Print ISSN: 2288-4637 / Online ISSN 2288-4645
doi:10.13106/jafeb.2019.vol6.no2.25

Differences among Credit Rating Agencies and the Information Environment*

Hyunjun PARK[1], Youngtae YOO[2]

Received: January 06, 2019 Revised: March 26, 2019 Accepted: March 30, 2019

Abstract

In the Korean capital market, there are three credit rating agencies. Potential credit ratings based on credibility in the financial market are calculated independently for each rating agency. It often happens that despite the fact that the grades of the rating agencies are the same and have the same rating system, their actual ratings are different, even for the same firm. In such circumstances, investors may wonder why. In this study, we assume that the cause is the information environment in which the company operates. The credit ratings of rating agencies are mainly classified into bonds or commercial papers. The bonds are rated primarily for long-term of three years or more, and commercial papers specify ratings for less than one year. The information environment to be verified in this study was observed with a commercial paper. Under the assumption the larger the analyst following is, the more transparent is the information environment, we analyzed the influence of the number of analysts following on the degree to which ratings conflicted among credit rating agencies. The results of our analysis confirmed that opinion conflict among credit rating agencies is clearly reduced for companies with good information environments.

Keywords: Credit Rating, Analyst Following, Commercial Paper, Information Environment, Financial Structure.

JEL Classification Code: G24, G32, M42, M48.

1. Introduction

Credit rating information contributes to the efficiency of the capital market while eliminating the problem of information asymmetry between companies and investors (Lu, Chen, & Liao, 2010; Tang, 2009). At the same time, it transforms a collateral-oriented financial structure into a credit-based financial environment, thereby developing the financial market (Lee & Son, 2015; Lee & Lee, 2018). In addition, a credit rating may be used in making reasonable investment decisions for investors, and as a basis for determining the price and interest rates in the market. Issuers can inform investors of their own credit ratings, thereby making it possible to attract investment while reducing funding costs. Through higher credit ratings, every firm can reduce capital costs and, at the same time, build a foundation to maintain the current stock prices. They can also raise the stock prices and diversify the business. For this reason, most firms in the capital market strive to obtain better credit ratings. This tendency is more pronounced in multinational companies.

The differences in the concepts of ownership and management in corporations has led to the agency problem. As one of the basic devices for mitigating this problem, financial statements are disclosed and audited. However, managers cannot completely avoid accounting transparency because it is exposed to incentives to pursue the firm's private interests. Accounting transparency means that accounting trends are presented consistently and are comparable in the long run, starting with compliance with accounting standards. These standards can be assessed using analyst forecasts. If more analysts report on a particular company, it will be possible to disclose a lot of information about the company, thereby eliminating information asymmetry and creating a more transparent information environment (Cheng & Subramanyam, 2008; Kim & Lee, 2018).

* This work was supported by the Incheon National University Research Grant in 2016.

1 First Author. Assistant Professor, Strategic Management and International Business, Incheon National University, South Korea. E-mail: sampark@inu.ac.kr

2 Corresponding Author. Assistant Professor, Tax and Accounting Department, Incheon National University, South Korea [Postal Address: 119 Academy-ro, Yeonsu-gu, Incheon, 22012 Korea] E-mail: ytae@inu.ac.kr

In the Korean capital market, there are three credit rating agencies: the Korea Ratings (Fitch Ratings affiliate), Korea Investors Service (Moody's affiliate) and NICE. Credit ratings are available in all sectors where credit is provided, but it is mandatory to have credit ratings, especially for corporate bills, unsecured bonds, asset-backed securities, and social overhead capital (SOC) bonds. Companies that intend to issue corporate bonds and the like must necessarily receive an evaluation from multiple rating agencies conducting at least two new assessments. Under these circumstances, it is understandable that different rating agencies set different grades for the same bond. In this study, several reasons are suggested as to why credit ratings differ between rating agencies. Each rating agency has the same rating system, but the details of the rating process may differ from one agency to the next, resulting in different grades for the same bond. If the information environment surrounding a firm is not transparent, it may be difficult for credit rating agencies to assess firms accurately (Yu, 2005; White, 2010). In other words, as information asymmetry between companies and investors grows, that between firms and rating agencies also increases. In addition, information about a company may be unclear, resulting in further disagreement among rating agencies. In this study, we can take a closer look at Korean capital markets and the influence of information asymmetry in credit ratings on those markets.

