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Default Risk Prediction using Merton's Model and Altman's Z-Score

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Abstract

This research focuses on predicting the default risk of a financially distressed firm with KMV-Merton's model and Altman's Z-Score model. Part of the objectives of this research were to estimate the probability of default with Merton's model and to compare and validate this probability with Altman's Z-Score. Merton's model, which is a structural model, was used to estimate default probability, while Altman's Z-Score model, a reduced-form model, was used as a verification tool. The research involved collecting past financial data from the company's financial statements. The result indicated an extremely high degree of correspondence among the models. Merton's model estimated a default probability of 100%, while Altman's Z-Score model gave a default risk forecast of -4.018, which is an exceptionally high bankruptcy likelihood. These were expected results within the known standards of both models. Challenges in research were encountered primarily in obtaining effective data and achieving a final comparability tool for model accuracy. Future research can explore variations of model comparison to further evaluate the predictive ability of Merton's model to predict default risk and review enhancements to Altman's Z-Score model to enhance prediction accuracy. The practical significance of this study lies in providing a comparative study on two of the most used default risk models and highlighting the importance of solid financial distress assessment for companies with a history of financial distress.

Keywords*:* Default Risk, Merton's Model, Altman Z-Score, Bankruptcy Prediction

Introduction

Businesses exist in various forms, including sole proprietorships, partnerships, and corporations. This study focuses on companies, which commonly prioritize profit maximization and risk minimization. Effective business management and the avoidance of bankruptcy are paramount to achieving these goals. Furthermore, [1] demonstrated proactive risk management approach ensuring firms financial stability and longevity, especially for banks [2 – 6]. Ineffective management of default risk can lead to substantial losses, financial distress, and even bankruptcy. This research seeks to contribute to a better understanding of default risk assessment to help companies mitigate these negative impacts.

Companies often face challenges in accurately assessing the probability of default when evaluating borrowers or their financial stability. This difficulty arises from the lack of universally accepted or easily applicable methods for quantifying default risk, leading to potential misjudgements in lending decisions and financial planning. While various models exist for predicting default risk, empirical tests are necessary to determine their accuracy and reliability. This study fills this gap by comparing the performance of two widely used models, Merton's model and Altman's Z-Score model, to analyse their concordance in estimating default risk.

Merton's model provides a powerful approach to predicting firm defaults based on market value [7], while Altman's Z-Score model can forecast firms' default by analysing the firm financial status over periods longer than one or two years [8]. Some studies would focus on the theoretical nature of default risk models, while others would utilize simulated data. There may be a shortage of research that properly tests the models against actual firm performance and financial outcomes over some period. Merton's model and Altman's Z-Score performance may differ when estimating default risk in the case of a chosen firm or industry. This research can do this by employing the models on historical data and contrasting the model predictions with the actual financial trajectory of the company, thus providing real-world validation. So, this research contributes by providing a direct comparison of predictive power of these models in one specific case, empirically supporting the argument regarding their relative strengths and weaknesses.

KMV-Merton Model

KMV-Merton's model, a structural model, is a cornerstone in default probability assessment. The model emphasizes its reliance on the market value of equity as a key input for robust results [9]. The model utilizes option pricing theory, conceptualizing default as occurring when a company's asset value falls below its debt obligations at a specific time [10]. Cakici et al. [11] show that the KMV-Merton model framework can capture complex relationships between default risk and financial positions which highlights the model's practical applicability. Jumbe and Gor [12] suggest the key determinants in assessing default probabilities and show the relevance of volatility and expected returns in hedging default risk exposures using the KMV-Merton model. Specifically, [10] present a three-step method of estimating default probability, based on KMV model:1) estimation of asset value and volatility; 2) calculation of distance-to-default; and 3) calculation of default probability from distance-to-default.

The KMV-Merton model is nonetheless relevant in the modern financial markets in estimating probabilities of default [13]. A decade ago, [14] employed the Merton's model in forecasting default risk among publicly non-financial firms in the United Kingdom. The research demonstrated that the model provides a strong signal of potential failure one year in advance, showcasing its predictive power. Furthermore, [14] found that Merton's model outperformed a reduced-form model in predicting default, demonstrating its relative effectiveness. Norliza and Maheran [15] implemented Merton's model to estimate default probabilities value of Malaysian companies listed on Bursa Malaysia. The value of the default probabilities was then compared with the company rating by Malaysian Rating Corporation Berhad (MARC) and RAM Rating Holding Berhad. The research identified a high degree of correlation between the predictions made by the model and the ratings provided by the rating agencies. This indicates that Merton's model is efficient in capturing default probabilities and can accurately forecast changes in the rating outlook of companies up to two years ahead. Furthermore, it supports the application of the model in an emerging market scenario. As time passes by, the KMV-Merton model goes on to further evolve with many modifications [16-18].

