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# THE EFFECTS OF NEWS SENTIMENT AND COVERAGE ON CREDIT RATING ANALYSIS

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## Abstract

*Credit ratings convey credit risk information to participants in financial markets, including investors, issuers, intermediaries and regulators. This paper proposes an automatic text analysis system for financial news and analyzes the effects of news coverage and sentiment factors on credit ratings. Our experiment results show that firms with higher news coverage received worse ratings in the next quarter. The effect is especially stronger for speculative grade firms. We have also found that news polarity is linked to credit rating in the following quarter for investment grade firms. These results suggest that news data are useful in credit rating modelling and should not be omitted in this type of research.*

*Keywords: credit rating, text mining, news coverage, sentiment score.*

# 1 INTRODUCTION

Credit risk management is one of the core issues in banking and insurance industries. In order to manage credit risk, researchers and rating agencies have developed statistical and artificial intelligence (AI) models to measure the creditworthiness of obligors and their obligations. Current credit rating models mainly adopted two types of input variables (e.g., Huang et al. (2004), Cao et al. (2006) and Chen and Shih (2006)). The first type of variables is accounting numbers published in financial reports. It is believed that the performance reported in the balance sheets can truly reflect worsening credit quality in vulnerable companies (e.g., Beaver (1966), Altman (1968) and Ohlson (1980)). The other type of variables is obtained from financial markets. Examples include stock returns, debt prices and activities in related derivatives. Financial market variables may complement accounting variables by providing updated information between quarter and annual announcements.

Based on Merton's (1973) credit rating study, rating agency Moody's developed KMV model based on market variables and their idea is low stock price implies that a firm has higher probability to default. They used distance to default (DD) to measure a firm's credit risk. However, the timeliness of financial market variables comes with the disadvantages of higher noise and potential biases. It means that financial market variables may be very volatile compared to the accounting variables. Moreover, market frenzy may bias the results, which make the outcome misleading. A case in point is Enron (Bharath and Shumway (2008)), which is indicative of pitfalls of relying on market information. The probability of default from market-based models was lower than that assigned by agency ratings when Enron's stock price was artificially high before bankruptcy.

Current credit rating studies, nonetheless, ignore the fact that qualitative public information sources such as news papers and newswires may complement existing independent variables and improve the performance of credit rating models. Public qualitative information may improve credit rating models for the following reasons. First, news about a firm may provide early warning or clues on its deteriorating credit situation before accounting numbers in financial statements are communicated to investors. For privately held firms, news is even more valuable because these firms lack market information. Second, news sources may provide useful information for firms with illiquid stocks since their market prices can deviate from their true values. News may provide additional information for firms with poor accounting quality caused by accounting manipulations. Finally, media reports and exaggerates may induce depositors or lenders withdrawing their funds and further cause bankruptcy of unhealthy firms or a run on the bank.

Motivated by the deficiency of existing credit rating studies, we aim at utilizing rich news information to create additional predictors for credit ratings. We design a firm-based news coverage and sentiment analysis system to study whether news coverage and news sentiment can be used to explain the cross-sectional variation of credit ratings assigned by rating agencies. We contribute to the credit rating literature by expanding the information set for credit rating modelling to include sentiment components in public media to explain the variation of issuer ratings. The remainder of this paper is organized as follows. In Section 2, we briefly introduce the studies on the economic impact of mass media, credit rating predictors, and the modelling techniques. In Section 3, we propose research questions according to our additional predictors. In Section 4, we describe our testbed, the automatic news coverage and sentiment analysis system, and empirical models. Our experiment results are presented and discussed in Section 5. We conclude our discussion with a summary of further research directions in Section 6.

## 2 BACKGROUND

We first review recent studies on the economic impact of mass media, followed by a summary of financial ratios adopted in credit rating prediction literature. The credit modelling techniques are then presented.

## 2.1 Economic Impacts of Mass Media

Recent financial studies in stock markets found that media coverage and its sentiment are related to stock performance. For example, Chan (2003) found that stocks experienced strong drift after bad news. Tetlock (2007, 2008) discovered that the fraction of negative words in firm-specific news predicted low earnings and stock returns. The results in Fang and Peress (2009) further showed that media coverage is a factor to explain expected stock returns.

