The Effect Of Credit Rating Categories On Analysts' Information Environment: Evidence From The Korean Market

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ABSTRACT

Credit ratings have been widely utilized for their ability to convey information to investors easily and quickly. Credit ratings agencies have prospered due to their superior positions in the information-gathering process in the business world. However, recent news about grade reversals, abrupt downgrades, and unanticipated bankruptcy suggests that the market value of credit ratings may have been overstated. Hence, in this study, we evaluate the legitimacy of the suggestion that credit rating categories may provide analysts with useful information.

In order to measure the variables in the information environment, we use analyst forecasts. Differences between forecasts in the various rating categories are found to be statistically significant. Furthermore, a comparative analysis of information intensity for ungraded firms with that of other firms demonstrates that overestimates of ungraded firms create problems of the same nature as those in the information environment of firms with speculative grades.

In the inter- and intra-category analyses, various factors determine the transparency of the information environment for firms of investment grade, including accruals quality, conservatism, the interest coverage ratio, and the proportion of intangible assets. However, for less credible firms, such as speculative or ungraded firms, these determinants do not function as expected. We find that the interest coverage ratio may be used to provide detailed differentiation between less credible firms. This paper introduces a new approach to credit rating categories and related strategies, emphasizing the importance of the ability to repay debt.

Keywords: Information Environment; Credit Rating Categories; Analyst Forecast; Accrual Quality

INTRODUCTION

In this paper, we empirically examine to what extent broad rating categories[1] directly impact the characteristics of the forecasts of financial analysts. Firms of investment grade, speculative grade, and no grade (ungraded firms) are considered in this study. As Easley and O'Hara (2004) asserted, analysts strive to reduce uncertainty and information asymmetry in the market by improving information quality, thereby decreasing information risk, which in turn reduces default risk (Francis *et al*., 2005). In addition to the analysis of broad rating categories, we also examine the choices open to firms at the margin of the investment and speculative grades compared to those of other firms in the same broad rating category. Finally, in order to demonstrate how these categories work, we conduct both inter-group and intra-group analyses, investigating the features of financial analyst forecasts in each category and how they differ according to the information environment within the broad rating categories. Specifically, we hypothesize that firms with good information environments, as measured by the quality of accruals, conservatism, and the interest coverage ratio (hereafter ICR), will exhibit low information uncertainty, whereas for firms with opaque information environments, as reflected by the proportion of net intangible assets, information uncertainty will be relatively high.

[1] Commonly used rating categories include AAA, AA, A, BBB, BB, B, CCC, CC, C, and D. Since no superordinate concept of rating categories has been established, we use the term "broad rating category" to distinguish investment (AAA, AA, A, BBB) and speculative (BB, B, CCC, CC, C, D) grades.

Credit ratings are qualified assessments of the probability of default. They have been associated with *ex post* payment defaults and corporate yield spreads (Anderson *et al*., 2003). Issuer credit ratings, in contrast to issue-specific credit ratings, indicate default probabilities for the entire firm, independent of the extent of the protections afforded to the firm's creditors (Cheng and Subramanyam, 2007). Investors apply credit ratings to create portfolio allocation decisions, particularly those related to pension funds. Banks and insurance companies employ credit ratings as investment standards, using them to allocate regulatory capital. Central banks use credit ratings as a proxy for the quality of collateral. Corporate managers evaluate corporate policies partly on the basis of how their firms' credit ratings may be affected (Hilscher and Wilson, 2011). Recent events and related arguments focus on the importance of understanding if ratings are appropriate for these purposes.

Reports of numerous unexpected defaults and abrupt credit downgrades in recent years call into question the informational value of credit ratings. Corporate bond issuers may have incentives to inflate or maintain credit ratings because investors use these ratings to evaluate issuers' financial circumstances and their ability to make payments. Ratings have considerable cost implications for companies, including not only the cost of capital, but also substantial capital market reactions to rating changes. Despite efforts by rating agencies to reduce opportunistic behavior, conflicts of interest may result from their dependence on rating fees paid by bond issuers. Pressure from issuers, investment banks, and commercial banks may also affect credit rating agencies (Covitz and Harrison, 2003). Since 1968, the revenue structure of credit rating agencies in the United States has moved from investor-based compensation (e.g., subscription fees received from investors) to issuer-based payments (e.g., rating fees from the assessing firms) due to increasing costs of maintaining the quality of credit ratings and growing demand for more ratings coverage (Jung *et al*., 2012).

The needs of bond issuers and the revenue structure of credit rating agencies indicate how credit ratings can have great market value, but little informational value. If this claim is correct, rating-reliant regulation may not be optimal; it may require revision or replacement by other criteria-dependent regulation. Table 1 displays the ratings performance of Korean firms listed by NICE[2] in 2010. Distinctive features are evident between firms of investment and speculative grades.

Table 1. Trends of default risk

(Unit : %)

Year	AAA	AA	A	BBB	BB	B	CCC	CC	C	Investment[a]	Speculation[b]	Total[c]
1998	0.00	0.00	0.00	0.00	4.36	36.36	100.00	0.00	-	0.00	16.67	5.88
1999	0.00	0.00	0.00	0.00	0.00	42.68	0.00	0.00	16.67	0.00	5.63	2.00
2000	0.00	0.00	0.00	0.00	2.33	12.50	0.00	0.00	0.00	0.00	2.59	1.01
2001	0.00	0.00	0.00	0.97	4.71	33.33	0.00	0.00	50.00	0.52	6.73	2.70
2002	0.00	0.00	0.00	0.00	2.50	25.00	-	0.00	-	0.00	4.40	1.42
2003	0.00	0.00	0.00	0.00	0.00	0.00	-	33.33	-	0.00	6.45	1.65
2004	0.00	0.00	0.00	0.00	11.54	7.69	100.00	-	0.00	0.00	12.20	2.17
2005	0.00	0.00	0.00	0.00	0.00	7.69	50.00	-	33.33	0.00	8.16	1.57
2006	0.00	0.00	0.00	1.23	0.00	0.00	0.00	-	0.00	0.47	0.00	0.40
2007	0.00	0.00	0.00	0.00	0.00	0.00	0.00	-	0.00	0.00	0.00	0.00
2008	0.00	0.00	0.00	1.69	0.00	2.94	0.00	-	-	0.45	1.64	0.70
2009	0.00	0.00	0.00	0.00	9.09	0.00	10.00	-	66.67	0.00	8.06	1.71
2010	0.00	0.00	0.00	0.00	0.00	10.53	12.50	-	66.67	0.00	10.87	1.63
Average[d]	0.00	0.00	0.00	0.32	3.45	8.14	9.09	3.67	30.43	0.12	5.85	1.55

a. Investment: referred to investment grade which ranges from AAA to BBB.
b. Speculation: referred to speculative grade which ranges from BB to C.
c. Total: referred to all credit grades which range from AAA to C.
d. Average: average of default rate in each grade which ranges from 1998 to 2010.

[2] NICE started off as a corporate financial center in 1985, changing its title to the Korea Investors Service in the same year. It was the very first company to evaluate corporate notes and bonds in Korea. Since December 2001, it has been affiliated with Moody's, and 50% of its shares are owned by Moody's.

Table 2. Trends of analysts following

(Unit: number)

Credit Rating		Analysts Following[a]	
Investment[b]	AAA	21.90	13.11
	AA+	21.25	
	AA	20.44	
	AA-	19.35	
	A+	15.89	
	A	13.21	
	A-	11.57	
	BBB+	10.04	
	BBB	7.57	
	BBB-	5.93	
Speculation[c]	BB+	4.26	4.68
	BB	6.11	
	BB-	2.34	
	B+	3.00	
	B	1.36	
	B-	4.13	
	CCC	4.29	
	CC	.	
	C	10.18	

a. Analysts following: the average number of analysts who analyze the identical firm.
b. Investment: referred to investment grade which ranges from AAA to BBB.
c. Speculation: referred to speculative grade which ranges from BB to C.

If the nature of credit rating lies in the prediction of default risk, then there should be the degree of one-tier difference between BBB and BB level. The difference in default risk between firms of BBB and BB levels, which are on the border of the so-called investment and speculative grades, is large. However, information on credit ratings should reflect consistent intervals in default risk between levels. Table 2 displays information related to analyst following, where similar results for firms of investment and speculative grades can be observed.

The incremental information contained in broad rating categories is the focus of the paper. The purpose of this paper is to inform analysts of the implied differences in information environment between categories. In addition to these broad rating categories, information regarding ungraded firms is also analyzed. Ungraded firms are often regarded as being guaranteed in advanced economies. However, the features and behavior of these firms in emerging markets differ from those in more advanced economies due to their desire to avoid being graded as speculative firms. Our analysis of the characteristics of firms of investment and speculative grades and ungraded firms relies on the predictions of financial analysts and the information environment in each category. Information overlooked by analysts is examined in within-group and inter-group analyses.

Previous studies have investigated the gap between investment and speculative grades by grouping together the various tiers of investment and speculative firms on the assumption that incentives to make significant economic changes are homogeneously the same. However, the economic choices of firms at the margin of the investment and non-investment grades may differ from those of other firms in the same broad rating category. We anticipate that firms at the margin are more likely to strive for a higher ratings status by improving operating performance, reducing financial leverage, increasing firm size, and reporting positive net present value (NPV) projects to demonstrate their future potential. Moreover, firms at the margin may attempt to acquire favorable ratings by offering higher fees and putting pressure on rating agencies. Given that firms at the margin of the speculative and investment grades have greater incentives and are more likely to experience more favorable ratings outcomes, the information environment in marginal firms is expected to compare favorably with those of other firms in the same broad rating category.