Finally, the literature proves that the Merton model remains a primary method of forecasting default risk due to its consistency with theory and adaptability. Its applications span the entire economy, as an example of continuing to be at the leading edge of innovation and application when it comes to default risk management.

Altman's Z-Score Model

Altman's Z-Score model is a widely used tool for predicting financial distress and bankruptcy [19]. Its ability to analyse a company's financial health and predict potential financial problems has been highlighted in many studies [20-21]. Altman et al. [22] developed Altman's Z-Score model for manufacturing and non-manufacturing companies. The Altman's Z-Score model has become a key input for many internal rate-based models [22]. Utilized for over many years, Altman's Z-Score model remains a fundamental tool for bankruptcy and financial problem forecasting in research and practice. Altman collected a list of 22 potentially important financial ratios from balance sheet and income statement data, categorized into liquidity, leverage, profitability, solvency, and activity ratios. Altman selected five ratios for corporate bankruptcy prediction, using statistical significance, relative responsibilities of variables, interconnections between factors, predictive accuracy, and investigator judgment. Altman et al. [22] noted that modifications to the Altman's Z-Score model require changes to financial data and estimation techniques to improve results.

Gurau [23] emphasizes that Altman's Z-Score model is a valuable tool for investors to forecast bankruptcy. In a study of 33 bankrupt US companies, [23] found that by utilizing the information on company size, financial structure, performance, and current liquidity, bankruptcy can be predicted one year in advance. Li and Rahgozar [24] developed the use of asset volatility within Altman's Z-Score model for bankruptcy prediction. Li and Rahgozar [24] reported that approximately 95% of bankrupt organizations were correctly classified as bankrupt, and roughly 80% of non-bankrupt organizations were correctly classified as not bankrupt. Therefore, asset volatility is said to be the key variable in Altman's Z-Score model for manufacturing and non-manufacturing companies.

Mantziaris [25] used Altman's Z-Score model to assess the future of an industry after a global financial crisis, examine the impact of Chinese government regulations on the real estate industry, and predict future failures of Chinese real estate companies. Mantziaris [25] also found that Altman's Z-Score model correctly predicted company classifications by financial institutions in Lebanese manufacturing firms and company failures for the economy of Pakistan. Not only that, Altman’s model also can assess the current and future health of small and medium enterprises in the study of [26]. Singh and Singla [27] further extended the model's relevance in emerging markets such as the Indian corporate sector. Under dynamic market conditions, the Altman Z-Score model shows robustness in exploring the impact of environmental considerations on companies' financial health [28]. In terms of comparative analyses, the reliability of the Altman Z-Score model remains satisfactory compared to the alternative model [29].

In summary, the Altman Z-score model is still a great predictor of corporate default, as reflected by the diverse applications by industries and nations. Its empirical resilience, flexibility, and age-old prescience prove the model's strategic location in financial distress diagnosis and corporate governance.

Data Description and Sources

The selection of appropriate financial distress prediction models and the acquisition of relevant financial data are necessary to carry out an elaborate analysis for firms with a past record of financial distress. The study of an undisclosed Malaysian public manufacturing company firm characterized by a history tainted with massive financial losses, is an appropriate subject for financial distress analysis. Given this history of financial distress, models designed to assess the likelihood of bankruptcy, such as Merton's and Altman's Z-Score, are particularly suitable for analysing the company under study. By obtaining the company-specific financial data and implementing these models, this study can perform a sound and evidence-supported analysis of the company's financial distress.

Data for the selected Malaysian undisclosed public manufacturing company was gathered from two sources: the company's 2015 annual report and Bursa Malaysia's archived stock price database. The annual report gave financial variables including the number of outstanding shares, short-term borrowings, total liabilities, total assets, current assets, current liabilities, earnings before taxation, earnings after taxation, revenue, and book value of equity. Corresponding monthly stock prices were fetched from Bursa Malaysia website.

