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Research paper

Predicting Going Concern of Companies Using the Tone of Auditor Reporting

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Abstract:
Despite the growing need for research on the going concern and bankruptcy of companies, most of the conducted studies have used the approach of quantitative data for predicting the going concern and bankruptcy of companies; on the other hand, it is possible to manage these quantitative data by company managers. As a result, there appears to be a need to examine alternative methods for predicting going concern and bankruptcy based on qualitative data from the auditor's report. The purpose of this research is to determine the ability to predict the going concern of the companies using quantitative and qualitative data. The study period was from 2011 to 2021, with a sample of 54 companies admitted to the Tehran Stock Exchange. The results of the first hypothesis test show that the coefficient of determination of text-mining approach model prediction with the presence of a life cycle variable is greater than the determination coefficient of text-mining approach model prediction with the presence of a company size variable. The test of the second hypothesis shows that the difference in the increasing explanatory power of the first model compared to the second model in the companies accepted in the stock exchange is significant.

Keywords: Financial Forecasting, Going Concern, Tone Analysis, Auditor Reporting.
JEL Classification: C53, G33, M42.

1 Introduction

Bankruptcy prediction has been a constant research topic in the accounting and financial fields since the late 1960s. Many researchers have developed a more robust bankruptcy prediction model regarding classification accuracy. While early studies adopted statistical techniques such as multiple resolution analysis (Altman, 1968) and logit analysis (Hamer, 1983; Ohlson, 1980), later studies adopted artificial intelligence approaches such as artificial neural networks (Lashno and Spector, 1996;

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use other qualitative data.

2 Theoretical Foundations and Research Background

2.1 Theoretical

Nowadays, country is faced with increasing downward pressure on its economy, along with an expanding business risk on listed companies. Listed companies, as the solid foundation of the national economy, once they face a financial crisis, will experience hazards from multiple perspectives. Therefore, the construction of an effective financial crisis early warning model can help beneficiaries predict risks (Zhang et al., 2022). beneficiaries often look for ways to predict corporate bankruptcy. Therefore, the need for information, especially qualitative information, along with the quantitative information published by the company, has received the attention of beneficiaries more than in the past. Writings in financial reports can focus on persuasiveness. One of the important methods of persuasion is reflecting and repeating certain words of information in the text, and this method emphasizes the tone of information disclosure (Henry, 2008). Ideas and thoughts are reflected in the tone of the messages in annual reports (Huang et al., 2013; Yekini et al., 2016). In qualitative texts, positive words are used against negative words to evaluate the tone of the text (Kou, J., 2022). The pessimistic tone of financial statements will cause investors to respond negatively (Feldman et al., 2010; Loughran and McDonald, 2011). Previous research has linked the tone of financial reporting to the company's economic performance and business risk. Loughran and McDonald (2011) found that words that have a negative tone are more effective and reliable than positive words. This view is in line with the results of Law and Mills (2015) psychological research because humans tend to process more negative information than positive information. Another study found that a pessimistic tone influences readers' decisions in a statistically meaningful way (Garcia et al., 2013). To measure the tone of writing in managers' reports, researchers used a variety of methods. There are two common approaches to content analysis: the first is based on counting the frequency of specific words (dictionary), and the other is a machine learning classification algorithm method based on assigning an experimental data set to specific categories using a manual coding mechanism (Kashanipoor et al., 2020). In financial research, the methodology based on counting the frequency of specific words is more common and assigns words to different classifications based on predefined rules (Loughran and McDonald, 2011). In this research, a method based on counting the frequency of specific words was used. There is no general consensus in the research literature on text tone word lists, but two lists of words provide the most appropriate classification for use in text analysis (Davis et al., 2015). The first list includes the Loughran and McDonald (2011) dictionary, which is specifically designed to analyze the text of financial and accounting reports, while the second list, the Mohammad and Turney (2013) dictionary, contains the general word list (Mohammad et al., 2019). This study broadly refers to the information literature of the Annual Reports (Brown and Taker, 2011; Cole and Jones, 2005; Feldman et al., 2010), the bankruptcy prediction literature (Altman, 1968; Beaver et al., 2005; Ohlson, 1980; Shumway, 2001; Zmijewski, 1984), and the literature that studies the auditor's boundaries for its going concern (Carson et al. 2012). This study also contributes to the growing literature on the importance of qualitative disclosure using automated language techniques (Tetlock, 2007; Tetlock et al., 2008; Li, 2010) and in particular fills the gap identified by Li (2011) that linguistic analysis may be useful for predicting bankruptcy (Mayew et al., 2015). Two important research issues raise researchers' interest in giving investors early warning signals through auditor disclosure. Firstly, does the tone of the auditor's report and the business unit's going concern disclosures help predict whether a business will continue to operate? Secondly, to what extent are the outcomes of the first question different from the purely structured data? Discussing the advantages of extending the textual disclosure of financial statements can be aided by the answers to these questions.