2. Literature Review

In earlier research on credit ratings, stock price responses were evaluated according to changes in credit rating. Weinstein (1977) showed evidence of a stock response during the period of 7 to 18 months before a change in credit rating, but no significant stock response at 6 months. Holthausen and Leftwich (1986) reported a negative 2-day window of excessive returns in response to a credit rating downgrade. In relation to corporate debt ratio, Goh and Ederington (1993) showed that a decline in credit ratings generally led to a decline in share prices, but in the case of a downgrade due to a change in the debt ratio, the share response was small. Hite and Warga (1997) showed that the effect on the decline of the change in price was much greater than an increase in the credit rating; that study also proved a relationship between investment grade and a drastic drop in price compared to the decline in the speculative grade. Elayan, Maris, and Young (1996) showed that reissuing of commercial papers followed a stock price decline.

The following are studies on the qualitative characteristics of credit ratings. About credit rating agencies, Becker and Milbourn (2011) argued that the quality of a credit rating increases when a Fitch rating is added to a dominant credit rating issued by Moody's or Standard & Poor's. Related to corporate governance, Ashbaugh-Skaife, Collins, and LaFond (2006) confirmed that firms with good corporate governance have better credit ratings. There is also a close relationship between credit rating and accounting information because accounting information is a significant determinant of the credit rating process. Bae, Purda, Welker, and Zhong (2013) examined the relationship between credit rating and accounting information, confirming that an initial assessment improves the quality of accounting information for firms in emerging markets. In addition, Kisgen (2009) confirmed that firms with downgraded credit ratings tend to reduce their debt ratios, while those with lower speculative ratios tend to more than double their debt ratios to reduce interest payments. Investigating the cost of capital, DeBoskey and Gillett (2013) found that corporate transparency is closely related to the variability of credit ratings and capital costs. Cheng and Neamtiu (2009) argued that positive qualitative characteristics of accounting information would improve the accuracy and timeliness of the credit rating and the quality of accounting information.

There are also studies that examine managers' use of earnings management tools to receive better credit ratings. Kim, Kim, and Song (2013) showed that managers use various earnings adjustment methods to effect credit rating changes. Alissa, Bonsall, Koharki, and Penn (2014) found evidence of abnormal earnings and real earnings management activity and how these affect firms' credit ratings. Demirtas and Cornaggia (2013) confirmed that credit rating scores are positively correlated with accruals, which are closely related to earnings adjustments. Initial credit ratings, in particular, increased sharply. Credit rating information can perform a monitoring role in the capital market while also facilitating the efficient allocation of resources. Chong, Hwang, and Kim (2015) showed that credit ratings play a role in screening for lenders and the subsequent efficient allocation of resources, assuming that there is information asymmetry in the capital market. Cheng and Subramanyam (2008) showed that the higher the analysts following, the lower the default risk and the higher the credit rating due to the monitoring effect.

3. Methodology

3.1. Hypothesis Development

As previously mentioned, there are three credit rating agencies in the Korean capital market. The three rating agencies in South Korea are the Korea Ratings (Fitch Ratings affiliate), Korea Investors Service (Moody's affiliate) and NICE. The rating systems of these agencies differ slightly. However, the number of intervals in the rating system is the same, and in all studies, the ratings of the three institutions are considered indiscriminate. Even the evaluated firms do not differentiate between the ratings from these agencies. When calculating national ratings, Fitch, Moody's and S&P Ratings use very similar parameters. In this study, we assume that the rating systems of the three agencies are very similar. As shown in the following table, The three rating agencies have the same rating system, as follows: A1, A2+, A2, A2-, A3+, A3, A3-, B+, B, B-, C, D.