Finally, we investigate differences in features of financial analyst forecasts between broad rating categories. The link between the quality of financial reporting and the information environment has been the focus of several recent empirical papers (Francis *et al*., 2005; Aboody *et al*., 2005; Chen *et al*., 2007). For example, Easley and O'Hara (2004) argue that amongst other things, accounting information pertaining to a firm's expected cash flows affects the information environment. Poor-quality reporting impairs the coordination between firms and their investors with respect to firm value, thereby creating information uncertainty. Accruals quality and conservatism are directly linked to the characteristics of analyst forecasts. Accruals quality captures variations in the mapping of earnings into operating cash flows, a key element of the pay-off structure that is of interest to market participants (Francis *et al*., 2004). Conservatism has been identified in the corporate governance literature as a means of reducing information asymmetry between investors and firms. Thus, firms with good information environments, as measured by the quality of accruals and conservatism, are associated with low earnings forecast error and dispersion of forecasts. Investors therefore pay close attention to ICR, which represents grade information and ability to repay debt. This financial ratio also contributes to a good information environment. For firms with good information environments, the importance of the ICR is expected to be more pronounced for firms with undisclosed information such as intangible assets. Intangible assets include information about growth options, brand names, distribution networks, and organizational capital (Cornell *et al*., 1989). However, due to accounting reporting system, many intangible assets are omitted from the statement of financial position. Therefore, investors depend only on public information, whereas rating agencies use private information offered by management. Thus, greater information uncertainty may be associated with firms with a higher proportion of intangible assets.

This paper contributes to the finance research in the following ways. First, we contribute to the continuing policy debate regarding the proper role of credit ratings in investment and business and the call for potential alternatives to credit ratings. In the aftermath of the Enron and WorldCom tragedies, credit ratings have been criticized for their inability to predict firms' underlying default risk in a timely manner. Academic researchers have vigorously discussed the importance of the information reflected in credit ratings. However, the results of these studies have been inconclusive. In this study, we introduce a new approach to examining how information in broad rating categories can affect analyst forecasts. By reflecting different story on credit ratings, category information provides valuable guidelines for analysts.

Second, this paper adds to the extensive list of empirical papers on the information environment (Petersen and Rajan, 1994; Berger and Udell, 1995) by clarifying previously unexplored areas such as the margin of investment, ungraded firms, and firms of speculative grades. While previous studies tend to analyze the difference between firms of investment grade and those of non-investment grade by presuming that firms in the same category have identical incentives, we posit that the different incentives of firms at the margin can evoke information uncertainty. In addition, ungraded firms, such as those associated with the national government, are not subjected to rating because they are guaranteed. However, certain firms voluntarily choose to be ungraded due to the risk of being downgraded to junk status. Information uncertainty may also alert investors to the fact that certain information in ungraded firms may be similar to that of firms of non-investment grade.

Finally, interpretation of the information in broad rating categories may differ according to the information environment, especially due to the effect of accounting information, even for firms within the same broad rating category. The information environment may be affected by accruals quality, conservatism, the ICR, and the proportion of intangible assets. Accruals quality and conservatism, which may be used as a proxy for earnings quality, represent a transparent information environment characterized by relatively low information uncertainty and allowing accurate prediction of future earnings by financial analysts.

The paper proceeds as follows. We discuss related literature and the hypotheses in section 2. Section 3 outlines the research design. Section 4 provides data, while section 5 presents the empirical results. Section 6 concludes the paper.

RELATED RESEARCH AND HYPOTHESES DEVELOPMENT

Background on Credit Ratings

Credit rating agencies such as Moody's, Standard & Poor's (S&P), and Fitch assess credit risk and assign credit ratings on issues, issuers, or both. Credit risk is defined as the likelihood that a bond issuer will default due to failure to make principal and interest payments within the bond's maturity period. A credit rating is fundamentally an overall assessment offered by a rating agency about the credit default risk of an issuer. It is denoted with letter ratings. Each agency employs both ordinal (e.g., A, B, C, D) and cardinal (e.g., AAA, AA, A) ratings. For instance, S&P uses ten broad categories (i.e., AAA, AA, A, BBB, BB, B, CCC, CC, C, D). Each broad rating category from AA to CCC is divided into three subcategories, or "notches" (+/none/-). If rating agencies announce a downgrade, it means that the issuer's credit value has been reduced and the probability of default risk has increased.

Credit rating agencies also evaluate companies that can be generally classified in investment or speculative grades; the differences between these two broad categories can greatly affect a firm's ability to borrow and expand or maintain its operations. For example, an AAA bond is an investment grade bond of the highest quality. A BBB bond is of lower quality, but still qualifies for investment, while a B or CCC bond is treated as speculative, meaning that it carries considerable financial risk and should be avoided, if possible.

Investment grade bonds are rated independently. Investment grade indicates that a bond is sufficiently outstanding to be a rationally safe investment. For these bonds, a certain amount of return is guaranteed; the rating indicates a low possibility of default or other problems that might aggravate the possibility of bond repayment. Investors usually prefer the best investment grade bonds. Under certain circumstances, they may be willing or forced to accept bonds of lower grades for speculation or as part of a parcel where bonds of different grades are combined together and sold as one unit rather than individually. Risk-averse investors are watchful of bonds with low ratings, as they generally do not want to expose themselves to high and avoidable risks. In exceptional cases, some speculators may take on bonds at the higher end of the speculative rating table.

Certain types of bonds are ungraded. Generally, bonds issued by the national government are not subjected to rating because they are guaranteed. However, municipal bonds may be rated, depending on the nation and the policy of ratings agencies. Just like companies, municipalities can experience a cash flow crisis if their former investment grade bonds experience an unexpected downgrade and are classified as speculative by rating agencies, making it tough to access credit for various municipal endeavors.

The primary goal of credit assessment is to examine the ability to pay back interest and principal and prevent any possible loss to uninformed investors. Credit assessment provides opportunities to firms to fund themselves at low cost without security or guarantee. The subject of credit ratings is not a business entity (the issuer), but the issuer's respective bonds. However, credit ratings of issued bonds may be used as annual "overall performance grades". The ability to repay is widely accepted as a measure of the soundness of a firm. When it cannot pay the principal on the issued bonds, a firm is in danger of bankruptcy. In addition, credit ratings are used as the basis for determining interest rates; thus, they are closely related to the cost of capital for firms. Interested parties cannot afford to retrieve, inspect, and analyze data for all the firms in which they are interested. Therefore, credit rating agencies perform these analyses as a service. As a result, credit ratings are widely trusted in private contracting, useful in regulation of the financial industry, and helpful as a device for measuring and constraining risk. Commercial banks, insurance companies, and pension funds are among the institutions that must comply with regulatory rules based on credit ratings. Many investors can only hold bonds with investment grade ratings or must be equipped with sufficient capital based on the ratings of the bonds they hold. Thus, ratings are key in disseminating information in financial markets. They are considered important by legislators, regulators, issuers, and investors alike.

The use of credit ratings varies between nations. The U.S. began applying credit ratings to bank inspections and broadened their range of application to insurance companies, tasks on security issues, and other areas. The use of credit ratings in financial supervision is extensive in the U.S. The current global trend shows that application of credit ratings is increasing among countries in the European Union and emerging market states. U.S. banks and savings and loans companies are allowed to invest in securities of investment grade (e.g., BBB of S&P's) for pensions, securities above S&P's A grade, and money market funds above S&P's A1 grade. Securities companies are also permitted to underwrite investment level securities only. The Securities and Exchange Commission applies simplified registration and disclosure procedures for investment grade securities or asset-backed securities. Similarly, the Canadian government applies a simplified registration procedure when investment grade firms issue non-convertible bonds or preferred stocks. In Japan, firms of investment grade are allowed to issue commercial paper, and firms with grades over AA can issue Euro-Yen bonds. In Switzerland, only investment level bonds can go public. In countries with emerging markets, firms must meet certain credit grade qualifications in order to issue commercial papers (Indonesia), issue bonds overseas (Chile), or issue bonds at all (Mexico). The Taiwanese central bank can only hold bonds from other Taiwanese banks over a certain grade. The Indian Loan Investment Company can take savings from firms that meet a certain grade qualification. Korea makes less use of credit ratings in financial supervisory matters in comparison with other developed countries.

Related Research on Individual Analyst Forecasts

In this section, we describe the literature related to two frequently studied properties of analysts' earnings forecasts: the accuracy of individual analyst forecasts, and the dispersion in forecasts provided by all analysts for a firm.

Analyst Forecast Error

There are two reasons why studying the accuracy of earnings forecasts of individual analysts is important. First, investors gain from utilizing more accurate forecasts. Earnings forecasts are fundamental to analysts' stock recommendations; more accurate forecasters may provide more profitable stock recommendations, fulfilling the old saying that better input leads to better output (Loh and Mian, 2005). Second, from a researcher's perspective, identifying more accurate forecasts is important because the market's expectation should reflect the most accurate information available at any point in time in an efficient market. Research that uses analyst forecasts as a proxy for market earnings expectations should take into account differences in investors' ability to identify and weigh earnings forecasts of individual analysts (Maines, 1996).