2.2 Research Background

Mayew et al. (2015) examined the role of textual disclosure in a firm's financial statements to predict a firm's ability to continue as a going concern. Using a sample of 262 firms that filed for bankruptcy over the period 1995-2011 and a matched set of control firms, they find that both the managements opinion and the textual features of management discussion and analysis disclosure together provide significant explanatory power in predicting whether a firm will cease to exist as a going concern. In addition, the ability to predict MD&A disclosure is incremental to financial ratios, market-based variables, and the auditors opinion. According to Jo and Shin (2016), qualitative information should be added to the conventional bankruptcy prediction model to complement accounting information. The performance of the proposed method depends on how well the types of information are converted from qualitative to quantitative information suitable for incorporating into the bankruptcy prediction model. Experimental results showed that combining qualitative data based on extensive data analysis in the traditional model of bankruptcy forecasting based on accounting information effectively increases forecasting performance. Lopatta et al. (2017) examine whether the language used in 10-K filings reflects a firm's risk of bankruptcy. Based on a logit model of failing and vital firms, their findings indicate that firms at risk of bankruptcy use significantly more negative words in their 10-K filings than comparable vital companies. By creating a comprehensive corporate failure-related lexicon, Elsayed et al. (2020) explored the incremental explanatory power of narrative-related disclosures in predicting corporate failure. They found that corporate failure-related narrative disclosures significantly predict firms failure up to two years ahead of actual failure. Collectively, their results showed the feasibility of these narrative-related disclosures in improving the explanatory power of models that predict corporate failure. Lohmann and Ohliger (2020) say the structural and linguistic characteristics of companies annual reports (e.g., their length, complexity, and linguistic tone) and the qualitative information they contain (e.g., on the risks a company potentially faces) provide useful insights that can help increase the accuracy of predicting bankruptcy. Their findings provide empirical evidence that both the structural and linguistic characteristics of annual reports and the qualitative information they contain help discriminate between effectively bankrupt companies and companies that are solvent but financially distressed. Visvanathan (2021) in his study explores the managements discussion of the ability to continue as a going concern, and auditor going concern opinions in predicting the financial distress of a firm. His study is in line with the development of Mayew et al.s (2015) analysis. Using a sample of firms that filed for bankruptcy over the period 20022018; the study shows incrementally informative in predicting a firms ability to continue as a going concern after considering managements textual disclosures, linguistic tone of the MD&A, auditors going concern opinions, financial statement ratios, and market-based variables. NieSSner et al. (2022) conducted a study by considering qualitative criteria along with quantitative criteria to predict bankruptcy. they concluded that qualitative information of companies financial statements provides useful information that can increase the accuracy of bankruptcy prediction models. Zhao et al. (2022) conducted a study in which, in addition to financial features, they proposed a novel framework that combines sentiment tone features extracted from management discussion and analysis, and financial statement notes to predict financial distress. They found that financially distressed companies were more likely to have weak sentiment. They recommend incorporating sentiment tone features with financial features, as they contribute to predictive performance improvements of all models using only financial features.

3 Research Hypotheses

The two hypotheses of the present study are: 1. In the text mining approach, the ability to predict the going concern of companies with a life cycle intervening variable is greater than with a firm size intervening variable. 2. The ability to predict the going concern of companies using the life cycle intervening variable differs significantly from the ability to predict the going concern of companies using the firm size intervening variable in the text mining approach.

4 Research Method

The research is applied in terms of purpose because potential and actual investors; and beneficiaries can use its results. It is correlational in nature because it exam-

Figure 1: Text Mining Process

ines the relationships between variables using regression analysis. The necessary information about the research literature and theoretical foundations was obtained from library sources, scientific databases, and domestic and foreign articles. The Tehran Stock Exchange website, Rahavard Novin software database, and codal website were utilized to collect research data.

