the independent variable of interest is $CRA^i diff2$, the difference between the average of $CRA^i rating$ from period *t*-4 to *t* and the average rating of the rivals for the same period. In each panel, Columns (1), (2), and (3) show the results of the probit model, while Columns (4), (5), and (6) show the results of the logit model. *SIZE* is natural logarithm of total assets of firm *j*. *LEV* is total debt divided by total assets of firm *j*. *CF* is EBITDA divided by total assets of firm *j*. *PROF* is return on assets of firm *j*. *Tangible* is property, plant, and equipment divided by assets of firm *j*. *AGE* is elapsed years from the foundation date of firm *j*. *NoR* is the number of CRAs evaluating firm *j*. Z-statistics are in parentheses using robust standard errors clustered by firm. ***, ** and * denote significance at the 1 percent, 5 percent, and 10 percent levels, respectively.

$$CRA^i fire_{jt} = \beta_0 + \beta_1 CRA^i Diff1_{jt} + \beta_2 SIZE_{jt} + \beta_3 LEV_{jt} + \beta_4 CF_{jt} + \beta_5 PROF_{jt} + \beta_6 Tangible_{jt} + \beta_7 AGE_{jt} + \beta_8 NoR_{jt} + \Sigma YEAR + \Sigma IND + \varepsilon^i_{jt}$$

Panel A. *CRAdiff1*

Variables	Pred. Sign	Dependent Variable					
		KRfire	*NICEfire*	*KISfire*	*KRfire*	*NICEfire*	*KISfire*
		(1)	(2)	(3)	(4)	(5)	(6)
Intercept		5.6962	1.9419	1.1679	9.2931	-4.8515	2.0777
		(3.48)***	(0.71)	(0.69)	(3.3)***	(-1.77)*	(0.71)
CRAdiff1	-	-0.8235	-0.4780	-0.5609	-1.3449	-0.7982	-0.9687
		(-4.77)***	(-3.06)***	(-3.29)***	(-4.48)***	(-2.8)***	(-3.12)***
SIZE	-	-0.1681	0.1503	-0.0858	-0.2725	0.2488	-0.1479
		(-2.2)**	(2.07)**	(-1.1)	(-2.09)**	(2.02)**	(-1.1)
LEV	+	0.0010	0.0048	-0.0014	0.0009	0.0074	0.0022
		(0.19)	(0.84)	(-0.24)	(0.09)	(0.75)	(0.23)
CF	+	0.0306	-0.0330	0.0165	0.0529	-0.0488	0.0490
		(0.49)	(-0.53)	(0.29)	(0.49)	(-0.44)	(0.53)
PROF	+	0.0143	0.0092	-0.0137	0.0235	0.0139	-0.0155
		(1.23)	(0.76)	(-1.13)	(1.15)	(0.63)	(-0.79)
Tangible	-	-0.3724	-0.4969	0.4295	-0.6042	-0.8182	0.5538
		(-0.63)	(-0.84)	(0.75)	(-0.59)	(-0.78)	(0.58)
AGE	-	0.0114	-0.0086	0.0018	0.0187	-0.0146	-0.0003

		(1.74)*	(-1.26)	(0.27)	(1.68)*	(-1.21)	(-0.03)
NoR	+	-0.7105	-0.5185	-0.0002	-1.1500	-0.8589	-0.0732
		(-3.6)***	(-2.33)**	(0)	(-3.45)***	(-2.27)**	(-0.2)
Year Fixed Effects		Y	Y	Y	Y	Y	Y
Industry Fixed Effects		Y	Y	Y	Y	Y	Y
Model		Probit	Probit	Probit	Logit	Logit	Logit
Pseudo-R^2		0.1852	0.2012	0.1222	0.1824	0.1990	0.1229
Sample Size		288	288	288	288	288	288

$$CRA^{i}fire_{jt} = \beta_0 + \beta_1\, CRA^{i}Diff2_{jt} + \beta_2\, SIZE_{jt} + \beta_3\, LEV_{jt} + \beta_4\, CF_{jt} + \beta_5\, PROF_{jt} + \beta_6\, Tangible_{jt} + \beta_7\, AGE_{jt} + \beta_8\, NoR_{jt} + \Sigma YEAR + \Sigma IND + \varepsilon^{i}_{jt}$$