Table 1: Credit Rating Structure (commercial paper)

KOREA RATINGS (a Fitch Ratings affiliate)	KOREA INVESTORS SERVICE (a Moody's affiliate)	NICE
A1	A1	A1
A2+	A2+	A2+
A2	A2	A2
A2-	A2-	A2-
A3+	A3+	A3+
A3	A3	A3
A3-	A3-	A3-
B+	B+	B+
B	B	B
B-	B-	B-
C	C	C
D	D	D

Note: In Korea capital markets, credit ratings are rated by the above three rating agencies and have the same rating system.

The definitions of the ratings are also similar. In the short term, measuring credit risk may be more useful to the commercial paper rating than to the bond rating. In the Korean capital market, it is necessary to receive credit ratings from two or more rating agencies. There are cases where two rating agencies give the same ratings, although sometimes they are determined differently from each other. Furthermore, there are some cases that earnings are managed or high accruals are reported in order to get a better rating (Kim et al., 2013; Alissa et al., 2014; Demirtas & Cornaggia, 2013). In this case, the corporation may be trying to avoid a downgrade caused by excessive accruals or masking the opacity of accounting information due to earnings management. In such cases, the higher the number of financial analysts following the firm, the better the monitoring effect is, and the more reliable the accounting information and the credit rating (Cheng & Subramanyam, 2008).

In this study, we set the following hypothesis that the differences in ratings from different rating agencies will be small when the number of analysts following is larger based on the commercial papers:

H 1: As the number of analysts following increases, differences in credit ratings among credit rating agencies will decrease.

3.2. Variables

3.2.1. Differences in Credit Ratings

To measure differences in credit ratings, we must first define a credit rating score. As identified in Table 1 above, the corporate credit rating system of each rating agency was divided into 12 levels, from A1 to D. In this study, the credit score is defined by mapping the numbers from 1 to 12 for each step; the highest (A1) is 1 and the lowest (D) is 12. Therefore, credit ratings is scored as follows (Table 2).

Table 2: Credit rating scores

Korea Ratings (a Fitch Ratings affiliate)	Korea Investors Service (a Moody's affiliate)	NICE	Credit Rating Scores
A1	A1	A1	1
A2+	A2+	A2+	2
A2	A2	A2	3
A2-	A2-	A2-	4
A3+	A3+	A3+	5
A3	A3	A3	6
A3-	A3-	A3-	7
B+	B+	B+	8
B	B	B	9
B-	B-	B-	10
C	C	C	11
D	D	D	12

Note: Credit rating score is scored on a scale of 1 to 12.

The difference in credit ratings is calculated by estimating the difference between the highest and lowest ratings of the three rating agencies. For example, assuming Korea Investors Service's rating is A2-, that of Korea Ratings is A3-, and that of NICE is A3+, the credit rating difference of the company is measured by subtracting 4 from 7. After calculating the differences between the greatest and lowest values in a given firm's CP (commercial paper) rating score by firm-year-month, we determine the sum of every monthly value to obtain the CR_diff1 variable at the firm-year level. Then, CR_diff2 variable takes 1 if a difference in ratings among credit rating agencies exists in a given firm-year-month, and 0 if not. Therefore, the CR_diff2 variable can have a minimum value 0 and a maximum value 12. CR_diff3 is a dummy variable takes 1 if there is a difference in the credit rating between credit rating agencies even once in a given year, and 0 otherwise. CR_diff1 can measure the degree of credit rating difference: that is, the greater the difference in the credit rating among the rating agencies, the higher the value that is defined. In addition, CR_diff2 refers to the frequency (by month) with which a difference is seen in the credit ratings. On the other hand, CR_diff3 measures whether there is a disagreement among agencies over the observation period of one year. In other words, CR_diff1 measures the degree of disagreement among the agencies, CR_diff2 measures the frequency of opinion differences, and CR_diff3 measures the existence of disagreement.