Applying the Merton's model

Merton's model, a framework for assessing a firm's default risk, necessitates information on outstanding shares, liabilities, and stock prices. In this study, these data were used to compute the following variables:

a. The market value of equity, E: Calculated by multiplying the monthly stock price with the fixed number of outstanding shares issued by the company for one year, generating twelve monthly market values of equity starting for the year 2015.
b. Book value of debt, k: Assumed to be equivalent to the value of short-term borrowings reported in the annual report, and it is treated as constant.
c. Market Value of Asset, V: Derived by summing up the monthly values of E with the fixed value of k.
d. Growth or drift rate, μ: Defined as the firm's return on assets (ROA). Monthly ROA was calculated by dividing net income (fixed value) by the monthly values of V. Then, the annual growth rate was obtained by averaging these monthly ROA values.
e. Volatility of Asset, σ: Calculated as the annualized standard deviation of the monthly returns of V, achieved by multiplying the standard deviation by the square root of 12.

Based on the computed variables, the probability of default of the company is estimated. In this context, probability of default, indicates a probability (Pr) that the the market value of the company asset at time t, V_t will be worth less than the book value of liabilities, k by the time the debt matures [9 -10]. This is expressed as follows:

$$P_t = \Pr[V_t \le k] \tag{1}$$

. Let V_t be a function that satisfies the following stochastic differential equation:

$$V_t = \ln V + (\mu - \frac{\sigma^2}{2})t + \sigma\sqrt{t}\varepsilon \tag{2}$$

where ln V is defined as a log-distributed of an initial value market value of asset, μ is the drift rate, σ is the asset volatility, and ε is the random component of the firm's asset returns. Substituting (2) into (1):

$$P_t = \Pr\left[\ln V + (\mu - \frac{\sigma^2}{2})t + \sigma\sqrt{t}\varepsilon \le \ln k\right] \tag{3}$$

Then, rearranging (3)to be as follows:

$$P_t = \Pr\left[-\frac{\ln\left(\frac{V}{k}\right) + \left(\mu - \frac{\sigma^2}{2}\right)t}{\sigma\sqrt{t}} \ge \varepsilon\right] \tag{4}$$

Assuming the random component of the asset return is normally distributed $\varepsilon \sim N(0,1)$. Hence, the probability of default in terms of the standard cumulative normal distribution can be written as

$$P_t = N[-d] \tag{5}$$

where d is the distance-to-default of the firm that is expressed as:

$$d = \frac{\ln\left(\frac{V}{k}\right) + \left(\mu - \frac{\sigma^2}{2}\right)t}{\sigma\sqrt{t}} \tag{6}$$

The probability of default and distance to default of the company were calculated using equations 5 and 6, respectively with t =1 year.

Applying the Altman's discriminant model

This study also employed Altman's Z-Score model, a multivariate financial distress prediction tool that utilizes five distinct financial ratios (X_1, X_2, X_3, X_4, and X_5). The model aims to classify companies based on their likelihood of financial distress, with lower Z-scores indicating higher odds of bankruptcy. For public manufacturing companies, Altman modified the model using the book value of equity in place of market capitalization and applying specific variable weights. The data collected was utilized in this revised Altman's Z-Score model calculated as below [22]:

$$Z = 0.717X_1 + 0.847X_2 + 3.107X_3 + 0.420X_4 + 0.998X_5 \tag{7}$$

where,
X_1: Working Capital (current assets - current liabilities) / Total Assets
X_2: Retained earnings (Earnings after taxation) / Total Assets
X_3: Earnings Before Interest and Taxes / Total Assets
X_4: Book Value of Equity / Total Liabilities,
X_5: Sales (revenue) / Total Assets.

Comparative Analysis of Merton's and Altman's Z-Score Models

A comparative analysis was conducted between the default risk assessments provided by Merton's and Altman's Z-Score models. The comparison was made based on Tables 1 and 2.

Table 1: Default Rates Classification

Default rate %	Classification
0.01-1.41	Firms with a very strong capacity to meet financial commitments. Low default risk. A bond rated as AAA to A-
2.30-32.50	Firms with an adequate capacity to meet financial commitments. Moderate default risk. Bond rated as BBB to B-.
46.61-100	Firms with immediate financial problems, indicate a high probability of default. High default risk. A bond rated as CCC to D.

According to Table 1 [30], Merton's model ratings were categorized into three risk levels: low, moderate, and high default risk. Each level is represented by rating and default rate thresholds. Meanwhile, Altman’s Z-Score model classified companies into three categories: non-bankruptcy, gray zone, and bankruptcy, based on the thresholds shown in Table 2 [31].