To the best of our knowledge, news effects on credit risk have not been investigated in previous studies. The relationships between mass media and firms' credit rating posit a valuable research question that warrants more research efforts.

## 2.2 Credit Rating Predictors

There are several dimensions to describe the financial health of a firm according to their accounting numbers. Ratio analysis is widely adopted in credit rating (score) analysis. Altman's Z-Score models (1968) were based on five financial ratios to create a measure (a credit risk score) that best discriminates between firms that fail to fulfil their financial obligation and those that do not. Z-Score was widely applied in industry because failing firms exhibit ratios and financial trends very different from those companies that are financially sound. Ohlson's O-Score (1980) depended more on financial ratios and this measure was obtained using logit regression. Huang et al. (2004) adopted 21 financial ratios in Taiwan and U.S. markets and found that different factors contributed to issuer ratings in two markets. Cao et al. (2006) proposed 17 variables in five accounting categories and one market category for bond rating prediction. Chen and Shih (2006) used financial ratios and three addition new variables to capture market information and financial health in financial sector issuer credit rating prediction.

Table 1 summarizes important financial ratios considered in the previous studies. We divide these ratios into five categories: size, financial leverage, profitability, interest coverage and liquidity. The size ratios measure the company's book value, market value and debt capacity. The financial leverages measure the proportion of fund coming from borrowing. The profitability ratios measure the different kinds of profits before and after costs relative to its assets, equities or sales. A company's return on sales and return on equity, for example, provides information about different dimensions of its profitability. The interest coverage ratios measure earning capacity to cover its interest or debt. The liquidity ratios measure the ability of the firm to meet its short-term financial obligations in the future.

Category	Financial ratio name & description (Variable)
Size	Total assets(Z1) Total liabilities(Z2) Market size(Z3) Book to market value(Z4)
Financial leverage	Long-term debts / total invested capital(Z5) Debt ratio(Z6) Debt / equity(Z7)
Profitability	Return on total assets(Z8) Return on equity(Z9) Operating income before depreciation / sales(Z10) Operating income / received capitals(Z11) Non-operating income / sales(Z12) Net income before tax / received capitals(Z13) Net income before tax / sales(Z14) Gross profit margin(Z15) Net profit margin(Z16) Earnings per share(Z17) Retained earnings / total assets(Z18)
Interest coverage	EBIT interest coverage(Z19) EBIT / total debt(Z20)
Liquidity	Current ratio(Z21) Quick ratio(Z22)

Table 1. List of financial ratios

## 2.3 Modelling Techniques for Credit Rating Prediction

Ratio analysis and bankruptcy studies apply either statistical methods or AI methods. Statistical methods include ordinary least square, discriminant analysis, logit and probit models (Beaver (1966), Altman (1968), Altman (1977), Ohlson (1980) and etc.). AI methods cover neural networks, expert systems, decision trees and support vector machines (SVM). While AI methods were reported to outperform statistical methods in rating and bankruptcy predictions (e.g., Huang et al. (2004), Kim (2005), Min and Lee et al. (2006), Cao et al. (2006), Chen and Shih (2006), Lee (2007) Huang et al. (2007) Tsai and Wu (2008), Yu et al. (2008) and Bellotti and Crook (2009)), statistical methods usually generate models that are easier to interpret. Our study aims at understanding the value of qualitative public information on credit rating modelling. Statistical methods are preferred because of their interpretability and simplicity. We briefly illustrate two statistical methods, ordered logit and ordered probit models.