Forecast error is also significant to analysts. Analysts who publish more accurate forecasts are likely to be rewarded, and those who publish less accurate forecasts may be forced to change brokerage houses or find a new career. Rewards for accurate forecasts may come in the form of recognition and/or career advancement (Hong and Kubik, 2003). Mikhail *et al*. (1999) examine the relation between forecast error and analyst turnover. Analysts who contribute forecasts to the Zacks database are more likely to change brokerage firms or depart the profession altogether when their forecast accuracy is lower than that of their peers. They find that the accuracy of analysts' stock recommendations is unrelated to analyst turnover, implying that analysts may have more incentive to deliver accurate forecasts than to offer profitable stock recommendations.

Forecasts from different analysts for the same firm diverge on a number of dimensions, such as age and implied information. Recent forecasts are generally accepted as more accurate (O'Brien, 1988). Gleason and Lee (2003) find that the price impact of forecasts on price depends on whether the analyst brings new information to the market. Earnings forecast revisions may bring previous forecasts closer to the current consensus (generally referred to as herding), or they may diverge from the existing consensus. Gleason and Lee (2003) show that forecast revisions are more informative (i.e., they result in greater price responses) when they diverge from the consensus. Clement and Tse (2005) show that bold (diverging) forecasts have a greater impact on price because they are more accurate than other forecasts. Moreover, they find that bold forecast revisions have a tendency to improve previous forecasts by the same analyst to a greater extent than herding forecasts. This finding is consistent with the notion that bold forecasts transfer more of an analyst's private information about the firm. In agreement with the expectations of Trueman (1994), Clement and Tse (2005) also reveal that minor forecast revisions are more highly correlated with forecast errors after revision.

Using analyst forecast data from the International Brokers' Estimate System (IBES), Clement (1999) examines the associations among analyst experience, affiliation, specialization, and forecast accuracy. Like Mikhail *et al*. (1997), Clement (1999) also finds that the earnings forecasts of analysts with more experience are more accurate. Moreover, analysts affiliated with large brokerage houses and those who cover fewer firms and industries provide more accurate forecasts. Thus, available resources and specialization have a positive impact on forecast accuracy. Jacob *et al*. (1999) argue that certain analyst–firm alignments (referred to as "analyst aptitude") may be more successful in terms of accurate forecasting because some analysts may have a natural aptitude for forecasting earnings for certain firms. Increases in firm-specific experience, as measured by the length of time over which analysts have made earnings forecasts for a firm, may simply be a manifestation of analysts' ability to forecast earnings better for that firm. They reconsider Clement (1999)'s results, illustrating that the positive association between experience and forecast accuracy diminishes after controlling for analyst–firm alignment. They conclude that analysts' aptitude rather than overall experience is more likely to explain analyst forecasting superiority.

Dispersion in Analyst Forecasts as a Measure of Investor Uncertainty

Forecast dispersion (measured as the standard deviation in analyst forecasts), which is a signal of the extent of analyst discrepancy about a firm's upcoming earnings, is frequently used as a proxy for information uncertainty. Barron *et al*. (1998), in a methodical analysis, find that the mean forecast error, forecast dispersion, and number of forecasts can be used to estimate the total uncertainty and consensus of analysts. They show that higher dispersion implies higher total uncertainty, but lower consensus. More importantly, they illustrate that forecast dispersion is a measure of analysts' idiosyncratic uncertainty, and therefore does not fully capture total earnings uncertainty. Total uncertainty is a combination of forecast dispersion and the common uncertainty shared by all analysts. Decreases in forecast dispersion may not signal a decrease in overall uncertainty, but rather a decrease in uncertainty related to the idiosyncratic component of analyst forecasts.

Barron *et al*. (2002) use the measures of consensus and uncertainty from their previous study to observe the dispersion in annual earnings forecasts between analysts before and after interim earnings announcements. They investigate the reaction to earnings announcements after gathering of private information by analysts, as observed through forecast revision activity. Release of public information such as earnings announcements may decrease the need for private information gathering. Barron *et al*. (2002) find that consensus among analysts actually decreases in the days following the earnings announcement, which is consistent with analysts embedding more private information into their forecast revisions.

Using data from the IBES, Diether *et al*. (2002) find that stocks with high (low) earnings forecast dispersion earn negative (positive) returns in the subsequent month. The difference in returns between stocks in the highest and lowest quintiles of forecast dispersion is 9.48%. They also find that the forecast dispersion effect is strongest for small stocks, although return differences in larger stocks are examined as well.

Johnson (2004) argues that the finding in Diether *et al*. (2002) is consistent with a standard asset pricing model where forecast dispersion acts as a proxy for uncertainty about an upcoming signal of the value of the underlying asset. He suggests that this effect should be most obvious in highly leveraged firms where the value of equity should increase with uncertainty, leading to lower returns in the future. Results based on IBES forecast data are consistent with these predictions; the negative relation between forecast dispersion and future returns reported by Diether *et al*. (2002) exists only for firms with dangerous debt.

This study investigates whether the information contained in broad rating categories is properly construed by financial analysts, the vital interpreters of information in capital markets. Financial analysts are generally known to be superior to common investors in terms of information acquisition and interpretation. In this study, the impact of broad rating category on two different measures, forecast error and dispersion of forecasting, is examined.

Hypotheses Development

Credit ratings offer information about the likelihood of firm default and recovery rates of generally available securities, limiting duplication of effort in financial markets. They allow rapid assessment of the broad risk properties of tens of thousands of individual securities using a single well-known scale (Becker and Milbourn, 2010). In addition, ratings are utilized extensively in regulation and private contracting, and as a means for measuring and limiting risk. The quality of ratings is thus quite significant for the proper working of the financial system. Despite the importance of a stable ratings industry, the provision of accurate ratings is complicated by the weird market structure of the industry. The ratings industry in the U.S.is controlled by only three players: Moody's, S&P, and Fitch. This could be called a monopoly structure. Second, the firms being rated pay for assessment by credit rating agencies. Once ratings are produced, they are made publicly available, and investors may utilize them free of charge. Users of ratings, such as investors who are considering buying securities, obviously desire accurate ratings. However, the firms whose bonds are being rated obviously prefer favorable ratings and may not necessarily desire accurate ones. Since the revenues of rating agencies come from issuers, a basic conflict exists between the desire of agencies to satisfy their individual paying customers and their own need to maintain the accuracy of the information they publish and the content of credit ratings for the sake of their reputation. These various industry attributes and the conflict between the needs of agencies and bond issuers have raised questions about the value of credit ratings.

The value of an agency's credit ratings, like an accountant's audit opinions, should lie in its independent, reliable assessment of a firm's financial and non-financial data. Credit ratings should predict the likelihood of default on financial obligations and the expected repayment for actual bankruptcy. However, letter ratings such as AAA, BB, and C do not always convey pertinent information for predicting default risk, although this is their primary aim. The setup of the letter grade system implies that consistent differences exist between intervals. However, based on trends of default risk (Table 1), we can infer that this difference is larger than one level for some intervals. This inconsistency is more apparent between BBB and BB levels. BBB and BB grades are commonly known as resting on the border between investment and speculative grades.

In addition to verifying the usefulness of credit rating category information, we examine the information environment of ungraded firms, which has never been done in previous research. This is an unprecedented field of study because ungraded firms are often regarded as being guaranteed in advanced countries. However, these firms have different features in emerging markets due to their desire to avoid being rated as speculative firms. It is common practice to grant ungraded firms above-average grades in emerging markets, as they are usually outstanding and well-known companies. However, these grades may be unrealistically elevated due to the absence of information for ungraded firms. Thus, we first examine the information characteristics of ungraded firms, comparing them with the information traits of firms of investment and speculative grades. If ungraded firms are incorrectly graded as average, investors may be at risk if they choose to invest in these firms. Thus, a new investment strategy is required for ungraded firms.

We employ traits of analyst forecasts to compare the information environment in respective categories. Financial analysts are known as monitors and information intermediaries. By monitoring managerial actions, analysts may reduce agency costs related to the separation of ownership and control (Jensen and Meckling, 1976). This reduction in agency cost may increase a firm's expected cash flows (Chung and Jo, 1996) and decrease its leverage, thereby reducing its default risk (Ogden, 1987). By acting as significant information intermediaries between managers and market participants (Healy and Palepu, 2001; Frankel and Li, 2004) and by engaging in private information search activities, analysts may improve the quality of information in capital markets, thereby reducing uncertainty and information asymmetry in those markets. Information risk then decreases (Easley and O'Hara, 2004), which in turn reduces default risk (Francis *et al*., 2005).

In the analysis of characteristics of firms of investment and speculative grades and ungraded firms and the predictions of financial analysts, we hypothesize that:

H1: The characteristics of analyst forecasts differ between firms of investment grade, speculative grade, and no grade.

H1a: Forecast errors of financial analysts differ between firms of investment grade, speculative grade, and no grade.

H1b: Forecast dispersion of financial analysts differs between firms of investment grade, speculative grade, and no grade.

Among companies whose credit ratings are at the border between investment and speculative grades, credit rating changes may confer greater benefits or costs in future for companies that rely more on debt financing. For instance, pension funds and financial intermediaries are officially regulated in cases of investment in firms of speculative grade, whereas individual investors may make use of the distinction between investment and speculative grades to determine their choices. Managers of firms at the margin of the speculative and investment grades also attract the attention of bondholders. Such firms may have a stronger incentive to increase or preserve credit ratings, and may attempt to inflate credit ratings by improving operational performance, decreasing financial leverage, increasing external size, and reporting positive and promising NPV projects to prove their future growth potential. Moreover, firms at the margin may obtain favorable ratings by offering higher fees to and putting pressure on rating agencies. Given that firms at the border of speculative and investment grades have these greater incentives and are more apt to report favorable ratings outcomes, the information environment in these firms is expected to be less favorable compared to that in other firms in the same broad rating category. If ratings are higher than the actual operating performance, and they do not accurately reflect the circumstances of the firm, the amount of information released may be lower compared to that of other firms. This leads to the following hypothesis:

H2: Firms whose credit ratings are at the border of the investment and speculative grades will release different amounts of information in analyst forecasts in comparison to firms of the same grade.

