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A Comparative Analysis of Financial Performance With Altman Z, Springate S Score and Zmijewski Models: A Research on The Cement Sector in Istanbul Stock Exchange

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Abstract

The growth, development, survival, and profitability of companies depend on their ability to compete with rivals in the same sector. To achieve this, companies must utilize their resources effectively and efficiently while avoiding waste. This study estimates the financial risk exposure of cement companies listed on Borsa Istanbul. Using financial data covering 48 periods between 2021 and 2024, the bankruptcy risks of these firms were analyzed using the Altman Z, Springate S, and Zmijewski J-Score models. The results indicate that BSOKE and BTCIM were at risk of bankruptcy across all periods according to the Altman Z and Springate S models, and specifically during 2021-2022 according to the Zmijewski J model. Conversely, NUHCM, OYAKC, and BISCIM were found to be financially sound in all three models. While Altman Z and Springate S yielded highly consistent results, the Zmijewski J-score showed slight variations, primarily due to its lower risk parameters. Overall, the analysis demonstrates that the models used provide largely consistent findings regarding bankruptcy risk.

Key words: Financial Distress, Bankruptcy Risk, Altman Z, Springate S, Zmijewski J models

JEL Code: G32, G33, C52, M41.

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1. Introduction

The financial sustainability of businesses is shaped by the combined influence of not only internal management decisions but also external environmental factors, macroeconomic conditions, and sectoral competition. Therefore, accurate assessment of financial performance is critical for increasing the competitiveness of businesses, ensuring investor confidence, and early detection of potential financial problems (Altman, 2018; Marsenne et al., 2024). During periods of economic uncertainty, sound financial analysis has become essential for businesses' long-term success and sustainability (Upadhye et al., 2025). In this context, models based on accounting-based financial ratio analysis are widely used in the literature to measure the financial condition of businesses and predict bankruptcy risks (Beaver, 1966; Ohlson, 1980).

The Altman Z-score, Springate S-score, and Zmijewski J-score, which are among the financial performance evaluation tools, are prominent models for determining the financial stability and bankruptcy risks of businesses (Altman, 1968; Springate, 1978; Zmijewski, 1984). Altman's Z-score model, based on multiple discriminant analysis, classifies businesses as safe, gray, and danger zones by combining various financial ratios (Altman, 2013; Platt & Platt, 2002). The Springate model, on the other hand, offers a more practical structure, especially for SMEs, by using fewer variables (Jovancai Stakić et al., 2023; Gülal et al., 2023). The Zmijewski model, on the other hand, assesses the probability of financial distress of businesses with a simple formula based on logit analysis and is widely applied in emerging markets (Lin, 2009; Marsenne et al., 2024).

Despite their common objectives, these models exhibit varying performance across sectors and countries due to their different statistical foundations (Chava & Jarrow, 2004). While the Altman model is effective in large-scale manufacturing companies, the Springate model may yield more successful results in smaller businesses (Gülal et al., 2023). The Zmijewski model, on the other hand, offers advantages in emerging markets where financial ratios are more volatile (Mahesh et al., 2025).

The cement sector is an important area for financial performance analysis due to its capital-intensive structure and sensitivity to economic fluctuations. In Turkey, the sector is both a key component of construction and infrastructure investments and a crucial component of capital markets. Therefore, accurately identifying financial distress in the sector is crucial for the stability of the firm and the national economy (Burja & Burja, 2013; Rajin et al., 2016). This study aims to compare the discriminatory power and bankruptcy risk prediction performance of the Altman, Springate, and Zmijewski models in the Turkish cement sector using data from 2020 to 2024.

A literature review reveals numerous academic studies in Turkey concerning the measurement of financial performance in the cement industry. Various financial modeling approaches are employed in measuring the financial performance of firms operating in this sector. Studies in this area primarily utilize grey relational analysis, VIKOR, TOPSIS, MORAO, ratio analysis, data envelopment analysis, fuzzy logic, and DuPont methods. However, no academic studies have been found that combine Altman Z-score, Springate S-score, and Zmijewski J-score models in analyzing financial performance. This gap in the literature motivated us to undertake this study. The study, which is a continuation of previous studies in the literature (Altman, 2013; Gülal et al., 2023; Jovancai Stakić et al., 2023; Mahesh et al., 2025), aims to contribute to managers, investors and policy makers by presenting findings on the conditions under which financial distress prediction models are more effective.