In both ordered logit and ordered probit models, we have a measurement model in which a latent variable  $y^*$  is mapped to an observed variable  $y$  according to the following measurement equation:

$$y_i = m \quad \text{if} \quad c_{m-1} \leq y_i^* < c_m \quad \text{for} \quad m = 1 \dots J.$$

The  $c$ 's are the cutpoints for the  $J$  categories,  $c_0 = -\infty$  and  $c_J = \infty$ . The structural model for the latent variable  $y^*$  is of the following function form

$$y_i^* = \alpha + \sum_{l=1}^K \beta_l Z_{il} + \varepsilon_i,$$

where  $\alpha$  is the intercept term,  $K$  is the number of explanatory variables  $Z$  and  $\varepsilon$  denotes an error term. Under this settings, maximum likelihood (ML) can be used to estimate the regression of  $y^*$  on  $Z$ . To apply ML, we must assume a specific form of the error distribution and this is the difference between logit models ( $\Lambda(\varepsilon) = \frac{\exp(\varepsilon)}{1 + \exp(\varepsilon)}$ ) and probit models ( $\Phi(\varepsilon) = \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{\varepsilon} \exp(-\frac{x^2}{2}) dx$ ).

For the ordered logit model, the log likelihood equation can be written as

$$\ln L(\beta, c | y, Z) = \sum_{j=1}^J \sum_{y_i=j} \ln \left[ \Lambda \left( c_m - \alpha - \sum_{l=1}^K \beta_l Z_{il} \right) - \Lambda \left( c_{m-1} - \alpha - \sum_{l=1}^K \beta_l Z_{il} \right) \right].$$

For the ordered probit model, its log likelihood function as follows

$$\ln L(\beta, c | y, Z) = \sum_{j=1}^J \sum_{y_i=j} \ln \left[ \Phi \left( c_m - \alpha - \sum_{l=1}^K \beta_l Z_{il} \right) - \Phi \left( c_{m-1} - \alpha - \sum_{l=1}^K \beta_l Z_{il} \right) \right].$$

## 3 RESEARCH QUESTIONS

Our research aims at investigating the relationships between the mass media and issuer credit rating. The following three research questions were studied. First, does the amount of news coverage for a firm have impacts on its future rating after controlling other financial ratios? We speculate that higher news coverage may be driven by the change of firms' credit risk.

Second, how does news sentiment affect issuer credit rating? To be specific, is negative sentiment associated with low future rating and positive sentiment associated with high future rating? If bad news affects stock performance through investors sentiment as previous studies found, rating agencies may give a negative outlook or rating in the future.

Finally, do these results change if we consider only investment grade firms or speculative grade firms?

## 4 RESEARCH METHODOLOGY

Our independent variables came from two different sources. Financial ratios were downloaded from Compustat and news data were from the Wall Street Journal (WSJ). We extracted firm names in WSJ and linked news articles to publicly traded companies. Accordingly, we matched financial ratios and news information as our independent variables. Dependent variables are Standard & Poor's long-term issuers' credit rating downloaded from Compustat. We investigated their relationships using ordered logit and ordered probit models.

### 4.1 Research Testbed

Quarterly accounting variables from 1999 to 2006 were compiled from S&P Compustat dataset. We collected 283,457 WSJ news articles spanning from August 1999 to February 2007. To conduct firm-based news coverage and sentiment analysis, we created an automatic system that extracted and standardized firm names. We defined that a firm received news coverage in a news article if its name appeared at least once in the article.

We merged financial ratios and issuer ratings with news variables by firm ID (PERMCO). All missing values are discarded and the financial service companies with the SIC code 6000-6999 were also excluded from the study since they are subject to regulations and adopt different accounting conventions. Three credit rating classification tasks were considered: five-category classification (AA, A, BBB, BB, and B), investment grade classification (AA, A, and BBB), and speculative grade classification (BB, and B). Rating agencies explained that firms with ratings BBB and above indicated they have capacity to meet their financial commitments while firms with ratings below BBB are less likely to pay back its creditors and not suitable for investment by fiduciary organizations. Our sample consisted of 3892 firm-year. Figure 2 plots the distribution by ratings in years.