If the values of the CR_diff1, CR_diff2, and CR_diff3 variables are large, it means that the rating opinions differ among credit rating agencies according to the commercial papers.

3.2.2. Number of Analysts Following

ANAL_follow is the number of analysts forecasting for a given company in a relevant year. If the number of analysts is high, the monitoring effect is high. The higher the monitoring effect, the less information asymmetry there is between the investor and the firm. As a result, a large ANAL_follow is considered to be a good information environment for companies. ANAL_follow1 is defined as the number of monitored financial analysts, and ANAL_follow2 is defined by taking the natural logarithm. The definitions of specific variables are as follows.

ANAL_follow1: number of analysts providing forecasts for respective firms in the corresponding year
ANAL_follow2: natural logarithm of (1 + ANAL_follow1)

3.2.3. Research design

To test the hypothesis, we set up the following model for conducting the multiple regression analysis. The independent variables are ANAL_follow1 and ANAL_follow2, which measure the monitoring effect of financial analysts.

$$\begin{aligned} & CR_{diff}1 \text{ or } CR_{diff}2 \text{ or } CR_{diff}3 \\ & = a_0 + a_1\,(ANAL_{follow}1 \text{ or } ANAL_{follow}2) + a_2\,SIZE + a_3\,LEV \\ & \quad + a_4\,GRWA + a_5\,CFO + a_6\,LOSS + a_7\,NEGE + a_8\,TA \\ & \quad + a_9\,FY + IndustryDummy\_ + YearDummy + e \qquad (1) \end{aligned}$$

The variables SIZE, LEV, GRWA, CFO, LOSS, NEGE, TA, and FY, all of which can affect CR_diff, are included in the regression model as control variables. SIZE is the natural log of total asset. LEV is the liability divided by total asset. GRWA is sales divided by total asset. CFO is the cash flow from operations divided by total asset. LOSS is set to 0 for loss firms, and 1 otherwise. NEGE is set to 1 if capital is negative, and 1 otherwise. TA is total accruals divided by total assets. FY is set to 1 if the firm year-end occurs at the end of December and 0 otherwise.

3.2.4. Data

In this study, the sample included companies with shares traded in the Korean capital market from 2011 to 2015 according to the following criteria:

(1) Firms not belonging to the financial industry;
(2) Firms with commercial paper ratings;
(3) Firms for which financial statements are available from the KIS-VALUE database; and
(4) Firms for which analyst information is available from FnGuide.

Delisted companies were excluded from the analysis.

4. Results

4.1. Descriptive Statistics

Descriptive statistics for the period from 2011 to 2015 are provided in Table 3 below. The sample shows 616 firm-year observations. The mean value of CR_diff3, one of the main dependent variables, is 0.1753, indicating that 17.53% of the total sample showed a difference in credit rating. In addition, the mean of ANAL_follow1, an independent variable, is 14.1899, which means that 14 analysts report to an average firm. Next, we examine the control variables. SIZE is 28.6820, which means that the average total assets of the sample is KRW 2,860,449,796,792. The LEV average is 0.5090, with an average debt ratio of 50%, and the LOSS average is 00.2013, which is approximately 20%. A mean value of NEGE, representing capital impaired firms, is included in the sample of 0.0016, representing 0.16%. As shown in the table below, the normality of the distribution was not broken because of the difference between the mean and intermediate values of all the independent and control variables.

Prior to hypothesis testing, a Pearson correlation analysis of the main variables is conducted, the results are reported in Table 4. Values greater than 0.4 are presented in bold type. The dependent variable CR_diff and the independent variable ANAL_follow have a statistically significant negative relationship. The correlation between CR_diff1 and ANAL_follow1 was -0.118 and the correlation with ANAL_follow2 was -0.108, both at the 1% significance level. The correlation between the second dependent variable CR_diff2 and ANAL_follow1 is -0.142 at the 1% significance level and -0.110 with ANAL_follow2. The last dependent variable, CR_diff3, and ANAL_fall1 correlate to -0.081 at the 5% significance level, and ANAL_fall2 to -0.068 below the 10% significance level.