Table 1: Altman's Z-Score Model Rating for Public Manufacturing Companies

Z-Score Range	Classification
Above 2.9	Non- bankruptcy
1.23 – 2.9	Gray Zone
Below 1.23	Bankruptcy

Results and Discussion

The default risk assessments from Merton's model are presented and discussed based on the data in Figure 1 and Table 3. Figure 1 illustrates the market value of assets trend for an undisclosed company. The graph clearly shows significant fluctuations in the market value of assets throughout the year. This indicates volatility in the company's financial performance. The market value of assets is at its lowest point in January, indicating a potentially challenging start to the year. Then, the market value of assets reaches its highest point in July, suggesting a period of relatively strong performance or investor confidence during that month. After the peak in July, there is a general downward trend in the market value of assets, suggesting a potential decline in the company's financial health during the latter part of the year.

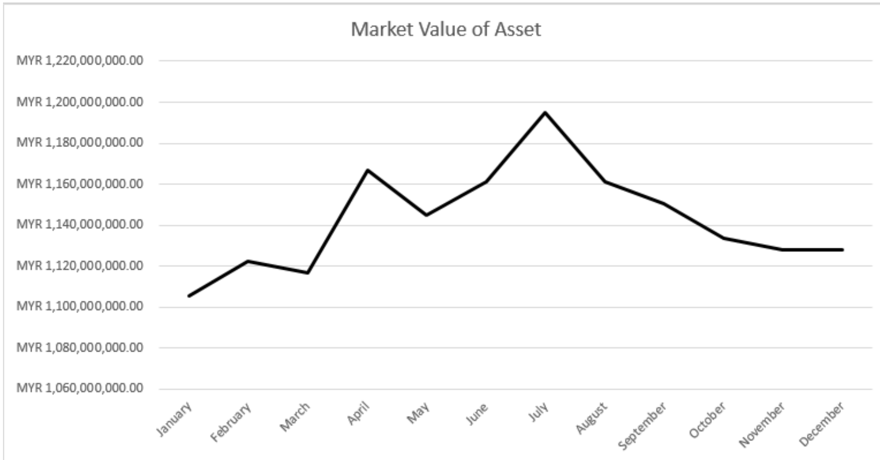

Figure 1: Market Value of Assets Trend for an Undisclosed Company in 2015

The volatility depicted in the graph supports the volatility figure (4.595%) calculated in Merton's model (Table 3). This volatility contributes to the negative distance to default and the 100% probability of default. The growth rate of -60.192% suggests significant losses. This further reinforces the company's precarious financial position, indicating that the company was deemed unable to meet its debt obligations.

Table 3: Merton's Model Default Risk Metrics

Volatility, σ	Growth Rate, μ	Distance-to-default, d	Probability of default, P_t
4.595%	-60.192%	-12.015	100%

Table 4 presents the annualized coefficients of Altman's Z-Score model for 2015. The calculated Z-Score of -4.018 indicates that the company was in the bankruptcy category, according to the criteria outlined in Table 2.

Table 4: Altman's Z-Score Coefficients

2015	x_1	x_2	x_3	x_4	x_5	Z
Value	-1.8888	-0.6767	-0.6768	0.0281	0.0008	-4.018

The overall results suggest that the company was facing financial challenges throughout 2015, which aligns with the conclusions drawn from both Merton's and Altman's models as concluded in Table 5. Table 5 compares the default risk assessments from Merton's and Altman's models. Both models indicate a high risk of bankruptcy. Merton's model predicts a 100% probability of default, while Altman's Z-Score indicates bankruptcy with a score of -4.018. These findings align with the company's documented financial difficulties, as discussed in the data section. The consistency between the results of Merton's and Altman's models supports the assessment of the company's financial distress.

Table 5: Comparison of Merton's and Altman's Model Results

Model	Merton’s	Altman’s Z-Score
Likelihood to default	100%	-4.018
Classification	High Default Risk	Bankruptcy

Conclusion

This research aimed to assess the default risk of a company using Merton's model and Altman's Z-Score model. Merton's model was employed to calculate the probability of default, while Altman's Z-Score model was employed to validate the estimated probability of default. These two models were employed to test the default risk of the selected undisclosed Malaysian manufacturing public company. Furthermore, this study provided a methodology for calculating key inputs for Merton's model, including the market value of assets, and asset volatility. Consequently, the distance-to-default was also determined. The results obtained from both models indicated high levels of agreement. Merton's model gave a default probability of 100%, while Altman's Z-Score model offered a default risk of -4.018. These results indicate a high likelihood of bankruptcy. The results are consistent with established benchmarks. The 100% default rate predicted by Merton's model aligns with the characteristics of a company in a state of financial distress. Similarly, Altman's Z-Score result of -4.018 falls within the range associated with bankruptcy.