H2a: Firms at the border of investment and speculative grades differ in the amount of forecast error in comparison to firms of the same grade.

H2b: Firms at the border of investment and speculative grades differ in terms of forecast dispersion in comparison to firms of the same grade.

Incremental information that may be overlooked by analysts is included in our within-group and inter-group analyses. Financial analysts base their forecasts for firms in the rating categories on accounting information. These forecasts may differ due to changes in the amount of accounting information that is reported. The following hypotheses are intended to address this phenomenon.

First, the information environment on which analyst forecasts are based may change depending on the earnings quality, as estimated by accruals quality and conservatism. Specifically, firms with good information environments are expected to show a high degree of information disclosure. The results of previous studies have shown that financial analysts modify their forecasts as firms disclose information about their actual performance. Thus, this accounting information is useful in the decision-making process involved in creating analyst forecasts and stock recommendations (Imhoff, 1992). Bradshaw *et al*. (2001) define earnings quality as the magnitude of accruals, which may differ in forecasts by different analysts. Lim (2001) and Das *et al*. (1998) report that analyst forecasts are influenced by earnings quality, and that analyst forecasts shift in accordance with the predictability of earnings.

Second, we add the degree of conservatism as one of the variables related to the information environment in order to measure earnings quality. Thus, earnings quality is measured in two ways using accruals quality and conservatism in order to determine more concrete and valid information. The amount of information disclosed is therefore expected to be greater in a more transparent environment in firms with high earnings quality within the same broad rating category.

Third, the ICR may be the most appropriate financial ratio for determining the ability to repay debt, which is the information necessary to determine the broad rating category. The most important financial ratio investors should take into account when interpreting information regarding broad rating category is the one that shows whether a firm possesses the ability to repay debt. Firms of investment grade have previously demonstrated their ability to repay, so the ICR may not be as important for these firms. However, the ability to repay of firms of speculative grade or ungraded firms may still be questioned depending on the ICR even within the same broad rating category. A firm of speculative grade may be subject to arbitrage when it is relegated to a speculative grade despite its ability to repay debt. Because no information is available for ungraded firms, the extent to which they are equipped to repay debt may be unknown.

Finally, the intrinsic value of intangible assets may be questioned. Intangible assets involve growth opportunity, brand value, distribution channels, and organizational capital, including human resources. However, the verifiability and faithful representation of these firms may be low. These are subconstituents of reliability, one of the qualitative characteristics of accounting information. Financial analysts occupy a superior position to that of common investors, who must rely heavily on publicly disclosed information; however, their position may be no better than that of credit rating agencies. Thus, this paper proposes the following hypotheses based upon our suggestion that the more significant the intangible assets, the more opaque the information environment will be, making it difficult for financial analysts to interpret category information.

H3: Characteristics of analyst forecasts for firms of investment and speculative grades and ungraded firms will vary in accordance with accruals quality, conservatism, the ICR, and the proportion of intangible assets.

H3a: Forecast error for firms of investment and speculative grades and ungraded firms will vary in accordance with accruals quality, conservatism, the ICR, and the proportion of intangible assets.

H3b: Forecast dispersion for firms of investment and speculative grades and ungraded firms will vary in accordance with accruals quality, conservatism, the ICR, and the proportion of intangible assets.

RESEARCH DESIGN

Characteristics of Analyst Forecasts

We measure forecast error for each firm-year observation based on the absolute value of the difference between the firms' forecasted and actual earnings, divided by the stock price on the date of forecast:

$$FOREERROR_{it} = |\ FORECAST_{it} - EARN_{it}\ |\ /\ PRICE_{it} \quad (1)$$

where $FOREERROR_{it}$ is the absolute earnings per share forecast error of firm i in year t, $FORECAST_{it}$ is the earnings per share forecast of period t earnings, $EARN_t$ is the actual earnings per share of firm i in year t, and $PRICE_{it}$ is the adjusted stock price for firm i at the time of forecast t. Thus, a firm attribute that is positively associated with $FOREERROR_{it}$ signals that the attribute indicates less accurate analyst forecasts.

Forecast dispersion is analyzed by observing the forecast distribution of analysts in charge of forecasting for certain firms. The forecast distribution is measured using the firm-year standard deviation of forecasts.

$$DISP_{it} = STD_{it}\ /\ PRICE_{it} \quad (2)$$

$DISP_{it}$ in equation (2) represents forecast dispersion of firm i in year t. It is computed as STD_{it}, the standard deviation of analyst forecasts, divided by the beginning adjusted stock price.

Accruals Quality

Accruals quality is estimated in two ways in this paper. Current accruals are set as the dependent variable, as in Dechow and Dichev (2002). It is regressed with operating cash flows of the previous, current, and following years as independent variables. In another model developed by Francis *et al*. (2005),[3] applied in equation (4), current accruals are regressed with operating cash flows of the previous, current, and following years and changes in accounts receivable, property, plant, and equipment as independent variables.

$$TCA_t = \alpha + \beta_1\ CFO_{t-1} + \beta_2\ CFO_t + \beta_3\ CFO_{t+1} + \varepsilon_t \quad (3)$$

$$TCA_t = \alpha + \beta_1\ CFO_{t-1} + \beta_2\ CFO_t + \beta_3\ CFO_{t+1} + \beta_4\ \Delta SALES_t + \beta_5\ \Delta PPE_t + \varepsilon_t \quad (4)$$

Where

$TCA_t = \{(\Delta CURRASET - \Delta CASH) - (\Delta CURRLIAB - \Delta CURRLONGLIAB)\}\ /\ AVERAGE(ASSET)$
$CFO_t = (OPCF)\ /\ AVERAGE(ASSET)$
$SALES_t = (SALES)\ /\ AVERAGE(ASSET)$
$PPE_t = (TANASSET - LAND - CIP)\ /\ AVERAGE(ASSET)$

CURRASET : current asset
CASH : cash
CURRLIAB : current liability
CURRLONGLIAB : long-term current liability
AVERAGE(ASSET) : (total asset at time t + total asset at time t – 1) / 2
OPCF : operating cash flow
SALES : total sales
TANASSET : tangible asset
LAND : land
CIP : construction in progress

[3] Francis *et al*. (2005) develop the suggestion of Dechow and Dichev (2002) further by embracing the model of McNichols (2002). According to Francis *et al*. (2005), current accruals are influenced by operating cash flows of the previous, current, and following years, and by changes in sales and property, plant, and equipment.

The residuals in equations (3) and (4) represent the accruals that are not realized in cash flow. In this study, accruals quality is computed using the absolute value of these residuals. When this value is substantial, poor accruals quality is inferred, as accruals would not be converted to cash flow regardless of the sign (positive or negative). In other words, the figure obtained in equation (5) is negatively related to accruals quality.

$$AQ_{it} = -\left| \varepsilon_{it} \right| \tag{5}$$

Conservatism

The proxy for conservatism is obtained from the following reverse regression model of Basu (1997), which analyzes the relation between net income and stock returns. He defines conservatism as a phenomenon where a decrease in net income is immediately recognized as bad news, but reaction to an increase in income is delayed until its realization. Measurement of conservatism using net income and stock returns is based on this definition. That is, loss is more rapidly reflected in stock price than gain. Therefore, the coefficient found in regression analyses on loss and negative stock returns is more significant than that of gain and positive stock returns. In Basu's (1997) model, β_3 is an indicator of conservatism. The larger the coefficient, the more conservative the particular accounting system is.

$$XP_{\mathrm{t}} = \alpha + \beta_1 DR_t + \beta_2 R_t + \beta_3 DR_t \cdot R_t + \varepsilon_t \tag{6}$$

Where

XP_t : net income in year t/ending stock price in year t – 1
DR_t : a dummy variable that is 1 when stock return is negative, otherwise 0
R_t : accumulated annual stock return from April in year t – 1 to March in year t.

Next, we adopt the discrepancy between book and market values with reference to Feltham and Ohlson (1995) and Zhang (2000).

$$CONS = 1-(BV_t / MV_t) \tag{7}$$

Where

BV : book value;
MV : market value.

Under conservatism, net assets are under-accounted and may be of less value that market assets. In this case, book value divided by market value becomes <1. Therefore, equation (7) represents the discrepancy between book and market values, and the product is expected to be higher with increased conservatism.

Interest Coverage Ratio (ICR)

The ICR is used to determine a company's ability to pay interest on outstanding debt. The ICR is calculated by dividing a company's earnings before interest and taxes (*EBIT*) from one period by the company's interest expenses for the same period:

$$Interest\ Coverage\ Ratio = EBIT(Earnings\ before\ Interests\ and\ Taxes) / Interest\ Expenses \tag{8}$$

The lower the ratio, the more the company is burdened by debt expense. When the ICR is ≤1.5, the company's ability to meet interest expenses may be questionable. An ICR <1 indicates that the company is not generating sufficient revenues to satisfy interest expenses.