2. Literature Review

This study evaluates the financial performance of cement companies operating on the Borsa Istanbul from a comparative perspective using the Altman Z, Springate S, and Zmijewski models. While the Altman Z score stands out in the literature as a classic and widespread tool for measuring bankruptcy risk, the Springate S score has been reported to be particularly sensitive in identifying short-term financial distress (Marsenne et al., 2024; Mahesh et al., 2025). The Zmijewski model quantitatively estimates potential risks related to companies' financial structures using a regression-based approach (Jocic et al., 2024).

Since its development by Edward Altman in 1968, the Altman Z-score model has gained a significant place in the literature as one of the most widely used accounting-based measures for predicting financial distress and bankruptcy (Altman, 2018). Recent studies have expanded the model's theoretical and applied scope by investigating its adaptability to different sectors, countries, and data types. In healthcare examples, Upadhye et al. (2025) showed that the modified Altman Z-score was effective in predicting financial distress in Federally Qualified Health Centers, while Lord et al. (2020) emphasized that it provides a practical tool for policy and management decisions by assessing the financial health of nursing homes. Studies in financial markets and the real sector also reveal that the model has a wide range of applications; Spulbar et al. (2025) examined the financial risks of firms in the Bucharest Stock Exchange, Matanga and Holman (2024) successfully predicted the probability of delisting of mining companies in the Johannesburg Stock Exchange, and Sareen and Sharma (2022) examined the usability of Altman Z-score in predicting stock price and financial distress in the Indian automotive sector. Additionally, Alcalde et al. (2022) applied the Z-score to economic sustainability analysis in the supply chain sector. Ch and Zulfiati (2018) examined the impact of the Z-score on financial health measurement and firm value in Indonesian state-owned companies. Apan, Oztel, and Islamoglu (2018) compared the Altman Z-score with the VIKOR method in the BIST food sector, demonstrating the importance of methodological diversity in performance and failure analyses. Focusing on the relationship between financial efficiency and credit risk, Bagade et al. (2023) and Bhuvaneskumar, Sivakumar, and Pushparaj (2023) used the Z-score integrated with other criteria in the performance evaluations of socially responsible companies. Gokturk and Yalcinkaya (2023) presented a comparison of the Altman and MFA scoring models in Turkish companies. Kapounek et al. (2022) investigated the predictive ability of the Z-score in European private companies, Alcalde et al. (2022) developed a classification of bankruptcy probability in the supply chain, and Ghosh and Kapil (2022) compared the effectiveness of the Altman Z-score with DEA and artificial neural network models. Machine learning-based studies also make significant contributions to the literature; Cindik and Armutlulu (2021) revised the Z-score using Random Forest in Turkish companies, while Syukur et al. (2024) improved the model with a two-stage classification method that handles imbalanced data and anomalies. Historical and international comparisons also support the validity of the model; Ko et al. (2017) in Taiwanese solar energy companies, Kiaupaite-Grushniene (2016) in Lithuanian agricultural companies, Mohammed (2016) in Oman cement companies, Postolov et al. (2016) evaluated the effectiveness of the Altman Z-score in predicting financial health in companies in Macedonia and Serbia. Spuchlakova and Michalikova (2016) examined the use of the Z-score by corporate managers in capital and credit decisions, and Lizarzaburu (2014) examined its adaptability in the Peruvian market. Finally, Elliott, Siu, and Fung (2014) combined the Z-score and credit ratings with a double hidden Markov model to provide new insights into financial quality. Wardayanti et al. (2017) analyzed bankruptcy strategies in spin-off companies using the Altman Z-score using the 5W+1H approach. Literature generally indicates that the Altman Z-score provides a strong basis for predicting financial distress, is highly adaptable to industry and country differences, and improves its predictive power when the classical discriminant analysis framework is integrated with modern data and methods.