In the following, to prepare the data related to auditors' reports, standard No. 570 of auditing standards was used, and to distinguish positive and negative words, Loughran and MacDonald's dictionary (2015) was used. Then MaxQDA software (2020) was used for word processing. Finally, the qualitative data obtained from the previous step and the quantitative data extracted from Rahevard Navin software were entered into EViews software version 10 to test the hypotheses. Logit regression was used to test the first hypothesis and Vuong Z Test was used to test the second hypothesis.

4.1 Statistical Population and Statistical Sample

The statistical population of the research is the companies listed on Tehran Stock Exchange and study period is from 2012 to 2021. In this study, a statistical sample was performed by systematic elimination method using Article 141 of the Commercial Code to select 27 bankrupt companies and Q-Tobin ratio to select 27 successful going concern companies.

4.2 Text Mining Process

The text mining process involves steps according to Figure 1 to extract data from the document (Kumar and Bhatia, 2013).

The present study uses the latest updated version of the Loughran and MacDonald dictionary (2015), which is available through the relevant site and contains 354 positive words and 2355 negative words. The translation of this dictionary has been used to analyze the content of the auditor's annual report on the activities and general situation of the company. For example, with the help of content analysis software, the number of positive words (such as desirable, excellent, and profit) and negative words (unfavorable, weak, and loss) can be counted within the accounting narratives. The frequency of positive and negative words reflects the tone of the language. We measure the auditor's going concern statement using an index variable (GC_AUD) and if the auditor doubts about the firm's going concern, its value becomes zero; otherwise it becomes one (Mayew et al., 2015). The researchers extracted the audit reports of the sample companies from the codal site for this section. They then entered the Maxqda software to determine the number of words in each report. Afterwards, they counted the number of positive and negative words found in the auditor reports using the Loughran and McDonald dictionary. Going concern Standard No. 570 of Auditing Standards was used for the index variable (GC_AUD). A company with going concern challenges has two cases (although only one is stated in the standard) of the signs mentioned in this standard that raise serious doubts about the existence of going concern.

4.3 Logit Model

The dependent variable in this model is a two-state variable equal to the logarithm of the probability of a specific event (bankruptcy) occurring. The linear probability model as equation 1 can be written in the form of logistic regression function as equation 2.

$$Y = b_1 + b_2 X_i \tag{1}$$

$$Ln(\frac{p}{1-p}) = b_1 + b_2 X_i + m \tag{2}$$

Therefore, the probability of an event occurring is described in equation 3.

$$p = \frac{1}{1 + e^{-(b_1 + b_2 X_i)}} \tag{3}$$

The maximum probability method is used to estimate Equation 3. We take zero to represent bankruptcy. If the result is greater than 0.5 decimal place (which is used for the company's equal index of bankruptcy or non-bankruptcy), the company has a lower chance of continuing as a going concern. Researchers who have used this method include Mayew et al. (2015) and Lee and Wang (2018).

4.4 Vuong Z Test

Suppose we want to compare the power of two models in a typical example. In that case, the coefficient of determination obtained from the estimation of the two models is important because the model's power is determined by the value specified. The power of a model with a higher coefficient of determination in explaining and predicting the dependent variable is greater. The difference in coefficients of determination between the two models, however, is significant. A test should be run to ensure that the difference between the two models' coefficients is statistically significant. The Vuong Z test was developed by Vuong (1989) to compare the differences in the coefficients of determination of the two models (Banimahd et al., 2016: 199).

5 Research Variables and Models

5.1 Dependent variables

Bankruptcy: In Iran, Article 141 of a 1968-approved amending bill to a section of the Commercial Law serves as the foundation for bankruptcy. According to this article, the board of directors is required to summon an extraordinary general meeting of shareholders as soon as at least half of the company's capital is lost as a result of losses so that the issue of the company's survival or liquidation can be discussed and voted on.

5.2 Independent Variables

Research variables are categorized into both quantitative and qualitative. The quantitative variables are retrieved from the financial statements. The qualitative variables were collected by counting the positive and negative words and dubious phrases from the going concern in the auditor's report.
In this study, 12 independent variables and 2 intervening variables were used, which are shown in Table 1 and have been utilized in prior studies by national and international researchers.