Net Intangible Assets

The value of using net intangible assets lies in accurate measurement of this variable. The market value method, abnormal earnings model, and accounting-based evaluation methods can be used for this purpose. In the market value method, intangible assets are estimated as the difference between the book value and market value of a firm. That is, the measure is computed as the difference between monetary assets in financial statements and the fair value of tangible assets based on the stock market value and fair value of liability. However, two problems arise with the market value method. Due to variability in the moment of measurement, the market value is uncertain using this method. In addition, the degree of discretion in determining the fair value of the components of liability, monetary assets, and tangible assets may be excessive. Discretion in measurement of normal earnings, abnormal earnings, and the cost of capital is a shortcoming of the abnormal earnings model of Ohlson. Nevertheless, as the model has been more often tested in research, it has become widely accepted as an appropriate model for intellectual property assessment in empirical studies evaluating intangible assets such as corporate goodwill.

In this study, an abnormal earnings model using an accounting-based valuation method which has proved effective in intellectual property assessment in previous studies is adopted to measure net intangible assets. Using the definition in Ohlson's model, firm value is the sum of the book value of equity and the present value of future abnormal earnings, as shown in equation (9).

$$P_t = y_t + \sum_{\tau=1}^{\infty} (1 + r)^{-\tau} \cdot E_t\,[x^a{}_{t+\tau}] \tag{9}$$

Future abnormal earnings is here defined as the difference between net income and the cost of capital (i.e., net income minus the beginning book value times the cost of capital).

$$x^a{}_t \equiv x_t - (\, x_t \cdot y_{t-1} \,) \tag{10}$$

The cost of capital, which can also be interpreted as normal earnings, introduces the notion of abnormal earnings. Abnormal earnings are the unexpected gain beyond normal earnings. The rate of normal earnings is required in order to compute abnormal earnings. It should be equal to the cost of capital, since the value for existing shareholders must be sustained. That is, when the future expected earnings ratio is expected to exceed the cost of capital, intangible assets derived from abnormal earnings may be approved. The return on equity (*ROE*) is often used as a proxy for the cost of capital, but we adopt the capital asset prizing model to measure the cost of capital in this study.

$$r_t = r\,f_t + \beta_t \cdot PREM \tag{11}$$

To determine a risk-free rate, the annual average return of housing corporate bonds (first class, 5 years) is applied, and for the beta coefficient, we use the figure attained from the market value model, which is adopted to calculate abnormal returns. We assume the risk premium to be 8%. Then, equation (9) is simplified as equation (12). Consequently, the market value is equivalent to the book value modified by abnormal earnings and other information.

$$P_t = y_t + \alpha_1\, x^a{}_t + \alpha_2 \upsilon_i \tag{12}$$

Elimination of υ_i, the value-relevant event that can alter financial statements but cannot be estimated, leaves us with abnormal earnings as a sole determinant of the difference between book value and market value as well as the intangible asset (goodwill). Even when the present value of abnormal earnings is not recognized as goodwill, it is ultimately reflected in the stock price, which leads to the difference between market and book values. Thus, if a firm possesses considerable intangible assets, future abnormal earnings are expected to be positive for a certain period, meaning that the market value will exceed the book value. The market value falls short of the book value in the opposite case.

The present value of future expected abnormal earnings must be measured for a certain period (t) by estimating the earnings persistence coefficient (ω) in order to calculate the present value of future abnormal earnings accurately.

$$x^{a}_{t+1} = \omega\, x^{a}_{t} + \upsilon_{t} + \varepsilon_{t+1} \tag{13}$$

$$P_{t} = y_{t} + \sum_{\tau=1} (1+r)^{-\tau} \cdot E_{t}\,[x^{a}_{t+\tau}] \tag{14}$$

Since the primary purpose of this study is not to achieve accurate measurement of intangible assets, we only consider abnormal earnings of the first year divided by total assets from equation (10) in our regression model on the assumption that firms showing considerable abnormal earnings in the first year would display relatively significant abnormal earnings in the second year as well.

Research Design for Tests of H1, H2, and H3

Paired t-test and multiple regression analysis are carried out to determine the significance of independent variables and to verify inter-category (H1, H2) and intra-category differences (H3). Forecast error and forecast dispersion are often utilized as dependent variables. Their respective definitions can be found in section 3.1.

The paired t-test for inter-group forecast errors, forecast dispersion, and other parameters is adopted to test H1, which examines differences between firms of investment and speculative grades and ungraded firms. In order to test H2, we first select the lowest of the investment grades (BBB-) and the highest of the speculative grades (BB+), using the difference in forecast error, forecast dispersion, and other parameters between the two grades to investigate differences in information environment.

By including accruals quality, conservatism, the ICR, intangible assets, and other parameters as independent variables in the regression, we analyze the information environment within intervals (H3).

$$FOREERROR(or\ DISP) = \alpha + \beta_1(INDEPENDENT\ VARIABLES) + \beta_2 ASSET + \beta_3 FOLLOW + \beta_4 DIFF + \beta_5 LEV + \beta_6\, ROE + \beta_7\, BIG4 + YEAR\_DUMMY + \varepsilon_t \tag{15}$$

Where

INDEPENDENT VARIABLES : accruals quality, conservatism, ICR, net intangible assets;
ASSET : natural log of total assets of respective firms;
FOLLOW : number of analysts providing forecasts of respective firms in the corresponding year;
DIFF : number of days between the forecast day and fiscal year-end;
LEV : leverage of corresponding firms (total liabilities / total assets);
ROE : return on equity of corresponding firms (net income / equity);
BIG4 : If one of the Big 4 auditing firms, 1, and otherwise 0.

We control for firm size (*ASSET*), measured as the natural logarithm of total assets, as a proxy for the general information environment for a firm (Atiase, 1985). In addition, we include analyst following (*FOLLOW*) in accordance with Lys and Soo (1995)'s suggestion that greater analyst following indicates more intense competition among analysts and greater incentive for analysts to enhance forecast accuracy. We further control for forecast horizon (*DIFF*), the length of time between the forecasting date and the earnings announcement date. *DIFF* is likely to affect the amount of information available to analysts and forecast accuracy, such that *DIFF* is predicted to be positively associated with forecast error. Previous research (Brown *et al*., 1987; O'Brien and Bhushan, 1990; Brown, 1993) indicates that longer forecast horizons are associated with less accurate analyst earnings forecasts. Leverage (*LEV*) captures the information demand by debtholders who are particularly concerned about downside risk (Goss and Roberts, 2009; Simnett *et al*., 2009). *BIG4* has been used as a proxy for audit quality in prior research (Behn *et al*., 2008; Byard *et al*., 2011). According to Behn *et al*. (2008), higher audit quality leads to an increase in predictability of accounting income, thus improving the forecast accuracy of analysts and reducing forecast dispersion.

We conduct an analysis on respective intervals of credit rating categories using the above regression model to identify determinants of the information environment in each credit rating category. The analysis is carried out in each category, with separate analyses for firms of the lowest investment grade and the highest speculative grade. Respective independent variables and their detailed definitions are provided in the Results section.

DATA COLLECTION

The observations are selected from firms listed on the KOSPI and KOSDAQ markets as of December 31, 2010 that satisfy the following criteria: (1) companies (except financial companies) listed on the KOSPI and KOSDAQ markets with accounts closing in December; (2) companies with credit ratings, financial statements, stock prices, and analyst forecasts available in the FN-DataguidePro and KIS-VALUE databases.

We use 11 years of data (2000 to 2010) that satisfy the above conditions. Values for analyst forecast accuracy exceeding 200% are eliminated.[4] Furthermore, to minimize the effect of outliers, the top and bottom 1% of the results for the independent and dependent variables are winsorized. A total of 317,432 firm-year-analyst observations are used for the analysis.

FINDINGS

Univariate Tests

Table 3 lists the sample distribution by fiscal year and presents means/medians for the variables.

Table 3. Descriptive statistics

Variables	N	Mean	Median	Standard Deviation	Min	Max
FOREERROR[a]	6,286	0.149	0.050	0.274	0.000	1.432
DISP[b]	5,330	0.112	0.024	2.136	0.000	154.182
AQ1[c]	5,968	-0.073	-0.048	0.082	-1.632	0.000
AQ2[d]	5,968	-0.050	-0.031	0.062	-1.582	0.000
NIA[e]	6,286	0.016	0.003	0.156	0.000	8.174
CONS1[f]	4,525	-0.439	0.000	17.397	-667.720	66.185
CONS2[g]	5,068	-0.404	0.251	22.872	-875.002	315.010
ICR[h]	4,839	2.564	2.140	2.111	-4.600	11.220
ASSET[i]	6,286	26.254	25.884	1.7213	22.355	32.740
FOLLOW[j]	6,286	7.460	4.000	8.207	1.000	45.000
DIFF[k]	6,286	177.873	177.671	65.457	1.000	364.000
LEV[l]	6,286	0.427	0.420	0.220	0.000	4.717
ROE[m]	6,286	0.083	0.102	0.798	-44.340	25.587
BIG4[n]	6,286	0.642	1.000	0.479	0.000	1.000

a. *FOREERROR* : the absolute value of the difference between the firm's forecasted and actual earnings, divided by the stock price at the forecast date.
b. *DISP* : the standard deviation of analyst forecasts, divided by the beginning stock price.
c. *AQ1* : current accruals is set as a dependent variable as in Dechow and Dichev (2002).
d. *AQ2* : current accruals is regressed with operating cash flows of the previous, current, and following years, changes in accounts receivable, property, plant, and equipment as independent variables, as developed by Francis *et al*. (2005).
e. *NIA* : the difference between net income and cost of capital (i.e., net income minus beginning book value times cost of capital) scaled by initial total assets.
f. *CONS1* : The proxy for conservatism is obtained from the model of Basu (1997), which analyzes the relation between net income and stock return.
g. *CONS2* : the discrepancy between book and market values with reference to Feltham and Ohlson (1995) and Zhang (2000).
h. *ICR* : ICR is calculated by dividing a company's earnings before interest and taxes of one period by the company's interest expenses for the same period.
i. *ASSET* : natural log of total assets of relevant firms.
j. *FOLOW* : number of analysts providing forecasts of relevant firms in the corresponding year.
k. *DIFF*: number of days between the forecast day and fiscal year-end.
l. *LEV* : leverage of corresponding firms (total liability / total assets).
m. *ROE* : return on equity of corresponding firms.
n. *BIG4* : if one of the Big 4 auditing firms, 1, and otherwise 0

[4] Eddy and Seifert (1992) also eliminated analyst forecast values with large forecast errors. Excluded data may reflect a typing or transcription error.

