THE IMPACT OF THE ALTMAN SCORE ON THE ENERGY SECTOR COMPANIES

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Abstract
The financial literature regarding bankruptcy prediction models includes the application of several statistical tools which have progressively become accessible. This paper explores the impact of the Altman score on the stock prices of the Romanian companies listed on the Bucharest Stock Exchange during the period 2014-2022. The Altman score is calculated based on the annual reports of the analyzed companies collected from the Bloomberg database, while the stock exchange prices are collected from the Euromonitor database. The methodology used in the analysis is panel regression realized with the Generalized Method of Movements technique. The data is processed using the EViews software. This research study shows that there is a negative correlation between the Altman Z score and the companies' share price. In terms of theoretical contribution, this study investigates one of the bankruptcy prediction models that is used more often than other models, namely the Altman Z-Score.

Keywords
Altman score, stock price, bankruptcy, Romania

JEL Classification
O16, G32, G12, G33

Introduction

The technique of bankruptcy prediction involves projecting and forecasting financial distress for both public and private companies. Its purpose is to evaluate a company's financial position and its future prospects. This is a critical aspect of economics as the financial stability of a company is of utmost importance to a variety of stakeholders,

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including policymakers, investors, banks, internal management, and consumers. Predicting a company's financial performance with accuracy is crucial for these stakeholders when making important decisions regarding their engagement with the company (Zhang et al. 2013).

In addition, bankruptcy prediction is highly important for investors, suppliers, and retailers who are associated with the corporate environment. Credit lenders and investors require a thorough evaluation of a company's financial bankruptcy risk before making any investment or credit-granting decisions to avoid substantial losses. Suppliers and retailers who engage in credit transactions with the company also need to comprehend the company's financial status to make informed credit decisions. Accurately predicting an entity's financial distress is of great importance to the various stakeholders involved. The need to identify different stressors that impact companies has arisen due to problems related to bankruptcy, in order to assist investors in making informed investment decisions. The failures of prominent corporations have spurred research to better understand and develop predictive capabilities that can guide investment decision-making. Available information from listed firms, public organizations that have gone bankrupt, and accounting ratios can provide vital indicators or signals of impending danger.

Traditionally, credit risk decisions for corporate borrowers have been based solely on subjective decisions made by professionals (Thomas et al., 2002). However, this approach has two major drawbacks: first, it can be challenging to make reliable evaluations, and second, it has a tendency to be reactive instead of predictive (Cleofas-Sánchez et al., 2016).

The technique of predicting bankruptcy involves forecasting and projecting the financial distress of public and private companies. Its fundamental purpose is to assess a company's financial position and its prospects for future operations. In economics, corporate bankruptcy forecast is a vital phenomenon, as the financial stability of an economic entity is essential to several performers and contributors of the business cycle (Ogachi et al., 2020).

Researchers examined the reasons for business failure that were indicated by bankruptcy scores established during the decline stage of the business. In Estonia, a survey was conducted on 70 manufacturing firms, and the findings showed the reasons for bankruptcy from court decisions. The firms classified the causes and types of failure, such as internal factors that differ from management deficiencies and external factors of the company. To calculate bankruptcy scores for the first and second pre-bankruptcy years, Ohlson's model and a local bankruptcy prediction model (Grünberg) were used. The findings suggest that several reasons led to a significantly higher risk of insolvency compared to a single cause for the year before bankruptcy disclosure (Lukason and Hoffman 2014).

Altman's (1968) first bankruptcy prediction model gained importance and is widely used by economists and scientists around the world. The early detection of a possible threat to a company's financial performance is a critical phenomenon in the field of economic analysis.

The occurrence of financial distress, as well as the subsequent collapse of an entity can be an incredibly expensive and disruptive occurrence. In order to predict whether a firm will be affected by financial distress in the future, statistical models have been developed. While discriminant examination and logistic regression have been commonly used, there are several other state-of-the-art data mining techniques available. The analysis of various cost ratios has been carried out, and the results indicate that conclusion trees and survival investigation models exhibit good forecast accuracy, which confirms their application and supports supplementary research.