This study encountered limitations, primarily in obtaining precise data corresponding to the annual reports of the selected company. Additionally, there was a challenge in establishing a definitive tool to measure the accuracy of the model comparison as default rates can be varied across companies. Future research could explore variations in model comparisons to further evaluate the effectiveness of Merton's model in forecasting default risk. In the context of Altman's Z-Score model, future studies might investigate the potential for refining the equation by adding or removing parameters to enhance default risk prediction accuracy.

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References

[1] Du, Y. & He, Y. (2024). Deleveraging, debt default risk, and enterprise innovation: Evidence from China. *Transactions on Economics, Business and Management Research*, 6, 250-263. https://doi.org/10.62051/ean14687

[2] Akomeah, J., Agumeh, R., & Frimpong, S. (2020). Credit risk management and financial performance of listed banks in Ghana. *Research Journal of Finance and Accounting*, 11, 6, 39-48. https://doi.org/10.7176/rjfa/11-6-05

[3] Chen, J. & Ma, L. (2022). Bank credit risk avoidance and countermeasures based on wireless communication. *Scientific Programming*, 1-7. https://doi.org/10.1155/2022/7793088

[4] Tien, D. P. & Nguyen, K. Q. T. (2023). Credit risk management and effectiveness of credit activities: Evidence from Vietnam. *Journal of Eastern European and Central Asian Research* (JEECAR), 10(5), 788-799. https://doi.org/10.15549/jeecar.v10i5.989

[5] Sutono, J. & Hermawan, A. A. (2024). Implementation of credit risk management Basel principles (evaluation study of an Indonesian commercial bank). *Owner*, 8(2), 1190-1199. https://doi.org/10.33395/owner.v8i2.2045

[6] Kamara, A. K. (2024). The study of credit risk in the banking sector and its effect on financial performance case study of the zenith bank Sierra Leone. *European Journal of Economic and Financial Research*, 8(4). https://doi.org/10.46827/ejefr.v8i4.1732

[7] Christoffersen, B., Lando, D., & Nielsen, S. F. (2022). Estimating volatility in the Merton model: The KMV estimate is not maximum likelihood. *Mathematical Finance*, 32(4), 1214-1230. https://doi.org/10.1111/mafi.12362

[8] Altman, E. I. (2000). Predicting financial distress of companies: Revisiting The Z-score and Zeta Models. *Journal of Banking and Finance*, 1(2); 1968 – 2000.

[9] Hull, J., Nelken, I., & White, A. (2004). Merton's Model, Credit Risk, and Volatility Skews. *Journal of Credit Risk*, *1*(1), 1–17.

[10] Crosbie, P., & Bohn, J. (2003). Modeling Default Risk - Modeling Methodology. *Moody´s KMV Working Paper*, 1–31. http://doi.org/10.1016/j.frl.2006.03.003

[11] Cakici, N., Chatterjee, S., & Chen, R. (2019). Default risk and cross section of returns. *Journal of Risk and Financial Management*, 12(2), 95. https://doi.org/10.3390/jrfm12020095

[12] Jumbe, G.& Gor, R. (2023). Examining the impact of debt maturity time, expected return and volatility on probability of default in credit risk modelling: The case of Merton and MKMV models. *International Journal of Engineering Science Technologies*, 7(1). https://doi.org/10.29121/ijoest.v7.i1.2023.442

[13] Aminda, R. S., Aziz, M. J., Suharti, T., subakti, J., Wibowo, S. S., & Subakti, A. K. (2023). Determining credit risk using contingent claim model approach (Merton model): A case study of Indonesian digital banks. *Advances in Economics, Business and Management Research*, 74-79. https://doi.org/10.2991/978-94-6463-244-6_14

[14] Tudela, M., & Young, G. (2005). A Merton-model approach to assessing the default risk of UK public companies. *International Journal of Theoretical and Applied Finance*, 8(06), 737–761.