The dependent variables observed in the table include forecast error (*FOREERROR*) and standard deviation of forecast error (*DISP*) measured based on their respective analyst forecasts from Fn-DataGuidePro. Table 3 presents means, medians, standard deviations, minimum values, and maximum values. The observation period ranges from 2000 to 2010. Forecast error is winsorized for the 1% at the extremes. The mean value for forecast error is 0.085, and 0.0249 is the median. This connotes that the absolute maximum value of forecast error is 1.432 even after winsorizing, indicating that relatively large figures are included in the variable.

The average of number of days between the day of forecasting and fiscal year-end is 180, meaning that financial analysts usually make forecasts 180 days in advance. We can infer that firms show 45% leverage on average (mean: 0.453, median: 0.458, Table 3). The variable *ROE* displays an average of 0.121 and a median of 0.128, indicating that the average value for *ROE* of the sample firms is 12%.

Overall, no significant differences are observed between the averages for the independent, dependent, and control variables and their standard deviations. Hence, the variables are not much skewed, and bias from outliers is not considered to be significant.

Table 4 presents the correlations between variables. Apart from the control variables, all correlation coefficients of the dependent variables – *FOREERROR*, *DISP* – and independent variables – *AQ1*, *AQ2*, *NIA*, *CONS1*, *CONS2*, and *ICR* – are low. However, the forecast should be based on the signs of the coefficients rather than their absolute values. The correlation coefficients of the dependent and independent variables are negative. Thus, we can infer that the higher the value, the lower the forecast error. In addition, the *NIA* variable is positively related to the dependent variables. Thus, we can anticipate that the forecast error increases along with the proportion of intangible assets.

As Table 4 exhibits correlations only, the validity of the investigation must be ensured through a multivariate regression model including control variables. In addition, even when all results are considered, all correlation coefficients (except those for *AQ1* and *AQ2*) are <0.6, which means that multicollinearity is not a problem.

Table 4. Pearson correlation coefficients matrix

	FOREERROR	*DISP*	*AQ1*	*AQ2*	*NIA*	*CONS1*	*CONS2*	*ICR*	*ASSET*	*FOLLOW*	*DIFF*	*LEV*	*ROE*	*BIG4*
FOREERROR	1	0.667	-0.076	-0.059	0.162	-0.077	-0.335	-0.009	-0.123	-0.201	0.108	0.158	-0.183	-0.063
DISP		1	-0.056	-0.039	0.113	-0.035	-0.026	-0.044	-0.119	-0.166	0.012	0.133	-0.278	-0.062
AQ1			1	0.665	-0.058	0.032	-0.081	-0.004	0.333	0.170	0.002	0.114	0.021	0.124
AQ2				1	-0.053	0.021	-0.089	0.008	0.333	0.154	-0.001	0.125	0.033	0.134
NIA					1	-0.042	-0.026	-0.002	-0.056	-0.018	0.000	-0.006	-0.492	-0.090
CONS1						1	-0.025	0.001	0.068	-0.013	-0.004	-0.024	0.003	-0.049
CONS2							1	0.001	-0.009	0.004	0.000	-0.048	0.005	0.007
ICR								1	-0.013	-0.015	0.002	-0.019	0.004	-0.037
ASSET									1	0.560	0.009	0.405	0.020	0.365
FOLLOW										1	-0.001	0.026	0.095	0.266
DIFF											1	-0.006	-0.017	0.007
LEV												1	-0.030	0.128
ROE													1	-0.024
BIG4														1

The definitions of variables are presented in TABLE 3.

Empirical Results

This section presents evidence from the various tests of credit rating categories and how they are affected by different independent variables.

Broad Rating Category and Analyst Forecast Attributes

Table 5. Results of t-test between rating categories

	Invest. VS Speculation.				**Invest. VS Ungraded.**				**Speculation. VS Ungraded.**			
	Paired-TTEST		**F-TEST**		**Paired-TTEST**		**F-TEST**		**Paired-TTEST**		**F-TEST**	
	P-value	**T-value**	**P-value**	**F-value**	**P-value**	**T-value**	**P-value**	**F-value**	**P-value**	**T-value**	**P-value**	**F-value**
FOREERROR	<.0001	33.42	<.0001	6.52	<.0001	29.09	<.0001	1.3	<.0001	-26.21	<.0001	5.02
DISP	<.0001	23.44	<.0001	3.05	<.0001	20.48	<.0001	5296.5	0.2191	0.2191	<.0001	1735.5

The definitions of variables are presented in TABLE 3.

Table 5 presents the results of the t-test for testing of H1. H1 argues that the new category information affects the degree of information asymmetry measured by analyst forecast characteristics. The t-test is used to determine significant differences between category groups. However, we complement the analysis with regression models in the following section, since the t-test is a univariate test. For the test of information asymmetry between firms of investment and speculative grades and ungraded firms, the dependent variables (*FOREERROR* and *DISP*) are utilized in the t-test. These dependent variables are adopted again to verify the difference in averages between respective dependent variables in a paired t-test. In addition, we check the model fit by analyzing differences in variance. The difference in average is statistically significant at the 99% confidence level, with the exception of the *DISP* variable in the interval between speculative grades and no grade. The validity of the model is further ensured using the F-test (analysis of variance) by showing that the regression models of all dependent variables are statistically significant at the 99% confidence level. In the F-test, the F-value for differences in variance of firms of investment grade and no grade is 5296.54, and that for difference in variance of firms of speculative grade and no ungrade is 1735.56. This means that the ungraded firms have a different distribution in comparison with those of investment and speculative grades. In summary, this study identifies analyst forecast characteristics using two variables (*FOREERROR* and *DISP*) in predicting the information environment of firms of investment and speculative grades and ungraded firms. We find significant differences in the respective variables in all categories, thus supporting H1.

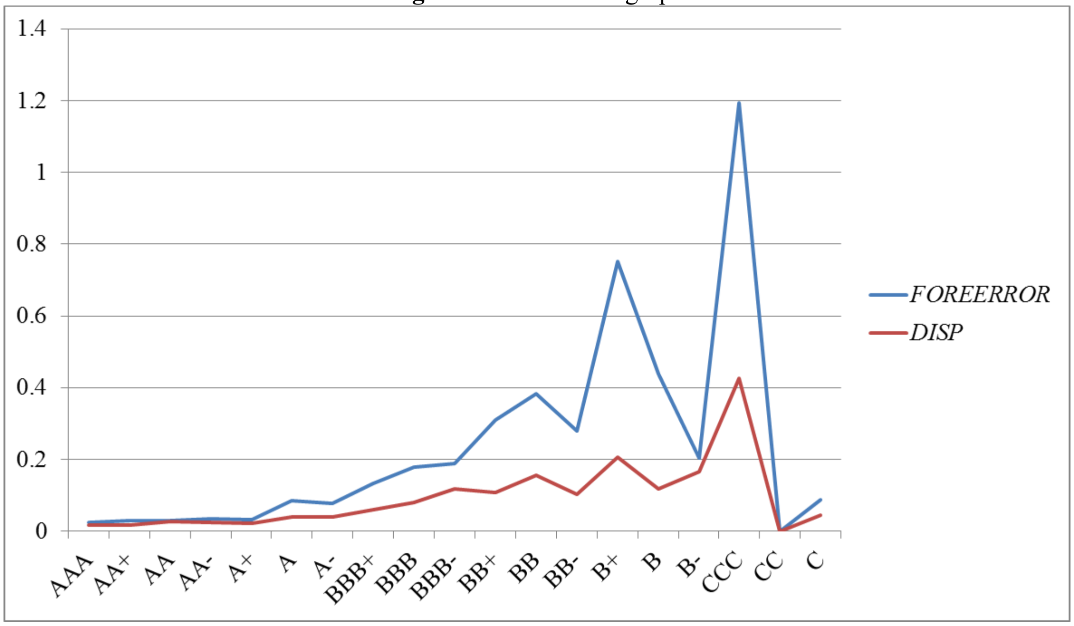
Analyses of Marginal Firms

In this section, firms at the margin of the investment and speculative grades are discussed. These firms have more incentives to manage their grades by enhancing or manipulating their performance in comparison to other firms in the same broad rating category. Therefore, the intensity of information asymmetry for these firms will be high. Hence, we take firms at the margin of the investment and speculative grades (i.e., those of BBB– and BB+ grades) and compare them to analyst forecast characteristics to gain understanding of the information environment.