In López-Gutiérrez et al.'s (2015) study, the authors examine how financial distress affects the investment decisions of firms across several countries, including the UK, Spain, Germany, France, Canada, the USA, and Italy, which have different formal environments. The study employs panel data estimation and the Generalized Method of Moments to allow control for both unobservable heterogeneity and endogeneity issues in the explanatory variables. The findings suggest that the impact of financial distress on investment behavior varies based on the investment prospects available to firms. More precisely, businesses experiencing financial difficulties and limited opportunities tend to under-invest, while those with better occasions exhibit investment behavior similar to healthy companies.

The decline in profitability of publicly traded companies poses a threat not only to firms and their staff, but also to investors who could experience substantial financial losses. It is crucial to create an efficient and early warning system for predicting financial crises, which would help promote better corporate governance. A study was carried out to examine the phenomenon of financial distress in 107 Chinese companies that received a special treatment tag from the Shanghai Stock Exchange and the Shenzhen Stock Exchange from 2001 to 2008. By comparing these companies to the ones in a control group, the authors of the study have applied data mining procedures to construct financial distress warning representations based on a number of 31 financial indicators, for three different time periods. A noteworthy involvement of this research is the discovery that financial pointers, such as earnings per share, net profit margin of total assets, cash flow per share, and return on total assets, play a crucial role in predicting the decline in profitability. This study proposes a suitable approach for predicting financial distress.

Another bankruptcy prediction model was created in Lithuania, where limited liability companies are dominant, to evaluate the likelihood of bankruptcy in firms. The research looked at 73 bankrupt firms and 72 operational ones to establish a bankruptcy prediction model, which could be employed to forecast the collapse of commercial entities. The research showed that the model had an 89% accuracy rate in predicting the bankruptcy of private firms in Lithuania (Šlefendorfas, 2016).

For centuries, forecasting bankruptcy has been an interesting task. Models were based on financial figures, specific enterprises variables and share prices, including small data and management and director data. According to Tobback et al. (2017), relational models provide better predictions compared to simplistic financial models when identifying risky firms. Merging economic and relational information provides the greatest significant performance improvement. It is anticipated that managers could meticulously develop bankruptcy prediction methodologies and tailor them according to a company's type, risk and size (Boraty´nska and Grzegorzewska, 2018).

Most bankruptcy studies have used parametric representations, such as logit and multiple discriminant analysis. These models have a limitation since they can only handle a restricted number of predictors. A study carried out on 1,115 bankruptcy filings in the US and 91 prognosticator variables found that ownership composition and CEO compensation were reliable non-traditional forecasters, while marketplace and bookkeeping non-scale variables were respectable prognosticators when studying the impact of enterprise size. Furthermore, macroeconomic variables, expert predictions, and industry variables remained identified as weak predictors (Jones, 2017).

In a study by Klepac and Hampel (2017), 250 European Union agricultural companies were cross-examined to predict financial difficulties. Out of these, 62 were in a state of non-repayment in 2014. The study found that, as the distance to bankruptcy increased, the average accuracy of predicting financial difficulty decreased. This revealed a significant difference between active and distressed economic entities regarding liquidity, profitability, and debt ratios.

Another study was carried out in India, which is an emerging economy, in order to establish a prediction of corporate difficulties. This research used enterprise-specific restrictions to identify any symbols of distress in the Indian business sector. The findings demonstrated that the Bayesian method is reliable in recognizing early catastrophe signals in Indian corporate sector (Shrivastava et al. 2018).

Although more than a few models have been developed worldwide to quantify the insolvency of firms, each methodology has some deficiencies during its application. One of the main issues faced by representations is the inability to transfer and apply a model from one state to another due to differences in economic conditions. Therefore, Svabova et al. (2018) recommend developing a projecting model that considers the specific circumstances of a particular country by using real data of the financial situation.