Table 1: Research Variables

Variable type	variables	symbols
Dependent	Bankruptcy	Brupt
Independent	Retained earnings to total assets ratio	Reta
Independent	Net profit to total assets ratio	Neta
Independent	Operating profit to total assets ratio	Ebitta
Independent	Current assets to current liabilities ratio	Cacl
Independent	Working capital to total assets ratio	Wcta
Independent	Sale revenue to total assets ratio	Saleta
Independent	Total liabilities to total assets ratio	Tlta
Independent	Positive words	Posmda
Independent	Negative words	Negmda
Independent	Auditor sentences	Gc_aud
Intervening	Growth period	Cycle-gro
Intervening	Maturity period	Cycle-mat
Intervening	Decline period	Cycle-dec
Intervening	Company size	Size

5.3 Research model

According to the studies of Mayow et al. (2015) and Visvanathan (2021), the research model is based on research hypotheses and data mining approach as equation 4 .

$$\begin{aligned} pr(BRUPT_{i+1}) &= \beta_0 + \beta_1 RETA_t + \beta_2 NETA_t + \beta_3 EBITTA_t + \beta_4 CACL_t \\ &+ \beta_5 WCTA_t + \beta_6 SALETA_t + \beta_7 TATL_t + \beta_8 POSMDA_t \\ &+ \beta_9 NEGMDA_t + \beta_{10} CG\_AUD_t + \beta_{11} Cycle_t + \vartheta_t \end{aligned} \tag{4}$$

And the research model is based on research hypotheses and text analysis approach as equation 5.

$$\begin{aligned} pr(BRUPT_{i+1}) &= \beta_0 + \beta_1 RETA_t + \beta_2 NETA_t + \beta_3 EBITTA_t + \beta_4 CACL_t \\ &+ \beta_5 WCTA_t + \beta_6 SALETA_t + \beta_7 TATL_t + \beta_8 POSMDA_t \\ &+ \beta_9 NEGMDA_t + \beta_{10} CG\_AUD_t + \beta_{11} Size_t + \vartheta_t \end{aligned} \tag{5}$$

6 Analysis of Research Data and Findings

6.1 Unit Root Test

Dummy regression occurs when nonstationary variables are present in the model. The test presented by Levin et al. (2002: 5) was used to evaluate the significance of the variables. When the time dimensions are large enough, this test is more efficient and has more power than other static tests (Najafzadeh et al., 2022). Table 2 shows the results of a test of the reliability of independent research variables.

If the variables are nonstationary, the co-integration method is used to allow the original values of the variables to be used while ensuring that the regression results are not dummy. If one of their linear combinations is stationary, a set of values is said to be co-integrated. Therefore, if the explanatory and dependent variable processes co-integrate in a regression model, the possibility of dummy regression is eliminated (Banimahd et al., 2016: 184). The unit root test results shows that the distribution of error values in both models in Table 3 is significant. As a result, the explanatory and dependent variables' linear relationships are co-integrated.

6.2 Results of Fitting the Regression Models of the Research

To compare the explanatory ability of text mining models for bankruptcy prediction, table 3 reports the results of the estimation of the logit regression equation in a comparative form. The logit regression model used in the text mining approach has a coefficient of determination of 64 percent for the intervening variable of company size 65, 65 and 63 percent for the intervening variable of life cycle (growth, maturity, and decline). These coefficients indicate that adding the intervening variable of life

Table 2: Test of Reliability of Independent Research Variables

variables	Levin, Lin-Chu test statistics	Significance level(prob.)
Reta	-4.34626	0.000
Neta	-7.21567	0.000
Ebitta	-6.81778	0.000
Cacl	-8.16295	0.000
Wcta	-7.80360	0.000
Saleta	-10.8886	0.000
Tlta	-6.89345	0.000
Posmda	-7.84598	0.000
Negmda	-9.04359	0.000
Gc_aud	-7.44742	0.000
Cycle-gro	-6.91130	0.000
Cycle-mat	-10.0349	0.000
Cycle-dec	-6.58149	0.000
Size	-2.42201	0.007

cycle (growth and maturity) to the model improves the models explanatory power when compared to adding the intervening variable of company size.

6.3 Results of Vuong Test of Research Regression Models

The increasing explanatory power of text mining models with the presence of life cycle and company size intervening variables was tested by Vuong Z statistic in table 4, and it was confirmed that they are not equal; thus, a model with a larger R2 has a greater increasing explanatory power. The text mining model with the presence of the life cycle intervening variable (growth and maturity) has greater increasing explanatory power than the text mining model with the presence of the company size intervening variable, and thus the second hypothesis of the research is accepted.