The Springate model has a wide range of applications in different sectors and countries in predicting financial distress and bankruptcy risk. Marsenne et al. (2024) examined the financial statements of PT Garuda Indonesia (Persero) Tbk and found that the Springate model revealed that the company was in financial distress in 2020 and 2022, and was in a gray zone in 2021. Similarly, Mahesh et al. (2025) used the Springate S-Score to assess the financial health of small enterprises in India and showed that liquidity, leverage, profitability, and macroeconomic variables are critical determinants in predicting the financial condition of companies. Jocic et al. (2024) reported that in medium-sized agricultural and food companies in the AP Vojvodina region, the Springate model yielded similar bankruptcy predictions to Altman's modified Z' score in most cases, while the Kralicek Quick test produced different results. Csikosova et al. (2019) emphasized the limited predictive capacity of various financial health indices, including the Springate model, for companies in post-communist countries, thus necessitating adaptation of the methods to local conditions. Stefko et al. (2019) compared the Springate model with the Taffler and Aspect Global Rating models in the Slovakian electrical engineering sector, demonstrating that the Springate model contributes to competitiveness and risk analysis in assessing the financial health of companies. Finally, Stoyancheva and Angelova (2024) applied the Springate model to the Bulgarian agricultural sector, determining the financial sustainability levels of enterprises and demonstrating that a high degree of overlap between model predictions is a reliable indicator of financial stability. All these studies support the Springate model as an important and applicable tool for analyzing financial health and bankruptcy risk in both developed and emerging markets.

Current academic literature focuses on the assessment of the financial performance of enterprises in light of the challenges brought by the Industrial Revolution 4.0 era and the reliability of various bankruptcy prediction models, particularly the Zmijewski model (Lam, Yeoh, Lam, & Lai, 2020). In this context, the effectiveness of models developed to predict the risk of bankruptcy and financial distress has been comparatively analyzed by different study groups (Marsenne et al., 2024). In these analyses, the Zmijewski model has been tested for its ability to predict financial health during crisis periods; for example, this model was utilized in interpreting the financial condition of the Indian Real Estate Sector in the pre- and post-COVID-19 pandemic period (Agarwal et al., 2021). Furthermore, since enterprises are affected by cyclical economic developments and corporate life cycle stages, the reliability of early warning mechanisms is of critical importance; A study by Michalkova and Ponisciakova (2025) examined the reliability of various models, including a modified Zmijewski model, at different stages of the corporate life cycle. After all, while the development of the first bankruptcy assessment models dates back half a century, the ability of existing models like Zmijewski to timely predict solvency problems during crises such as the COVID-19 pandemic remains a central topic of current research (Mujkic & Novakovic, 2022). This literature review highlights the central role of the Zmijewski model in predicting financial distress under changing economic conditions and institutional structures.

In this study, analyses using the Altman Z, Springate S, and Zmijewski models to evaluate the financial performance of companies operating in the cement sector of Borsa Istanbul reveal the distinct strengths of each of these three methods. The Altman Z-score, with its long-standing application experience and adaptability to different industry and country conditions, provides a strong foundation for predicting financial distress. Its predictive power is enhanced when integrated with modern data analytics and machine learning techniques. The Springate S model, on the other hand, demonstrates high sensitivity in predicting short-term financial distress, proving to be an effective tool for assessing liquidity, leverage, and profitability indicators of companies, particularly in developed and emerging markets. The Zmijewski model, with its regression-based structure, makes a significant contribution to quantitatively predicting risks related to the financial structure of companies during periods of crisis and economic fluctuations. Overall, the findings demonstrate that all three models are complementary and that their combined use yields more reliable and comprehensive results in holistically assessing financial performance and bankruptcy risk in the cement sector. In this context, the importance of a multidimensional approach in financial analysis is once again emphasized.

3. Methods Used in Determining Financial Failure

Effectively evaluating financial performance is critical for both investors and managers in terms of company sustainability and predicting bankruptcy risks (Altman, 2018). The complexity of financial decisions and increasing economic volatility today necessitate accurate analysis of businesses' financial health. In this context, accounting-based and statistical methods are widely applied in the literature to analyze companies' financial structures, anticipate potential financial difficulties, and make strategic decisions (Altman, 2018; Upadhye et al., 2025; Marsenne et al., 2024).