Table 3: Descriptive statistics

Variables	N	Mean	SD	Minimum	Median	Maximum
CR_diff1	616	1.5844	8.0887	0.0000	0.0000	154.0000
CR_diff2	616	0.9740	2.5762	0.0000	0.0000	12.0000
CR_diff3	616	0.1753	0.3806	0.0000	0.0000	1.0000
ANAL_follow1	616	14.1899	10.6084	1.0000	13.0000	38.0000
ANAL_follow2	616	2.3744	0.9266	0.6932	2.6391	3.6636
SIZE	616	28.6820	1.2832	25.2163	28.5894	32.2974
LEV	616	0.5089	0.1649	0.1095	0.5227	1.0934
GRWA	616	0.0010	0.2574	-4.0193	0.0202	0.8622
CFO	616	0.0566	0.0670	-0.1481	0.0539	0.5014
LOSS	616	0.2013	0.4013	0.0000	0.0000	1.0000
NEGE	616	0.0016	0.0403	0.0000	0.0000	1.0000
TA	616	-0.0201	0.1451	-0.6949	-0.0201	2.8622
FY	616	0.9951	0.0697	0.0000	1.0000	1.0000

Note: To reduce the effect of outliers, 1% of the upper and lower levels of all variables were winsorized.

Table 4: Pearson correlation coefficients matrix

Variables	2.	3.	4.	5.	6.	7.	8.	9.	10.	11.	12.	13.
1. CR_diff1	-0.144 (<.001)	**0.425** (<.001)	-0.118 (0.004)	-0.108 (0.007)	-0.040 (0.322)	0.143 (<.001)	-0.099 (0.014)	-0.030 (0.452)	0.087 (0.031)	0.007 (0.861)	-0.176 (<.001)	0.014 (0.734)
2. CR_diff2	1.000	**0.821** (<.001)	-0.142 (<.001)	-0.110 (0.006)	-0.074 (0.066)	0.083 (0.041)	-0.020 (0.613)	-0.023 (0.574)	0.079 (0.050)	0.032 (0.432)	-0.080 (0.048)	0.027 (0.512)
3. CR_diff3		1.000	-0.081 (0.044)	-0.068 (0.091)	-0.028 (0.493)	0.111 (0.006)	-0.031 (0.441)	-0.052 (0.197)	0.141 (<.001)	0.088 (0.030)	-0.083 (0.041)	0.032 (0.424)
4. ANAL_follow1			1.000	**0.941** (<.001)	**0.735** (<.001)	-0.082 (0.041)	0.031 (0.445)	0.184 (<.001)	-0.022 (0.593)	0.007 (0.865)	0.037 (0.358)	0.056 (0.163)
5. ANAL_follow2				1.000	**0.708** (<.001)	-0.033 (0.419)	0.039 (0.338)	0.129 (0.001)	-0.030 (0.454)	0.020 (0.621)	0.038 (0.353)	0.038 (0.353)
6. SIZE					1.000	0.115 (0.004)	0.030 (0.456)	0.003 (0.933)	0.106 (0.008)	0.015 (0.709)	-0.063 (0.116)	0.077 (0.058)
7. LEV						1.000	-0.002 (0.966)	-0.385 (<.001)	0.395 (<.001)	0.143 (<.001)	-0.169 (<.001)	-0.035 (0.384)
8. GRWA							1.000	-0.123 (0.002)	-0.128 (0.001)	-0.087 (0.031)	-0.525 (<.001)	0.077 (0.057)
9. CFO								1.000	-0.287 (<.001)	-0.123 (0.002)	-0.003 (0.951)	0.028 (0.482)
10. LOSS									1.000	0.080 (0.046)	-0.167 (<.001)	-0.081 (0.044)
11. NEGE										1.000	-0.035 (0.393)	0.003 (0.944)
12. TA											1.000	0.013 (0.750)
13. FY												1.000

Note: Bold type represents a value which the Pearson correlation coefficient is greater than 0.4.