According to research, companies that have a long history of affirmative corporate social responsibility (CSR) are less susceptible to filing for bankruptcy when they face financial difficulties. Nevertheless, they are likely to recover more quickly after the setback. According to Lin and Dong (2018), moral capital is shown to decrease the likelihood of bankruptcy for larger companies, as well as for those that rely on intangible assets and operate in a more litigious corporate environment.

Bankruptcy prediction has been a topic of interest in economics for almost a century, with the aim of designing a model that combines various economic variables to predict a company’s state. Statistical modeling and artificial intelligence have been proposed as methods to achieve this goal (Zieba et al., 2016).

The increasing difficulty of global economies and the growing number of corporate failures triggered by the 2008 global financial crisis have led many institutions and researchers to focus on bankruptcy prediction (García et al., 2019).

Over the years, many studies have been conducted to analyze the risk of bankruptcy, including those by Hosaca (2009), Agrawal and Maheshwari (2019), Alifiah (2014), Jabeur (2017), Li et al. (2017), and Feng et al. (2019).

As previously mentioned, the aim of this paper is to investigate the impact of the Altman score on the stock prices of the Romanian companies listed on the Bucharest Stock Exchange during the period 2014-2021, as well as to examine the impact of the evolution of the Z score on the stock price of the companies in the basket of the BET_NG index. The paper is organized as follows: Section 1 is an introduction to the explored field and describes the theoretical framework related to the topic; Section 2 represents a review of the literature on the subject matter; Section 3 explains the research methodology and data collection; Section 4 illustrates and discusses the empirical results. The final section presents the conclusions, the paper’s limitations, and further research directions.

1. Review of the scientific literature

In the area of bankruptcy prediction models, scholars in accounting and finance literature have pursued two main research directions. The first line of inquiry has investigated the forecasting ability of various bankruptcy models, which can be classified into two broad categories: accounting-based models (such as the Altman (1968) model or the Ohlson (1980) model) and predictive models that calculate bankruptcy probabilities by utilizing option pricing models that rely on market data (such as Hillegeist et al. (2004) and Agarwal and Taffler (2007)) to establish their relationship with market variables. The central concept examined underpinning the second line of research is that bankruptcy model scores are linked to the company’s systematic risk, which is integrated into the company’s market capitalization. Consequently, the key proposition is that companies with a high score concerning bankruptcy risk are likely to provide shareholders with greater profits to recompense the high risk. In their study, Altman and Brenner (1981) analyzed the existence of unusual returns for several firms to supply evidence of the share price response to "new" data measured through the modification of the Altman Z score. Based on the study of Dichev (1998), he revealed negative correlation coefficients between the Altman Z score and actual returns consistent with the aforementioned hypothesis. Nevertheless, subsequent regression and portfolio analysis tests do not provide compelling evidence of the relationship between bankruptcy risk, as reflected by the Altman Z score, and market returns. Furthermore, Piotroski (2000) disclosed higher market returns for enterprises with low stages of financial distress (which was measured by the Altman methodology) compared to those with high levels of financial distress. Griffin and Lemmon (2002) and Campbell et al. (2006) observed an adverse correlation between bankruptcy probabilities and market profitability.

The results of Vassalou and Xing (2004) show that their measure of default risk has a positive influence on market capitalization, and small firms with a high accounting/market ratio and high default risk obtain higher returns. Garlappi et al. (2008) suggest that the variation of market return in firms with high probability of default is explained by shareholder bargaining power in debt negotiations. While testing the informational content of SAS No. 59, the results of Holder-Webb and Wilkins (2000) found a connection between the Altman Z-score and excess returns around the bankruptcy announcement. Basu (1997), Fama and French (1992), Jaffe et al. (1989), and Lakonishok et al. (1994) have documented the presence of a PE effect on stock prices in different time periods. They found that low PE stocks are associated with future high stock returns. Chan et al. (1991) and Fama and French (1992) found that organizations with low price-to-book ratios are linked with higher returns for stockholders.