Table 6. Results of the univariate test

Credit_Grade		***FOREERROR***		***DISP***	
		MEAN	**MEDIAN**	**MEAN**	**MEDIAN**
Investment Grade	AAA	0.025	0.017	0.017	0.012
	AA+	0.030	0.012	0.018	0.013
	AA	0.029	0.017	0.027	0.014
	AA-	0.034	0.017	0.024	0.013
	A+	0.032	0.017	0.021	0.013
	A	0.084	0.024	0.039	0.015
	A-	0.077	0.033	0.041	0.026
	BBB+	0.134	0.047	0.060	0.027
	BBB	0.178	0.066	0.080	0.045
	BBB-	0.189	0.042	0.119	0.031
Speculative Grade[c]	BB+	0.309	0.122	0.108	0.087
	BB	0.384	0.181	0.157	0.093
	BB-	0.280	0.063	0.103	0.035
	B+	0.753	0.966	0.206	0.164
	B	0.440	0.337	0.119	0.098
	B-	0.204	0.074	0.166	0.125
	CCC	1.193	1.432	0.426	0.566
	CC	-	-	-	-
	C	0.088	0.030	0.044	0.019

Figure 1. Fluctuation graph



The results do not support our former expectation that analyst forecast characteristics of firms at the border of investment and speculative grades would be significantly different from other firms in the same broad rating category. The underlying reason for this finding is found in the diverse methods used by these firms to achieve higher grades. When marginal firms make strenuous efforts to enhance their situation by improving performance or lowering leverage, the information environment of these firms also improves. However, if firms at the margin of the investment and speculative grades choose to manage their earnings in pursuit of a better grade, the information environment of these firms will be more intense. In this study, the different reactions of firms with identical incentives were not examined; thus, we are left with cross-dimensional or mixed results. We will rectify this drawback in future studies.

In Table 6, traits of firms of BBB– grade, the lowest of the investment grades, are closer to those of firms of speculative grade than to those of firms of investment grade. Although BBB– is officially classified as an investment grade in the market, its information environment is similar to that of speculative grades.

Within Category Analyses Using Various Independent Variables

This paper offers a profound and thorough introduction to the information environments in broad rating categories through intra-category analysis. Thus, in this section, we investigate how the information environment changes by category in accordance with the independent variables examined in this study (*AQ1*, *AQ2*, *NIA*, *CONS1*, *CONS2*, and *ICR*), the determinants of the information environment. Both *AQ* and conservatism are measured twice with models suggested by Dechow and Dichev (2002) and by Francis *et al*. (2005). All three variables – *AQ*, *CONS* and *ICR* – form a good informational environment, whereas *NIA* is associated with an opaque informational environment.

As for investment grade, forecast error is significantly and negatively correlated with accruals quality (*AQ1*, *AQ2*), meaning that the higher the earnings quality, the more transparent the information environment, which implies less forecast error. The coefficient of the proportion of intangible assets (*NIA*) is significantly positive, indicating that the more substantial the proportion of intangible assets, the higher the level of uncertainty, which brings about greater forecast error. *CONS1* and *CONS2* represent conservatism of respective firms. Through the coefficients of these variables we observe that the more conservative the firm, the lower the forecast error. Identical results are found for firms of speculative grade and for ungraded firms. As seen in Table 7, the standard deviation of analyst forecasts

(*DISP*) is identical for forecast error and the other variables. To summarize, in the analysis of firms of investment grade, accruals quality and conservatism, the variables associated with a good information environment, are seen to reduce information asymmetry within categories. By contrast, in analyzing intangible assets, which are associated with an opaque information environment, we found a variable that can intensify information asymmetry within categories. Overall, therefore, H3 is supported by the results of our analyses.

In a similar sense, *AQ1*, *AQ2*, and *NIA* are significant to the informational environment confronted by financial analysts for firms of speculative grade and ungraded firms. Likewise, *AQ1*, *AQ2*, and conservatism form a good informational environment in each category, alleviating information asymmetry, whereas *NIA* is associated with an opaque informational environment, intensifying information asymmetry. In conclusion, the corresponding variables are determinants of the kind of information environment in which financial analysts make their forecasts.

The analysis of the *ICR* variable presents rather intriguing results. Forecast error and the standard deviation of forecasts for firms of speculative grades and ungraded firms decrease with an increase in *ICR*, which represents the ability to repay debt, while the coefficient of analyst forecasts for firms of investment grade is not statistically significant. This suggests that analyst forecast activity for firms of investment grade are not significantly affected by *ICR*, whereas *ICR* conveys effective information on an opaque information environment for firms of speculative grades and ungraded firms. Traditionally, these firms are regarded as not worth investment due to their inability to repay debt in comparison to firms of investment grades. However, in the intra-group analysis, we see that the information environment may vary in firms of the same category depending on their ability to repay debt. This fact reveals that even firms of speculative grades or ungraded firms may be assessed differently in accordance with *ICR*, and that some firms may have been underestimated. Firms of investment grade display relatively less severe information environments since they are already assured in the capital market. On the other hand, firms of speculative grades and ungraded firms either exhibit no information at all or may vary in their capacity to repay debt. Thus, *ICR* plays a vital role in determining the intensity of the information environment in those firms.

Table 7. Results of multiple regression within rating categories

(Panel A. Investment Grade)

	***FOREERROR* (Investment Grade)**											
Variable	**Estimate**	**t value**	**Estimate**	**t value**	**Estimate**	**t value**	**Estimate**	**t value**	**Estimate**	**t value**	**Estimate**	**t value**
Intercept	0.192	18.50***	0.194	18.65***	0.104	10.79***	0.293	31.54***	0.482	52.32***	0.203	19.44***
AQ1	-0.132	-12.15***										
AQ2			-0.169	-11.22***								
NIA					6.663	157.80***						
CONS1							0.010	16.08				
CONS2									-0.025	-91.47***		
ICR											0.000	0.59
ASSET	-0.004	-11.15***	-0.004	-11.17***	-0.002	-6.50***	-0.008	-22.98***	-0.016	-45.30***	-0.005	-11.67***
FOLLOW	-0.001	-14.76***	-0.001	-14.99***	-0.002	-30.00***	0.000	-0.81***	0.002	27.53***	-0.001	-15.17***
DIFF	0.000	41.16***	0.000	41.10***	0.000	45.46***	0.000	43.11***	0.000	43.14***	0.000	40.93***
LEV	0.135	54.04***	0.135	53.89***	0.152	65.43***	0.077	35.80***	-0.004	-1.72*	0.138	54.27***
ROE	-0.519	-156.77***	-0.520	-156.69***	-0.661	-206.43***	-0.419	-144.99***	-0.311	-102.57***	-0.517	-154.93***
BIG4	-0.025	-16.08***	-0.025	-16.35***	-0.018	-12.44***	-0.022	-14.06***	-0.018	-11.96***	-0.027	-17.22***
YEAR_DUMMY	INCLUDED		INCLUDED		INCLUDED		INCLUDED		INCLUDED		INCLUDED	
Adj. R square	0.2450		0.2449		0.3495		0.2062		0.2526		0.2440	

	***DISP* (Investment Grade)**											
Variable	**Estimate**	**t value**	**Estimate**	**t value**	**Estimate**	**t value**	**Estimate**	**t value**	**Estimate**	**t value**	**Estimate**	**t value**
Intercept	0.086	21.67***	0.086	21.76***	0.051	14.11***	0.127	35.31***	0.199	55.69***	0.092	23.17***
AQ1	-0.049	-11.98***										
AQ2			-0.066	-11.57***								
NIA					2.553	159.38***						
CONS1							0.002	7.08				
CONS2									-0.009	-85.57***		
ICR											0.000	0.82
ASSET	-0.001	-10.09***	-0.001	-10.08***	-0.001	-5.30***	-0.003	-22.66***	-0.006	-44.48***	-0.002	-11.10***
FOLLOW	0.000	-12.27***	0.000	-12.48***	-0.001	-27.46***	0.000	8.29***	0.001	36.00***	0.000	-12.23***
DIFF	0.000	4.98***	0.000	4.93***	0.000	6.49***	0.000	2.64***	0.000	1.36	0.000	4.82***
LEV	0.043	44.76***	0.042	44.59***	0.049	55.58***	0.030	35.91***	0.001	0.59	0.043	45.23***
ROE	-0.173	-137.38***	-0.173	-137.38***	-0.227	-187.03***	-0.167	-148.95***	-0.128	-108.54***	-0.172	-135.87***
BIG4	-0.012	-19.70***	-0.012	-19.95***	-0.009	-16.26***	-0.012	-20.04***	-0.011	-18.18***	-0.012	-21.22***
YEAR_DUMMY	INCLUDED		INCLUDED		INCLUDED		INCLUDED		INCLUDED		INCLUDED	
Adj. R square	0.2261		0.2261		0.3352		0.2002		0.2424		0.2239	

(Panel B. Speculative Grade)

	FOREERROR (Speculative Grade)											
Variable	**Estimate**	**t value**	**Estimate**	**t value**	**Estimate**	**t value**	**Estimate**	**t value**	**Estimate**	**t value**	**Estimate**	**t value**
Intercept	-0.320	-2.65***	0.299	2.42***	1.049	8.90***	0.694	3.57***	1.047	5.77***	1.320	11.02***
AQ1	-3.127	-29.19***										
AQ2			-3.513	-20.33***								
NIA					5.085	13.52***					0.77	
CONS1							-0.060	-3.99***				
CONS2									-0.001	-0.18		
ICR											-0.031	-2.58***
ASSET	-0.024	-5.48***	-0.042	-9.16***	-0.062	-13.66***	-0.039	-4.99***	-0.054	-7.38***	-0.074	-16.22***
FOLLOW	-0.006	-7.72***	-0.008	-10.25***	-0.014	-15.02***	0.002	2.74***	0.004	5.14***	-0.009	-10.19***
DIFF	0.000	8.31***	0.000	6.91***	0.000	8.09***	0.000	5.79***	0.000	5.54***	0.000	6.82***
LEV	1.123	24.85***	1.066	22.16***	0.908	16.86***	0.958	14.23***	1.054	15.80*	1.212	24.13***
ROE	-0.431	-20.06***	-0.370	-15.46***	-0.218	-6.53***	-0.805	-18.12***	-0.882	-21.93***	-0.555	-19.38***
BIG4	-0.067	-5.11***	0.014	0.99	0.093	4.11	-0.227	-11.30***	-0.236	-11.77***	0.011	0.77
YEAR_DUMMY	INCLUDED		INCLUDED		INCLUDED		INCLUDED		INCLUDED		INCLUDED	
Adj. R square	0.5988		0.5541		0.5264		0.8288		0.8266		0.5019	