This result supports the hypothesis that as the number of analysts following increases, opinion conflicts among rating agencies are reduced. However, since this has no effect on other variables affecting differences in credit ratings according to the results of a simple correlation analysis, it is impossible to generalize. The variables LEV, GRWA, LOSS, and TA showed a significant correlation with the dependent variable. The correlation coefficient between SIZE and CR_diff2 is -0.074 at the 10% significance level. LEV is positively correlated with three dependent variables and is below the 5% significance level. The values for each correlation coefficient are 0.143, 0.083, and 0.111, respectively. The correlation coefficient between GRWA and CR_diff1 is -0.099 at the 5% significance level, and CFO is not significant in the univariate correlation. The LOSS variable shows a positive correlation with all dependent variables at the 5% significance level, and the values were 0.087, 0.079, and 0.141, respectively. The NEGE variable shows a correlation coefficient of 0.088 at a level of 5% significance with CR_diff3. The NEGE variable shows a correlation coefficient value of 0.088. Finally, the TA variables show a negative correlation between the three dependent variables and the 5% significance levels, with values of -0.176, -0.180, and -0.083 respectively at a level of 5% significance with CR_diff3. According to the univariate analysis, the higher the debt ratio, the lower the ratio of sales to total assets and the lower the loss ratio; similarly, the smaller the accruals, the higher the value of the dependent variable.

In addition, the variance inflation factor (VIF) value is verified for each model to test for multicollinearity. All VIF values are less than 5, confirming that no serious multicollinearity problem is evident among the independent variables in the model.

4.2. Results of the Empirical Analysis

Tables 5 and 6 represent the results on the effect of the number of analysts following on the conflicts of opinion among rating agencies. This is the result of testing the hypothesis using multiple regression equation (1). The dependent variables are CR_diff1, CR_diff2 and CR_diff3, and the independent variables are ANAL_follow1 and ANAL_follow2. Table 5 shows that the coefficients of the variable representing the number of analysts following are -2.50, -2.78, and -1.62, respectively, even after controlling for various variables affecting credit ratings. That is, the results confirmed that the larger the number of analysts following, the smaller the difference in credit ratings among the credit rating agencies.

The main independent variable in Table 6 is ANAL_follow 2, which is the natural logarithm of (ANAL_follow 1 + 1). The coefficients of ANAL_follow 2 are -2.20, -1.89 and -1.49, respectively. The coefficients of CR_diff1 and CR_diff2 are negative with a significance level of 5%. Overall, the results reported in Tables 5 and 6 support the hypothesis that the larger the number of analysts following, the smaller the disagreement among rating agencies. After all, the better the information environment, the better the reliability of the credit evaluation.

Table 5: Results of the multiple regression analyses

Independent Variables	Dependent Variable: CR_diff1 or CR_diff2 or CR_diff3					
	(1) CR_diff1		(2) CR_diff2		(3) CR_diff3	
	Estimate	T-value	Estimate	T-value	Estimate	T-value
Intercept	-17.3665	-1.44	-4.2928	-1.09	-0.5985	-1.03
ANAL_follow1	-0.1291	-2.50**	-0.0469	-2.78***	-0.0040	-1.62*
SIZE	0.4523	1.08	0.1504	1.10	0.0192	0.95
LEV	3.7076	1.54	0.4933	0.63	0.1100	0.95
GRWA	-9.6461	-6.03***	-0.4116	-0.79	-0.0612	-0.79
CFO	-3.5079	-0.63	1.8858	1.03	0.1422	0.53
LOSS	-1.2274	-1.31	0.1718	0.56	0.0773	1.71*
NEGE	-7.8282	-0.99	0.8796	0.34	0.5606	1.47
TA	-18.8391	-6.56***	-1.2605	-1.34	-0.1610	-1.16
FY	5.5501	1.18	1.0428	0.68	0.2067	0.92
IndDummy	Included		Included		Included	
YearDummy	Included		Included		Included	
Adj. R^2	0.0941		0.0467		0.0505	
Obs.	616		616		616	

Note: ***, **, and * denote at the 1%, 5%, and 10% significance levels, respectively.