3.1. Altman Z Score

The Altman Z-score is considered one of the most widely used tools among financial distress prediction models. Developed by Edward Altman in 1968, this model adopts a multivariate approach to predict the risk of bankruptcy for companies (Altman, 1968). The model combines factors such as liquidity, profitability, leverage, market capitalization, and operating efficiency based on financial ratios. Its basic formula is expressed as $Z = 1.2X1 + 1.4X2 + 3.3X3 + 0.6X4 + 1.0X5$, where X1 represents working capital/total assets, X2 represents retained earnings/total assets, X3 represents earnings before interest and taxes/total assets, X4 Net Sales/Total Assets, and X5 represents Sales/Total Assets (Altman, 2013). This model is designed specifically for publicly traded companies operating in the manufacturing sector and serves as an early warning system for financial stability (Beaver, 1966; Ohlson, 1980).

Various versions of the Altman Z-score have been developed and adapted to different sectors and company structures. The original model (the Z-score) was created for publicly traded manufacturing companies and has been expanded with versions Z' and Z''. The Z' model was adapted for private companies and uses book value instead of market value, with the formula $Z' = 0.717\ X1 + 0.847\ X2 + 3.107\ X3 + 0.420\ X4 + 0.998\ X5$ (Altman, 1983). The Z'' model, on the other hand, was designed for emerging markets and interprets financial ratios more flexibly, with the formula $Z'' = 3.25 + 6.56\ X1 + 3.26\ X2 + 6.72\ X3 + 1.05\ X4$ (Altman et al., 1995). These types increase the adaptability of the model and enable it to be used in different economic contexts (Zmijewski, 1984; Taffler, 1983).

The key features of the Altman Z-score are its statistical reliability and practical applicability. The model weights financial ratios using multiple discriminant analysis (MDA) and classifies companies into three categories: safe zone ($Z > 3.0$), gray zone ($1.8 < Z < 3.0$), and danger zone ($Z < 1.8$) (Altman, 2013). This feature increases the model's forecast accuracy to 85–90%, but it is sensitive to macroeconomic fluctuations (Platt & Platt, 2002). Furthermore, updating the model over time takes into account inflation and industry-specific factors, strengthening its long-term validity (Altman & Hotchkiss, 2006; Hillegeist et al., 2004).

The Altman Z-score begins with collecting financial data and calculating ratios. First, five key ratios are determined using balance sheet and income statement data; these ratios are then plugged into the formula to calculate the Z-score (Altman, 1977). The model's power is a proactive tool for predicting revenue and bankruptcy probability from statistical regressions based on historical data (Deakin, 1972; Argenti, 1976). However, data quality and timeframe are critical during its operation; data from the past 3-5 years is generally preferred (Shumway, 2001; Chava & Jarrow, 2004).

The Altman Z-score is frequently applied to predict financial distress in the agricultural sector. For example, in medium-sized agricultural enterprises in Serbia, the model classifies enterprises with a low probability of bankruptcy as having a high innovation potential (Đuričin & Beraha, 2021). Similarly, in large agricultural companies, the Z-score is compared with the Kralicek DF and Quick Test to assess financial stability, demonstrating that the Z-score provides more robust predictions (Milić et al., 2021). These applications highlight the model's sector-specific adaptability (Burja & Burja, 2013; Rajin et al., 2016).

In state-owned enterprises, the Altman Z-score relates the likelihood of sustainability to external and internal factors. In Indonesian state-owned enterprises, the model shows that inflation negatively affects bankruptcy profitability, while highlighting the moderating role of corporate governance (Widnyana et al., 2024). This allows the model to be integrated with macroeconomic variables (Stošić & Domazet, 2014; Novaković, 2019).

In the automotive sector, the Altman Z-score is a robust tool for predicting financial distress and stock prices. In the Indian automotive sector, the model captures the impact of the financial crisis and the GST regime on the sector and shows that EBITDA/TA and MV/TL ratios determine stock prices (Sareen & Sharma, 2022). This supports the integration of the model with panel data modeling (Martani et al., 2009).

