ISSN 2959-6130

Can Negative Emotions on Social Media Predict Corporate Financial Risks: Perspective from Baidu Tieba

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Abstract:

The intrinsic relationship between social media and corporate development has emerged as one of the key research topics today. Most current studies focus on the positive impacts and opportunities that social media can bring to enterprises. However, there remains a lack of a unified explanation for the influence of negative news on social media on businesses. Consequently, the research theme of this paper is to explore whether negative sentiments on social media can predict corporate financial risks. Firstly, this paper collects data related to bearish posts on social media and financial risks of enterprises. Subsequently, regression analysis is conducted on the data using SPSS. The results reveal that, under the condition of controlling the asset-liability ratio, negative posts on social media do have an impact on corporate financial risks, with a greater number of negative posts correlating to a higher level of financial risk for the enterprise. This paper fills a gap in understanding the negative implications of social media on certain aspects of businesses and provides data support for researching the influence of negative sentiments on social media on corporate financial risks.

Keywords: Social Media; Negative Sentiment; Financial Risk; Baidu Post Bar.

1. Introduction

1.1 Research Background and Significance

In today's society, as traditional media declines, social media has gradually emerged as a significant platform for the public to express opinions and share viewpoints. Its influence has gradually permeated into the operations of various enterprises. However, with the expansion of social media user bases and the acceleration of transmission speeds, negative sentiments have begun to spread on social media, not only affecting corporate brands and public perceptions but also potentially having profound impacts on corporate financial conditions. In particular, numerous public opinion incidents in recent years have demonstrated that negative sentiments on social media can rapidly coalesce into a formidable force, inflicting significant blows on enterprises. Therefore, exploring whether negative sentiments on social media can serve as an important indicator for predicting corporate financial risks holds significant importance for both enterprises and investors. If negative sentiments indeed prove to be a predictive indicator of corporate financial risks, then by monitoring and analyzing sentiment changes on social media, enterprises can promptly identify potential danger signals, thereby reducing the probability of corporate financial risks occurring. Simultaneously, this also provides investors with a new perspective to gain a more comprehensive understanding of a company's financial health.

In essence, the objective of this paper is to explore and understand the intricate relationship that exists between negative sentiments expressed on social media platforms and the financial risks faced by corporations. Through empirical research and relevant data analysis, it hopes to better grasp corporate financial risks and provide valuable reference for relevant decision-makers.

1.2 Literature Review

Up to now, numerous scholars have observed the relationship between sentiment changes on social media and corporate financial risks. For instance, as China's economy transitions from a high-speed growth model to a high-quality growth model, a stable economic environment is essential to ensure both the speed and quality of China's market economic development [1]. However, with the intensifying competition among enterprises, some studies have examined the impact of negative information disclosure on investors' decision-making and found a significant correlation between negative sentiments and investor decisions [2]. Furthermore, data and sentiment shift from social media have been utilized to generate a green score for enterprises, involving quantitative analysis, technology, or mathematical processes such as complex and sentiment processing modules to model and analyze the value of financial securities [3]. Research into whether corporate social media opinion is a double-edged sword offers crucial insights for the management and application of corporate social media [4].

Due to the complexity and variability of social media sentiments, existing studies vary in data sources, analytical methods, and research perspectives, leading to disagreements and uncertainties in their conclusions. Hence, there are still limitations and room for further exploration. Based on the above analysis, this study aims to delve into the underlying mechanisms between negative social media sentiments and corporate financial risks, thereby establishing a correlation between them. Simultaneously, enterprises should prioritize the management and monitoring of social media sentiments to promptly address potential risks and challenges.

2. Research Design

2.1 Sample Selection and Data Sources

Given the prevalence of negative incidents on social media, which has garnered increasing attention, and recognizing the sheer volume of data available, this paper ensures comprehensiveness and data validity by focusing its research on the aggregate number of users posting bearish content from 2023 to 2024. The data on the total quantity of users posting bearish posts in this paper is obtained from the China Stock Market & Accounting Research Database (CSMAR) social media database. Firstly, the paper takes the period from August 2023 to June 2024 as the time frame and consults the data of the past year through the CSMAR social media database. By searching the investor sentiment statistics table, it excludes information unrelated to negative sentiments and filters out the information that matches the text. This paper selects the variable Z-score as an indicator representing corporate financial risk [5-7]. The Z-score formula is calculated as follows:

$$Zscore = 1.2X_1 + 1.4X_2 + 3.3X_3 + 0.6X_4 + 0.999X_5 \quad (1)$$

Where X1 represents the ratio of working capital to total assets, reflecting the liquidity and scale characteristics of assets. X2 represents the ratio of accumulated earnings to aggregate assets, Indicating the company’s overall profitability over time. X3 represents the ratio of earnings before interest and taxes (EBIT) to total assets, reflecting the profitability of assets. X4 represents the ratio of the market capitalization of equity to the book value of total obligations; It serves as a metric that assesses a company’s financial architecture, elucidating the balance between shareholders’ equity and creditors’ claims, thereby mirroring the firm’s solvency position. X5 represents the ratio of operating income to total assets, reflecting the asset turnover of an enterprise and measuring assessing the company’s productivity and performance in utilizing its assets. Finally, the screened samples were processed, and samples with missing key variables were excluded, resulting in a final dataset of 223 observations. The corporate financial risk data was sourced from CSMAR. In terms of control variable selection, this paper selects the asset-liability ratio (ALR) as the control variable [8-10]. The asset-liability ratio is the ratio of liabilities to assets and is an important indicator for measuring a company’s financial health.

3. Empirical Analysis

3.1 Descriptive Statistics

This section first provides a descriptive statistic of the basic characteristics of the explanatory variables, explained variables, and control variables. The results are shown in Table 1.

Table 1. Descriptive Statistics

Name	Sample Size	Minimum Value	Maximum Value	Average Value	Standard Deviation	Median
Number of Bearish Posts	223	0.000	3046.000	140.561	383.444	29.000
Average Number of Comments on Bearish Posts	223	0.000	446.420	46.953	80.076	16.170
Zscore	223	-1.627	63.027	3.048	6.375	1.419
Average Number of Reposts for Bearish Posts	223	0.000	16.510	0.829	1.972	0.000
Asset-Liability Ratio	223	0.047	1.083	0.560	0.206	0.594

As can be seen from Table 1, the maximum values of Zscore, average number of reposts for bearish posts, number of bearish posts, and average number of comments on bearish posts, all four items, exceed the mean by more than three standard deviations, indicating significant data volatility. Therefore, using the median to describe the overall level is more appropriate than the mean.

3.2 Correlation Analysis

Performing a correlation analysis on the data is a commonly adopted analytical approach in regression models. The purpose of this analysis is to investigate whether there exists a certain correlation between two or more variables, and to further quantify the strength of this correlation. Through link analysis, this study can preliminarily verify the rationality and scientificity of the model setup.

Table 2. Correlation analysis of variables

	Zscore	1	2	3	4
Zscore	1				
Average Number of Reposts for Bearish Posts(1)	0.026	1			
Number of Bearish Posts(2)	0.161*	0.525**	1		
Average Number of Comments on Bearish Posts(3)	0.148*	0.597**	0.666**	1	
Asset-Liability Ratio(4)	-0.590**	0.121	0.153*	0.119	1

Note: * $p<0.05$ ** $p<0.01$

As can be seen from Table 2, a correlation analysis was conducted to investigate the relationship between Zscore and the average number of reposts for bearish posts, the number of bearish posts, the average number of comments on bearish posts, and the asset-to-liability ratio. The Pearson correlation coefficient was employed as a metric to quantify the intensity of these relationships. The detailed analysis divulges that:

The correlation coefficients between Zscore and three variables - the number of bearish posts, the average number of comments on bearish posts, and the asset-to-liability ratio - all show statistical significance. Specifically, the correlation between Z-score and the count of bearish posts yields a coefficient of 0.161, a value that demonstrates statistical significance at the 0.05 threshold, pointing to a meaningful positive relationship between the two variables. This finding underscores a substantial and positive correlation linking Z-score with the number of bearish posts.

Expressed in a different manner, the correlation coefficient between Z-score and the mean number of comments on bearish posts amounts to 0.148, and this correlation holds statistical significance at the 0.05 level. This signifies a notable and positive correlation existing between Z-score and the average number of comments on bearish posts, which is statistically significant.

The correlation coefficient between Zscore and the asset-to-liability ratio is -0.590, which is statistically significant at the 0.01 level. This indicates that there is a significant negative correlation between Zscore and the asset-to-liability ratio.

Additionally, the correlation coefficient between Zscore and the average number of reposts for bearish posts does not show statistical significance, indicating that there is no correlation between Zscore and the average number of reposts for bearish posts.

3.3 Regression Analysis

Performing regression analysis on data, especially when analyzing a multi-factor model, is more straightforward and convenient. By using a model that is consistent with the data, a unique result can be calculated, enabling accurate measurement of the degree of correlation between various factors.