To avoid losses by avoiding cooperation with potentially bankrupt companies, it is crucial to conduct a study to anticipate the risk of economic failure. Initial detection of signs of financial deterioration is necessary in order to take corrective measures. The use of efficient company failure forecasting tools can identify potential bankruptcy and serve as an early warning system against bankruptcy, allowing companies to take remedial actions to improve their financial position and guarantee firm viability (Prusak, 2018).

According to Ogachi et al. (2020), it is important to examine a company facing bankruptcy in order to support investors in making appropriate investment choices. If a company experiences financial difficulties and bankruptcy becomes inevitable, it has two options: to evaluate whether a reorganization plan is feasible and make all necessary efforts to improve from the circumstances, or to terminate operations (Amendola et al., 2015). Researchers have developed at least five models to estimate bankruptcy, which have been applied to companies around the world (Salim and Sudiono, 2017). Although many financial failure prediction models are available, it remains unclear which model performs best.

The study of predicting financial difficulties has been extensively researched by scholars in empirical finance. Mselmi et al. (2017) found that smaller companies with greater leverage and lower repayment capacity, profitability, liquidity, and solvency are more likely to face financial distress. Thus, creditors should carefully assess a company's financial position to avoid incurring losses and risks. It was also established that the support vector machine is the best and most accurate method of forecasting bankruptcy during a year, whereas the hybrid methodology integrating support vector machine with partial least squares is preferred for predicting financial difficulties within two years, with an overall accuracy of 94.28%.

To design a model for predicting financial disasters, the economic ratio selection and the classifier design play the most important roles. Researchers have used a methodology that combines statistical data, computational intelligence methods and expert judgement. Chou et al. (2017) developed a hybrid approach based on judgment designed for the selection of crucial ratios. In their research, two sets of financial ratios were used to evaluate the proposed ratio selection schemes. The trial results based on financial information from less than four years before the incidence of bankruptcy were used to assess the performance of the proposed estimate model.

2. Research methodology

The primary aim of the financial accounting analysis is to supply different information regarding the financial well-being of a company to all interested parties. Investors are one of those parties who aim to assess a company based on all the data provided by financial analysts. An important parameter that investors should consider is a company's likelihood of going bankrupt. Therefore, several financial models have been devised to determine this probability. However, the Altman Z-score model is the most widely used model in practice.

Altman's (1968) model employed five financial ratios that are combined and scrutinized using discriminant analysis. In this manner, a linear model was formulated where the financial ratios are weighed to enhance the predictive capability of bankruptcy and to generate a score that signifies the financial soundness of the company.

The research is made on panel data by using Generalized Method of Moments. In order to analyze the impact of Altman score on share prices, we created the following regression:

$$\text{Price} = c0 + c1 * \text{Altman} + \varepsilon t \quad (1)$$

where:

Price - the share prices calculated as an increase percentage from year to year

Altman –Altman score calculated as an increase percentage from year to year

Ɛt – the residual value

In the initial regression fixed and random effects were introduced both in period, and in cross-section, finally resulting nine regressions.

The analyzed period is 2014-2021. The sample comprises 10 companies from the BET-NG index. The Altman score was calculated based on the annual reports of analyzed companies. Financial data was taken from the Eikon database, while the share prices were collected from the Bucharest Stock Exchange website. The frequency data is annual, resulting in a number of 80 observations. The data was processed with the help of the EViews software.

Table no. 1. Analyzed companies

Symbol	Company	Weight (%)
SNG	SNGN Romgaz SA	32.06
SNP	OMV Petrom SA	27.95
SNN	SN Nuclearelectrica SA	17.01
TGN	SNTGN Transgaz SA	8.74
EL	Societatea Energetica Electrica SA	7.53
TEL	CNTEE Transelectrica	3.45
COTE	Conpet SA	1.53
RRC	Rompetrol Rafinare SA	1.19
PTR	Rompetrol Well Services SA	0.3
OIL	Oil Terminal SA	0.24

Source: Bucharest Stock Exchange

The main descriptive statistics of the analyzed series corresponding to the ten companies related to the analyzed period are presented in Table 2. According to these results, it can be observed that the value of the average of the Altman series is negative (due to the negative values of the Altman score recorded by Rompetrol Rafinare SA), while the value of the average price is positive. The analyzed series do not follow the normal distribution law.