Panel B. *CRAdiff2*

Variables	Pred. Sign	*Dependent Variable*					
		KRfire	*NICEfire*	*KISfire*	*KRfire*	*NICEfire*	*KISfire*
		(1)	(2)	(3)	(4)	(5)	(6)
Intercept		5.7338	-2.9144	1.0694	9.4005	-4.7930	1.9396
		(3.46)***	(-1.8)*	(0.63)	(3.27)***	(-1.74)*	(0.64)
CRAdiff2	-	-0.8730	-0.5921	-0.5899	-0.5515	-0.9896	-1.0228
		(-4.5)***	(-3.31)***	(-3.2)***	(-2.02)**	(-3.05)***	(-3.01)***
SIZE	-	-0.1659	0.1440	-0.0854	-0.2726	0.2412	-0.1440
		(-2.15)**	(1.96)**	(-1.09)	(-2.06)**	(1.92)*	(-1.03)
LEV	+	0.0012	0.0047	-0.0013	0.0012	0.0071	-0.0022
		(0.22)	(0.81)	(-0.21)	(0.13)	(0.71)	(-0.23)
CF	+	0.0250	-0.0262	0.0143	0.0448	-0.0416	0.0307
		(0.41)	(-0.42)	(0.25)	(0.43)	(-0.38)	(0.31)
PROF	+	0.0149	0.0095	-0.0136	0.0246	0.0145	-0.0211
		(1.28)	(0.78)	(-1.12)	(1.2)	(0.65)	(-0.93)
Tangible	-	-0.3681	-0.5143	0.4004	-0.5889	-0.8438	0.6140
		(-0.62)	(-0.86)	(0.7)	(-0.58)	(-0.8)	(0.62)
AGE	-	0.0110	-0.0085	0.0017	0.0181	-0.0146	0.0035
		(1.69)*	(-1.24)	(0.26)	(1.64)	(-1.2)	(0.31)
NoR	+	-0.6920	-0.5261	0.0104	-1.1207	-0.8729	-0.0005

	(-3.5)***	(-2.36)**	(0.05)	(-3.35)***	(-2.29)**	(0)
Year Fixed Effects	Y	Y	Y	Y	Y	Y
Industry Fixed Effects	Y	Y	Y	Y	Y	Y
Model	Probit	Probit	Probit	Logit	Logit	Logit
Pseudo-R^2	0.1809	0.2054	0.1213	0.1782	0.2036	0.122
Sample Size	288	288	288	288	288	288

Table 8 Robustness Check for Testing of H2 (Subsample)

This table presents coefficient estimates from the probit regression model (2) using a subsample in which at least one of the three CRAs is hired as an additional CRA. The dependent variable is $CRA^i diff1$, the difference between $CRA^i rating$ and the average rating of the rivals. The independent variable of interest is $CRA^i hire$, a dummy variable indicating whether bond issuer *j* hires an additional CRA at period *t*. *SIZE* is natural logarithm of total assets of firm *j*. *LEV* is total debt divided by total assets of firm *j*. *CF* is EBITDA divided by total assets of firm *j*. *PROF* is return on assets of firm *j*. *Tangible* is property, plant, and equipment divided by assets of firm *j*. *AGE* is elapsed years from the foundation date of firm *j*. *NoR* is the number of CRAs evaluating firm *j*. Z-statistics are in parentheses using robust standard errors clustered by firm. ***, ** and * denote significance at the 1 percent, 5 percent, and 10 percent levels, respectively.

$$CRA^i diff1_{jt} = \beta_0 + \beta_1 CRA^i hire_{jt} + \beta_2 SIZE_{jt} + \beta_3 LEV_{jt} + \beta_4 CF_{jt} + \beta_5 PROF_{jt} + \beta_6 Tangible_{jt} + \beta_7 AGE_{jt} + \beta_8 NoR_{jt} + \Sigma YEAR + \Sigma IND + \varepsilon^i_{jt}$$

Variables	Pred. Sign	Dependent Variable		
		KRdiff1	*NICEdiff1*	*KISdiff1*
		(1)	(2)	(3)
Intercept		-1.8387	-0.0980	1.6543
		(-1.4)	(-0.06)	(1.5)
CRAhire	+	0.2719	0.3156	0.2245
		(3.15)***	(3.27)***	(2.52)**
SIZE	-	0.0165	-0.0091	-0.0205
		(0.41)	(-0.22)	(-0.58)
LEV	+	0.0062	-0.0048	-0.0017
		(1.36)	(-0.91)	(-0.5)
CF	+/-	0.0100	-0.0757	0.0423
		(0.37)	(-1.72)*	(1.21)
PROF	+/-	0.0238	0.0051	-0.0227
		(1.22)	(0.28)	(-1.8)*
Tangible	-	0.2835	0.2502	-0.2996
		(1.1)	(0.93)	(-1.34)
AGE	-	0.0019	-0.0082	0.0069
		(0.72)	(-2.35)**	(2.27)**
NoR	+	0.2385	-0.0201	-0.1558
		(1.77)*	(-0.1)	(-1.04)
Year Fixed Effects		Y	Y	Y
Industry Fixed Effects		Y	Y	Y
Adj-R^2		0.2115	0.1645	0.1995
Sample Size		242	242	242

***, ** and * denote significance at the 1 percent, 5 percent, and 10 percent levels, respectively. See Appendix A for definitions of variables.

Highlights

- Korean bond issuers tend to fire or switch CRAs that assign lower ratings.
- With an additional CRA, the new CRA assigns a higher rating than incumbent CRAs.
- Increased competition affects the likelihood of an upgrade occurring.