Table 6: Results of the multiple regression analyses

Independent Variables	Dependent Variable: CR_diff1 or CR_diff2 or CR_diff3					
	(1) CR_diff1		(2) CR_diff2		(3) CR_diff3	
	Estimate	T-value	Estimate	T-value	Estimate	T-value
Intercept	-10.9987	-1.01	-0.7552	-0.21	-0.4211	-0.80
ANAL_follow2	-1.1834	-2.20**	-0.3318	-1.89**	-0.0385	-1.49
SIZE	0.2722	0.70	0.0326	0.25	0.0145	0.77
LEV	3.9989	1.67*	0.6047	0.77	0.1189	1.03
GRWA	-9.6380	-6.01***	-0.4317	-0.82	-0.0606	-0.78
CFO	-4.4787	-0.80	1.4379	0.79	0.1136	0.42
LOSS	-1.2834	-1.36	0.1694	0.55	0.0753	1.66*
NEGE	-7.9653	-1.01	0.7557	0.29	0.5576	1.46
TA	-18.9850	-6.61***	-1.3706	-1.46	-0.1646	-1.19
FY	4.8995	1.04	0.8090	0.53	0.1864	0.83
IndDummy	Included		Included		Included	
YearDummy	Included		Included		Included	
Adj. R^2	0.0920		0.0401		0.0498	
Obs.	616		616		616	

Note: ***, **, and * denote at the 1%, 5%, and 10% significance levels, respectively.

A comprehensive analysis of Tables 5 and 6 shows that the first regression equation with the dependent variable CR_diff1 represents the most significant results. It can be seen that the regression coefficients were relatively high and that the explanatory power (R_square) is also high. CR_diff2 also showed relatively significant results, with the highest confidence level of the three models showing regression results. CR_diff3 shows the least significant result among the independent variables, but it still shows meaningful results. This confirms that the information environment has a bearing on the difference of opinion among rating agencies and that the effect on the frequency and magnitude of the difference of opinions is greater than whether there was a difference of opinion.

5. Conclusions

Credit rating information contributes to an efficient capital market while eliminating information asymmetry between companies and investors. At the same time, it helps to transform collateral-centered financial structures into credit-centered financial environments and developed financial markets. Thus, potential credit ratings based on credibility in the financial market are calculated independently for each rating agency. It often happens that despite the fact that the grades of the rating agencies are the same and have the same rating system, their actual ratings are different, even for the same firm. In such circumstances, investors may wonder why. In this study, we assume that the cause is the information environment in which the company operates. Under the assumption that the larger the analyst following is, the more transparent is the information environment, we analyzed the influence of the number of analysts following on the degree to which ratings conflicted among credit rating agencies. The results of our analysis confirmed that opinion conflict among credit rating agencies is clearly reduced for companies with good information environments.

This study can raise a new standard for investors in South Korean capital markets. A variety of corporate information can be reviewed for investment entities. Among them, credit rating information is an important factor. This study showed that the rating scale is important, but the difference of opinions among the credit rating agencies should also be noted. The information environment may be poor if there is a difference in credit ratings by the agencies, and the larger the difference in the credit rating, the worse the information environment becomes. With further development of the capital market, the information environment gradually becomes more transparent and the amount of conflict among credit rating agencies gradually decreases. Through similar additional research, we intend to investigate the possibility of a multiple evaluation system.

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