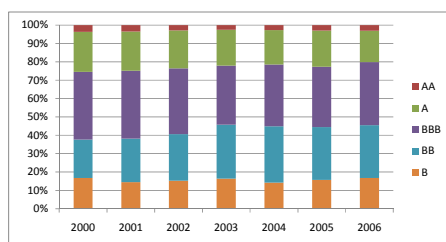


Figure 2. Distributions of credit ratings

### 4.2 News coverage and sentiment scores

We used the WSJ, a leading daily newspaper in U.S., as the representative source of financial news. The circulation of the WSJ ranked the second as of March, 2008. Our collection contained 283,457 news articles spanning from August 1999 to February 2007. To conduct firm-based news coverage and sentiment analysis, we created an automatic system that extracted and standardized firm names. We adopted firm-based news coverage and defined that a firm received news coverage in a news article if its name appeared at least once in the article. This procedure implicitly assumed that all firms mentioned in a news article are equally important.

We also designed and implemented a system that automatically computes the sentiment of firm-based news. The rational is to associate positive and negative sentiment words to firms mentioned in news articles. According to these positive and negative word counts, we further created one sentiment score. Therefore, our system consisted of two major modules: firm name extraction and sentiment analysis. For ease of exposition, we depicted our system structure in Figure 3.

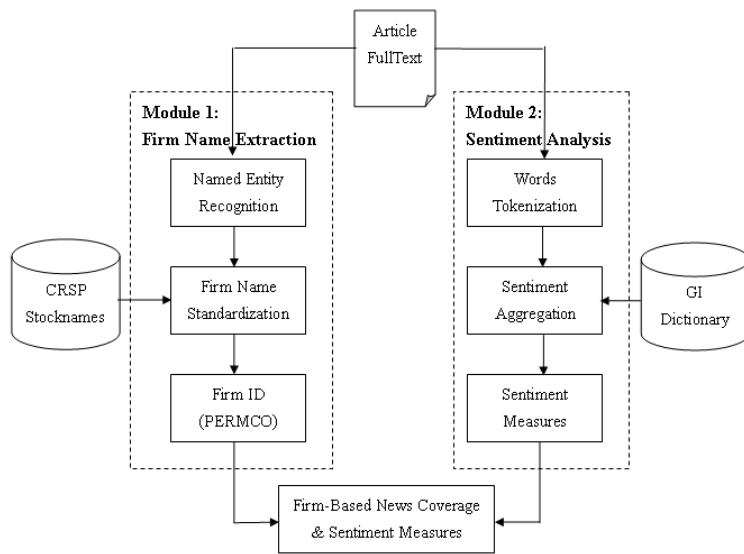


Figure 3. Firm-based sentiment analysis

The first module performs named entity recognition and standardizes the recognized company names by consulting the stocknames table in CRSP monthly stock price dataset. Standardized firm IDs (PERMCO) are then attached to the input news articles. The second module conducts sentiment analysis by executing word-level sentiment aggregation. The input news articles are first divided into word tokens and we compute the number of word tokens that belong to the positive or negative semantic categories in the General Inquirer (GI) dictionary following the procedure proposed by Tetlock et al. (2008).

Combining the output from these two modules, firm-based article numbers, positive and negative word counts and total word count in each quarter were produced. If a firm had no news coverage during the predefined period, both positive and negative word numbers were considered missing. Accordingly, we calculate the sentiment score as follows:

$$dpos\_senw = \frac{positive\_word\_count - negative\_word\_count}{positive\_word\_count + negative\_word\_count}.$$

### 4.3 Empirical Model

In our empirical study, we used the following criteria to arrive at a final profile of financial ratios. We considered relative contributions of variables by their fundamental meanings among each category accompanied with their correlations structures. The final list in our sample included size (Z2, and Z3), financial leverage (Z5), profitability (Z11, Z12, Z14, Z15, and Z18), interest coverage (Z19), and liquidity (Z22). Selected variables covered all independent variable categories considered in previous related studies.