	***DISP* (Speculative Grade)**											
Variable	**Estimate**	**t value**	**Estimate**	**t value**	**Estimate**	**t value**	**Estimate**	**t value**	**Estimate**	**t value**	**Estimate**	**t value**
Intercept	-0.103	-2.33**	0.484	10.35***	0.362	8.51***	-0.563	-10.39***	0.051	0.88	0.440	10.28***
AQ1	-1.015	-25.98***										
AQ2			0.164	2.50								
NIA					1.377	10.07***						
CONS1							-0.093	-22.57***				
CONS2									-0.002	-2.37**		
ICR											-0.001	-3.09***
ASSET	-0.004	-2.32**	-0.022	-12.42***	-0.017	-10.25***	0.023	10.33***	-0.001	-0.58	-0.020	-12.36***
FOLLOW	-0.003	-9.30***	-0.004	-11.85***	-0.005	-14.88***	-0.001	-3.02***	0.002	8.17***	-0.004	-11.71***
DIFF	0.000	0.92	0.000	0.35	0.000	1.07	0.000	-0.17	0.000	-1.16	0.000	0.27
LEV	0.193	11.70***	0.230	12.63***	0.139	7.11***	0.074	3.96***	0.223	10.38***	0.223	12.39***
ROE	-0.100	-12.82***	-0.145	-16.07***	-0.048	-3.92***	-0.340	-27.21***	-0.471	-35.87***	-0.143	-14.04***
BIG4	-0.001	-0.14	0.025	4.90	0.047	8.51	-0.080	-14.27***	-0.101	-15.45***	0.025	2.75
YEAR_DUMMY	INCLUDED		INCLUDED		INCLUDED		INCLUDED		INCLUDED		INCLUDED	
Adj. R square	0.5281		0.4377		0.4526		0.9193		0.8873		0.4368	

(Panel C. Ungraded)

	***FOREERROR* (Ungraded)**											
Variable	**Estimate**	**t value**	**Estimate**	**t value**	**Estimate**	**t value**	**Estimate**	**t value**	**Estimate**	**t value**	**Estimate**	**t value**
Intercept	0.217	11.69***	0.260	14.17***	0.144	8.16***	0.285	16.22***	0.383	21.57***	0.306	15.76***
AQ1	-0.109	-7.86***										
AQ2			0.019	1.00								
NIA					2.969	49.03***						
CONS1							-0.014	-16.07***				
CONS2									-0.025	-28.95***		
ICR											0.006	-9.46***
ASSET	-0.006	-8.74***	-0.008	-10.93***	-0.003	-5.08***	-0.009	-12.82***	-0.013	-19.53***	-0.008	-10.72***
FOLLOW	-0.002	-17.71***	-0.002	-16.57***	-0.002	-21.15***	-0.001	-6.86***	0.001	6.68***	-0.002	-18.29***
DIFF	0.000	29.21***	0.000	29.16***	0.000	31.04***	0.000	23.70***	0.000	23.19***	0.000	26.79***
LEV	0.158	34.89***	0.161	35.43***	0.178	39.99***	0.131	28.41***	0.091	19.45***	0.167	31.80***
ROE	-0.273	-41.18***	-0.266	-40.30***	-0.428	-59.02***	-0.259	-37.21***	-0.195	-26.93***	-0.327	-43.16***
BIG4	-0.019	-8.79***	-0.019	-8.64***	-0.026	-12.04***	-0.015	-6.28***	-0.008	-3.15***	-0.040	-16.82***
YEAR_DUMMY	INCLUDED		INCLUDED		INCLUDED		INCLUDED		INCLUDED		INCLUDED	
Adj. R square	0.1149		0.1140		0.1464		0.0843		0.0954		0.1464	

	***DISP* (Ungraded)**											
Variable	**Estimate**	**t value**	**Estimate**	**t value**	**Estimate**	**t value**	**Estimate**	**t value**	**Estimate**	**t value**	**Estimate**	**t value**
Intercept	0.171	19.79***	0.159	18.61***	0.090	10.91***	0.147	17.91***	0.196	23.49***	0.126	15.57***
AQ1	-0.084	-12.91***										
AQ2			-0.083	-9.41**								
NIA					1.375	48.67***						
CONS1							-0.007	-17.84***				
CONS2									-0.013	-31.06***		
ICR											0.005	-11.00***
ASSET	-0.004	-13.74***	-0.004	-12.61***	-0.002	-5.15***	-0.004	-11.93***	-0.006	-19.14***	-0.002	-5.19***
FOLLOW	0.000	-8.91**	0.000	-9.30***	-0.001	-14.77***	0.000	-2.03**	0.001	11.65***	-0.001	-23.21***
DIFF	0.000	1.47	0.000	1.43	0.000	2.87***	0.000	-0.81	0.000	-1.69*	0.000	1.89*
LEV	0.050	23.44***	0.047	22.23***	0.056	26.93***	0.035	16.30***	0.015	6.78***	0.046	21.21***
ROE	-0.059	-18.97***	-0.061	-19.94***	-0.139	-40.99***	-0.070	-21.32***	-0.036	-10.54***	-0.123	-38.79***
BIG4	-0.005	-4.95	-0.005	-5.32**	-0.009	-8.58***	-0.002	-1.59	0.002	1.84*	-0.016	-15.85***
YEAR_DUMMY	INCLUDED		INCLUDED		INCLUDED		INCLUDED		INCLUDED		INCLUDED	
Adj. R square	0.0902		0.0890		0.1209		0.0650		0.0762		0.1437	

*** Significant at the 1% level. ** Significant at the 5% level. * Significant at the 10% level. The definitions of variables are presented in TABLE 3.

CONCLUSION

Credit ratings have been widely utilized for their ability to convey information to investors easily and quickly. Credit ratings agencies have prospered due to their superior positions in the information-gathering process in the business world. However, recent news about grade reversals, sudden downgrades, and unanticipated bankruptcy suggests that the informational and market value of credit ratings has been overstated. In addition, the objectivity of the revenue structure has been called into question, as credit ratings agencies are paid by the very firms they are assessing.

In order to measure the variables in the information environment, we use analyst forecasts. Differences between forecasts in the various rating categories are found to be statistically significant. Furthermore, by scoring firms at equal intervals on the grading scale, we find that firms with outstanding (i.e., investment) grades enjoy a relatively better information environment. Our analysis of the effect of the information environment on ungraded firms is unique in the literature. Ungraded firms in developed countries are often supported with national bonds. However, ungraded firms in the Korean market may be graded as investment or speculative firms. Firms that are in danger of receiving a speculative grade have greater incentive to improve their information environment. They may prefer to be ungraded rather than to risk loss of debt financing due to the "scarlet letter on their chests". Because very little information is available to investors about these firms, except for a few firms with excellent credibility, we believe that the results of this study will be useful to analysts. The results demonstrate that the information environment in ungraded firms is similar to that of companies of speculative grade. That is, ungraded firms which may be similar to companies of average grade are analogous to firms of speculative grade in terms of the intensity of the information environment. Hence, ungraded firms warrant careful observation.

Future costs perform a critical function, providing incentives to firms to strive towards a better credit rating in a higher category. Hence, we test whether firms at the margin of the investment and speculative grades are more motivated to achieve investment grade rating. The results demonstrate that firms of the lowest investment grade or the highest speculative grade do not appear to impose a more severe information environment in comparison with the other firms in the corresponding categories. In fact, every firm is motivated to aspire to an investment grade, though they may achieve this status differently. The intensity of the information environment may change drastically depending on the ways in which firms achieve their goals. These differences may explain this result.

Lastly, after introducing new, useful credit categories, we conduct additional inter- and intra-category analyses. Using these categories, more detailed information about less credible firms may be presented to investors. Determinants such as accruals quality, conservatism, the *ICR*, and the proportion of intangible assets build the information environment in each category. Accruals quality, conservatism, and the proportion of intangible assets have statistically significant effects on the information environment. On the other hand, the *ICR* is shown to be a powerful determinant of the information environment for ungraded firms and those of speculative grades. However, this is not true for firms of investment grade. Unlike these latter firms, which attract much public attention and for which much information is available to the public, speculative or ungraded firms may remain unnoticed, or, even worse, their status may remain undisclosed. Nevertheless, our results suggest that assessment of these firms may be modified in accordance with their actual ability to repay debt. This finding indicates that investors may anticipate gains from arbitrage transactions with underestimated firms within a given category.

This research shares certain fundamental similarities with previous studies based on information available to financial analysts. However, we extend the former discussion by conducting inter- and intra-interval analyses. The categories introduced here may be more useful to investors than biased credit rating grades. Another noteworthy contribution of this study lies in the examination of ungraded firms and their information environment, and their similarity to firms of speculative grade.

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NOTES