Table no. 2. Descriptive statistics

	ALTMAN	PRICE
Mean	-0.21401	0.063514
Median	0	-0.00119
Maximum	7.695652	1.631579
Minimum	-21.5238	-0.28922
Std. Dev.	2.603686	0.298739
Skewness	-6.6418	2.27162
Kurtosis	58.63305	11.20036
Jarque-Bera	10904.97	292.9567
Probability	0	0

Source: Authors' own processing in EViews

3. Results and discussions

The empirical results, using the GMM method, show a negative impact of the Altman score on stock prices of the sample of 10 companies in the energetic industry. This situation coincides with the results of Syamni et al. (2018). Their analysis was carried out on a sample of companies in the mining industry in Indonesia.

In Romania, these results may be due to the fact that the sample is small, respectively it includes a period of crisis (Covid-19 pandemic).

Table no. 3. The empirical results

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
C	0.062701*	0.060149*	0.061687*	0.06118*	0.06190*	0.06193*	0.062592*	0.060986*	0.06094*
	(1.860039)	(1.924795)	(1.23077)	(1.91514)	(1.85158)	(1.33399)	(1.73109)	(1.9519)	(1.9506)
ALTMAN	-0.0038*	-0.01573*	-0.00854*	-0.0108*	-0.0075*	-0.0073*	-0.00431*	-0.01181*	-0.0120*
	(-0.29257)	(-1.18828)	(-0.68033)	(-0.8413)	(-0.5618)	(-0.5834)	(-0.33276)	(-0.9154)	(-0.9410)

Source: Authors' own processing in EViews

Note: t-statistic values are between brackets

* Significance threshold at 10 %

Regardless of the situation, the introduction of fixed or random effects in the period or cross-section in the regression obtained the same negative impact. The first regression does not contain effects. The second regression has fixed effects in both period and cross-section. The third regression contains random effects in period, respectively in cross-section. The fourth regression comprises fixed effects only in period. The fifth regression has random effects in period. The sixth regression includes fixed effects in cross-section, while the succeeding regression has random effects in cross-section. The following regression includes random effects in cross-section, respectively fixed effects in period, while the last regression has fixed effects in cross-section, respectively random effects in period.

Regarding the practical contribution of this research, first of all, it is intended that the government can encourage the implementation of various policies in an effort to restore the energy sector and its derivatives, including the control of the COVID-19 pandemic upstream.

Furthermore, our empirical research focuses on a small sample of companies. This may suggest that the results of our empirical study are not valid for stages of economic progress in which share prices are growing quickly, producing extremely positive yields for shares. We propose to expand the sample in our further research, thus to include all firms listed on the Bucharest Stock Exchange.

Conclusions

This study has revealed that there is a negative correlation between the Altman Z-score and the share price of a company. These findings are consistent with previous studies carried out by Campbell, Hilscher, and Szilagyi (2006), Griffin and Lemmon (2002), and Syamni et al., (2018).

The empirical results indicate that, when the bankruptcy indicator is lower in a company, stock prices are also lower. Conversely, when the bankruptcy indicator improves, stock prices rise. The findings suggest that investors give weight to economic information related to the financial health of the companies they invest in. It is important to note, however, that the empirical research is based on a limited sample size.

As a result, our findings may not hold true for stages of economic growth where share prices could rise quickly, resulting in excessively positive stock returns. This is particularly relevant in emerging markets, and, therefore, it is recommended to explore the relationships between share prices and elementary accounting and economic ratios during stages of unusual stock returns in both emerging and developed markets.

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