To analyze what determines future rating level, our empirical model tested the following relationship:

$$y_i = m \quad \text{if} \quad c_{m-1} \leq y_i^* < c_m \quad \text{for} \quad m = 1 \dots J(\text{numerical\_issuer\_rating})$$

$$y_i^* = \alpha + \beta_1 Z_{i2} + \beta_2 Z_{i3} + \beta_3 Z_{i5} + \beta_4 Z_{i11} + \beta_5 Z_{i12} + \beta_6 Z_{i14} + \beta_7 Z_{i15} + \beta_8 Z_{i18} + \beta_9 Z_{i19} + \beta_{10} Z_{i22} \\ + \beta_{11} \ln article + \beta_{12} dpos\_senw + \varepsilon_i$$

In the above setting, we have a pool of 3892 observations (firms with fiscal year-end ratings and their financial ratios and news variables in the previous quarters) and  $y_i$  is the  $i^{\text{th}}$  observed numerical issuer rating (e.g., AA=5, A=4, etc.) at the end of a firm's fiscal year.  $Z$ 's are controlled financial ratios. News coverage,  $\ln \text{article}$ , is the logarithm of number of news articles covering a firm one quarter before the end of its fiscal year. The approach to measure news sentiment is the relative frequency between positive and negative words ( $\text{dpos\_senw}$ ), i.e., polarity.

## 5 EMPREIMENT RESULTS AND ANALYSIS

Our results and analysis focus on answering the research questions we proposed. We present the results regarding news coverage effects, sentiment effects and cross-sample differences in the following three subsections.

### 5.1 News coverage effects

The effect of news coverage can be found in Table 4. We found that news coverage had a negative effect on credit rating. It is interesting to note that higher credit ratings are associated with higher news coverage in correlation analysis. However, after controlling for the effect of financial ratios, we observed a significant negative coefficient for news coverage. It is possible that large firms generally have wide news coverage and better credit rating and this result implied that news coverage is a negative signal on credit quality if firms are in the same market size. In addition, a significant difference of news coverage between high-rated firms and low-rated firms (average number of news articles per quarter for AA-rated and B rated firms are 36.65 and 3.23 respectively) led us to think about the distinct news coverage effect in rating grades. Our conjecture was verified when we divided the whole sample into investment grade and speculative grade groups. News coverage effects faded out in investment grade group and still have strong influences on ratings in speculative grade group. It suggested that the marginal increase of news coverage had greater impacts on low rated firms. The empirical results were similar for both ordered probit and ordered logit models.

Variables	Ordered logit model			Ordered probit model		
	All sample	Investment	Speculative	All sample	Investment	Speculative
Coverage	-0.244***	-0.047	-0.252***	-0.135***	-0.020	-0.147***
$\text{dpos\_senw}$	0.266**	0.435*	-0.055	0.181**	0.308**	-0.040

Table 4. The effect of news coverage and sentiment scores on credit ratings (Investment grade: AA-BBB; Speculative grade: BB-B; significant levels: 1%:\*\*\*, 5%:\*\*, 10 %:\*)

### 5.2 Sentiment effects

As listed in Table 4, we have found that  $\text{dpos\_senw}$ , the polarity score normalized by number of sentimental words in a news article, was associated with significantly positive coefficients. The result indicated that higher polarity score led to better rating performance in the following quarter.

### 5.3 Classification within investment grade firms and speculative grade firms

The estimation results using the subsample of investment grade firms indicate that mass media impact credit ratings mainly through the polarity score of the news articles ( $\text{dpos\_senw}$ ). It suggests that rating level is decided by expression tones in news articles among investment grade issuers and not by the amount of news in WSJ. However, in speculative grade firms, the effect of media coverage dominated other sentiment scores. One possible explanation is that speculative grade firms usually



receive lower media coverage. Appearing in mass media is often associated with news disseminating bad outlooks.

## 6 CONCLUSIONS AND SUGGESTIONS

An issuer credit rating provides important information for credit risk. Most studies only relied on accounting and/or market data. According to rating process revealed by rating agencies, there are many nonnumeric distinguishing characteristics that determine a company's creditworthiness. Our empirical results suggest that more text analysis beyond positive and negative words can effectively uplift model explanatory and prediction abilities. In addition, news content analysis can also be applied to industry-specific news research since industry effects were found important in bankruptcy prediction. We are working on refining our model by including macroeconomics-related news as explanatory factors to control for systematic risks.

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