This hierarchical regression analysis involves two models. Model 1 includes the control variable of asset-to-liability ratio as the independent variable. Model 2, building upon Model 1, incorporates the average number of reposts for bearish posts, the number of bearish posts, and the average number of comments on bearish posts as additional independent variables. The dependent variable for both models is Zscore.

Table 3. The results of regression model

	Model 1	Model 2
Constant	13.304** (13.245)	13.205** (13.750)
Asset-to-Liability Ratio	-18.303** (-10.874)	-19.483** (-12.062)

Average Number of Reposts for Bearish Posts		-0.297 (-1.401)
Number of Bearish Posts		0.004** (3.060)
Average Number of Comments on Bearish Posts		0.011 (1.789)
Sample Size	223	223
R 2	0.349	0.423
Adjusted R2	0.346	0.413
F-Value	F (1,221)=118.233**	F (4,218)=40.030**
△ R2	0.349	0.075
ΔF-Value	F (1,221)=118.233**	F (3,218)=9.445**

Note: * p<0.05 indicates statistical significance at the 0.05 level, ** p<0.01 indicates statistical significance at the 0.01 level; values in parentheses are t-values.

As evident from Table 3, a linear regression analysis was performed, with the asset-to-liability ratio serving as the predictor variable and Z-score as the response variable. The R2 value of the model is 0.349, indicating that the asset-to-liability ratio can explain 34.9% of the variation in Zscore. The application of the F-test to the model has validated its statistical significance, demonstrating that the asset-to-liability ratio exerts a meaningful influence on the Z-score. Alternatively, the F-test results confirm that the model is robust, indicating a notable effect of the asset-to-liability ratio on the Z-score. The model formula can be expressed as:

$$Zscore = 13.304 - 18.303 * ALR \quad (2)$$

The regression coefficient of -18.303 for the asset-to-liability ratio, being statistically significant, reveals a substantial negative correlation between the two variables, signifying that an increase in the asset-to-liability ratio results in a decrease in the Z-score. Alternatively, the notable negative impact of the asset-to-liability ratio on the Z-score is evident from its statistically significant regression coefficient of -18.303.

For Model 2, which incorporates the average number of reposts for bearish posts, the number of bearish posts, and the average number of comments on bearish posts in addition to the asset-to-liability ratio from Model 1, the significant change in the F-value indicates that these additional variables have explanatory power for the model. Furthermore, the increase in R2 from 0.349 to 0.423 suggests that these variables contribute an additional 7.5% of the explanation for Zscore.

The regression coefficient for the average number of reposts for bearish posts is -0.297, but it is not statistically significant, indicating that the average number of reposts for bearish posts does not have an impact on Zscore. The regression coefficient pertaining to the number of bearish posts is 0.004, and its statistical significance underscores that an increase in the number of bearish posts exerts a notable and positive influence on Z-score. Lastly, the regression coefficient for the average number of comments on bearish posts is 0.011, but it is not statistically significant, indicating that the average number of comments on bearish posts does not have an impact on Zscore.

4. Conclusion

This research endeavors to explore the complex interplay between negative sentiments prevalent on social media and the corporate financial risks they entail, offering fresh insights into their underlying relationships and presenting a novel theoretical framework that benefits both businesses and investors alike. It offers robust support for practical applications by analyzing the correlation between these two factors. Specifically, based on the current research landscape, this study examines the link between negative sentiments on social media and corporate financial risks by collecting and analyzing relevant sample data using correlation analysis and regression analysis methods. The results indicate that while the average number of reposts for bearish posts does not significantly impact Zscore, other variables exhibit a certain degree of correlation with Zscore, validating the significant relationship between negative sentiments on social media and corporate financial risks. This finding underscores the importance of negative social media sentiments in influencing corporate financial risks, pointing the way forward for future research and practice. In response to the issues revealed by this study and recognizing their multidimensional nature, it is recommended that scholars from different disciplines strengthen their collaboration to build interdisciplinary research frameworks and solutions. By integrating expertise and skills from various fields, the author can propel further research into this issue and develop effective strategies for addressing it.

Due to the relatively short time period selected, the research methodology and variables may have certain limitations. The incompleteness of knowledge and constraints of research conditions may lead to the inability to consider all possible variables and factors. Furthermore, the interpretation and generalization of the research findings may also be limited. Due to the constraints of empirical research, the results may only indicate correlation rather than causation, and there may be risks associated with applying the findings to different contexts.

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