7 Conclusions and Suggestions

Text mining is the process of obtaining high-quality information from text or so-called unstructured or semi-structured data (Marty, 2003). Accordingly, in modern accounting and behavioral finance topics, special attention has been paid to the relationship between the linguistic features of companies' annual reports and their behavior and economic results (Davis et al., 2012; Hong et al., 2014). In recent years, the study of linguistic features of financial reporting in experimental account-

Table 3: Results of Estimating Dependent Variable Hypotheses

variables	Life cycle-growth model	Life cycle-maturity model	Life cycle-decline model	Company size model
C	-0.65	-1.62***	-0.63	-0.36
Reta	4.46***	5.02***	5.31***	5.37***
Neta	-3.49	-3.37	-4.39	-3.67
Ebitta	1.74	0.96	0.91	0.86
Cacl	-3.83***	-3.69***	-3.36***	-3.48***
Wcta	2.99***	2.86***	2.62**	2.65**
Saleta	-0.45**	-0.57***	-0.56***	-0.51***
Tlta	-1.16***	-0.88***	-0.71**	-0.80***
Posmda	-0.35	-0.34	-0.29	-0.26
Negmda	0.69**	0.55*	0.46	0.55*
Gc_aud	1.20***	1.25***	1.16***	1.11***
Cycle-gro	-1.69***			
Cycle-mat		1.20***		
Cycle-dec			-0.55	
Size				-0.81**
R-squared	0.65	0.65	0.63	0.64

Symbols ***, ** and * indicate significance levels of 99%, 95% and 90%, respectively.

ing research has been prompted by the variety of disclosable issues, the diversity of different industries of international companies, and the existence of various institutions that formulate accounting standards at the global level. Although many studies have been conducted on bankruptcy and the influence of various factors in determining it, the influence of financial reporting tone as one of the linguistic features of the company's financial reports has not been investigated. According to the results of the research's first hypothesis test in table 3, applying the intervening variable of the life cycle (growth and maturity) to the text mining model rather than the intervening variable of the company size improves the coefficient of determination of the logit regression models .Furthermore, according to table 4, the first text mining model has a higher prediction power than the second model, and the difference is significant. Finally, the research hypotheses are confirmed based on the obtained results and relevant coefficients. Furthermore, the findings of this study are consistent with those of Mayow et al. (2015), Al-Sayed et al. (2020), Viswanathan (2021) and NieSSner et al. (2022). It is suggested that the Auditing Organization, Tehran Stock Exchange, and Securities Organization design a specific framework that includes compiling explanatory reports with specific lexicon for both formulating new laws and amending previous cases with the knowledge of how auditors manage perception. In addition, auditing firms are urged to take into

Table 4: Vuong Test Results of Regression Models

Comparison	Vuong statistic value	Z statistics	Significance level	Test result
growth model & size model	-2.4123	0.01	0.05	The hypothesis is confirmed.
maturity model & size model	2.1553	0.03	0.05	
decline model & size model	-0.7394	0.45	-	

account the tone of financial statements in assessing the level of risk to the client company, the planning of operations and the volume of audit tests, among other factors.

Ultimately, it is suggested that the following be investigated in future research: 1. Comparing the predictive power and going concern of companies using text mining and data mining approaches with qualitative variables of the activity report of the board of directors 2. The effect of financial reporting tone on the comparability of financial statements. 3. Further, It is suggested to use other intervening variables and a new period of time to do this research again.

In the research process, there is a set of conditions and cases that are out of control, but can potentially affect the results, it is necessary to examine the results of the research, taking into account the existing limitations. The limitations of this study were as follows: 1. Lack of Persian dictionaries that can be used as a standard tool to measuring the tone of writing in the field of financial research. Thus, due to the use of English dictionaries in translation and to the linguistic differences, if there were a standard dictionary in Persian, the reliability of research tools would increase. 2. As the word file of the auditors reports was unavailable, calculating the financial reporting tone index was very challenging. 3. According to the entire descriptions of the text in report, the results of the research are obtained in the tone inferred. Nonetheless, the tone inferred by the investor from a fraction of the text, differs from the tone inferred from the entire text because there is no guarantee of an equal distribution of positive, negative or neutral words in all paragraphs.

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