[15] Norliza, M. Y., & Maheran, M. J. (2012). Estimating the Credit Risk of Malaysian Companies using Merton Model. World Applied sciences Journal, 17(72-78), 1-7.

[16] Miao, H., Ramchander, S., Ryan, P., & Wang, T. (2018). Default prediction models: The role of forward-looking measures of returns and volatility. *Journal of Empirical Finance*, 46, 146-162. https://doi.org/10.1016/j.jempfin.2018.01.001

[17] Yusof, N. M., Alias, I. Q., Kassim, A. J. M., & Zaidi, F. L. N. M. (2021). Determining the credit score and credit rating of firms using the combination of KMV-Merton model and financial ratios. *Science and Technology Indonesia*, 6(3), 105-112. https://doi.org/10.26554/sti.2021.6.3.105-112

[18] Oluwo, A. K. and & Villamor, E. (2022). Quantitative structural models to assess credit risk on individuals. *Journal of Applied Mathematics and Physics*, 10(07), 2313-2340. https://doi.org/10.4236/jamp.2022.107158

[19] Altman, E. I. (2018). Applications of distress prediction models: What have we learned after 50 years from the z-score models? *International Journal of Financial Studies*, 6(3), 70. https://doi.org/10.3390/ijfs6030070

[20] Hayes, S. K., Hodge, K. A., & Hughes, L. W. (2010). A Study of the Efficacy of Altman's Z to Predict Bankruptcy of Specialty Retail Firm Doing Business in Contemporary Times. *Economics & Business Journal: Inquiries & Perspectives,* 3(1), 1-13.

[21] Gabbi, G. & Levich, R. M. (2019). Controlling risks to ensure financial stability and reducing volatility. *Journal of International Financial Management & Amp Accounting*, 30(3), 183-187. https://doi.org/10.1111/jifm.12107

[22] Altman, E. I., Drozdowska, M. I., Laitinen, E. K., & Suvas, A. (2014). Distressed firm and bankruptcy prediction in an international context: A review and empirical analysis of Altman's Z-Score Model (August 10, 2014). *Available at SSRN: https://ssrn.com/abstract=2536340* or http://dx.doi.org/10.2139/ssrn.2536340

[23] Gurau, T. (2013). A model of bankruptcy prediction. Business Economics. Bachelor Thesis, Erasmus University of Rotterdam. Retrieved from http://hdl.handle.net/2105/13759

[24] Li, J., & Rahgozar, R. (2012). Application of the Z-Score Model with Consideration of Total Assets Volatility in Predicting Corporate Financial Failures from 2000-2010. *Journal of Accounting and Finance,* 12 (2), 1-9.

[25] Mantziaris, S. Z. (2015). Bankruptcy Prediction Models: An Empirical Analysis of Altman's Z-Score model in Forty Greek Companies in the Period of Economic Recession. Master Thesis, University of Macedonia, Greece.

[26] Mitrašević, M. & Bardarova, S. (2020). Measuring the risk of lending to small and medium-sized enterprises in the republic of Serbia in light of modern banking regulations. *Ekonomski Horizonti*, 22(3), 263-277. https://doi.org/10.5937/ekonhor2003263m

[27] Singh, G. & Singla, R. (2021). Default risk and stock returns: Evidence from Indian corporate sector. *Vision: The Journal of Business Perspective*, 27(3), 347-359. https://doi.org/10.1177/09722629211003358

[28] Oyegunle, A., Weber, O., & Elalfy, A. F. (2023). Carbon costs and credit risk in a resource-based economy: carbon cost impact on the z-score of Canadian TSX 260 companies. *Journal of Management and Sustainability*, 13(1), 187. https://doi.org/10.5539/jms.v13n1p187

[29] Rybárová, D., Majdúchová, H., Štetka, P., & Luščíková, D. (2021). Reliability and accuracy of alternative default prediction models: Evidence from slovakia. *International Journal of Financial Studies*, 9(4), 65. https://doi.org/10.3390/ijfs9040065

[30] Altman, E.I. & Kishore, V. (2000). The Default Experience of U.S. Bonds, Working Paper, Salomon Center, New York University.

[31] Kumar, M. N., & Rao, V. S. H. (2014). A New Methodology for Estimating Internal Credit Risk and Bankruptcy Prediction under Basel II Regime. *Computational Economics, 46*(1), 83-102. doi: 10.1007/s10614-014-9452-9