The Altman Z-score is a fundamental reference in statistics and AI-based financial distress prediction models. In systematic literature reviews, the model achieves accuracy reaching 90% with hybrid AI models, compared to 34.5–70.2% with traditional statistical methods (Nugroho & Dewayanto, 2025). This encourages the integration of the model with AI (Alaka et al., 2015; Kuiziniene et al., 2022).

The development of the Altman Z-score began with Beaver's univariate analysis (1966) and evolved into Altman's MDA-based approach (Altman, 1968). Over time, the Z-score has demonstrated higher predictive power compared to logit and probit models (Ohlson, 1980; Zmijewski, 1984). Adapted versions of the model (Z'') are particularly robust to economic fluctuations in emerging markets (Altman et al., 1995; Altman, 2013).

Limitations of the model include its static nature and industry-specific assumptions; for example, it does not adequately integrate non-financial factors (corporate governance, macroeconomics) (Platt & Platt, 2002; Hillegeist et al., 2004). However, when combined with hybrid models, accuracy is improved (Shumway, 2001; Chava & Jarrow, 2004).

The Altman Z-score detects financial distress early during global crises. During the 2008 crisis, the model predicted increased risk in the agricultural and automotive sectors (Burja & Burja, 2013; Sareen & Sharma, 2022). During shocks such as pandemics, it captures the effects of inflation and exchange rates (Widnyana et al., 2024; Nugroho & Dewayanto, 2025).

As a result, the Altman Z-score is an indispensable tool in financial analysis and remains valid with continuous updates (Altman, 2013; Altman & Hotchkiss, 2006).

3.2. Springate S Score

The Springate S-score is a Canadian-based approach that holds a significant place among financial distress prediction models. Developed by Gordon L.V. Springate in 1978, this model is used to assess the financial health of businesses (Springate, 1978). Essentially, the Springate S-score can be defined as a multiple regression model that combines financial ratios to predict a business's risk of bankruptcy. Inspired by pioneering models such as the Altman Z-score, the model is particularly well-suited to small and medium-sized enterprises (SMEs) (Altman, 1968; Jovancai Stakić et al., 2023). Because financial distress is defined as a business's inability to pay its debts on time or maintain its operational activities, the Springate S-score is an effective tool for early detection of this risk (Mahesh et al., 2025).

The basic definition of the Springate S-score is based on a scoring system calculated using four financial ratios. The formula is as follows: $S = (1.3X1) + (3.07X2) + (0.66X3) + (0.4X4)$ (Springate, 1978).This formula produces a score by integrating liquidity, profitability, leverage, and efficiency. A score below 0.862 indicates a company is in financial distress, while a score above 0.862 indicates a healthy business (Gülal et al., 2023). The original study of the model states that it was tested on 24 bankrupt and 24 healthy Canadian companies, emphasizing that it is an empirically based approach (Springate, 1978; Platt & Platt, 2002).

The Springate S-score variants are often discussed in the context of their variations and adaptations. While the original model was designed for general businesses, industry-specific variants have been developed. For example, in studies examining the impact of the pandemic on the hotel industry, the Springate S-score was used in conjunction with the Altman Z"-score for credit risk analysis (Jovancai Stakić et al., 2023). Similarly, it appears as a variant integrated with clustering techniques in industrial sectors (Gülal et al., 2023). In emerging markets, a variant adapted for small businesses is seen, where the model is expanded by adding macroeconomic variables (Mahesh et al., 2025; Tian et al., 2015). Furthermore, hybrid variants have gained a more dynamic structure by combining them with machine learning algorithms (e.g., k-means clustering) (Gülal et al., 2023; Barboza et al., 2017).

The Springate S-score is based on a step-by-step calculation process. First, data such as working capital (current assets - current liabilities), earnings before interest and taxes, pre-tax profit, and sales are collected from financial statements (Springate, 1978). These data are multiplied by coefficients, representing the ratio of total assets to current liabilities (Gülal et al., 2023). The resulting score is compared to threshold values: a score below 0.862 is interpreted as distress, and above 0.862 as healthy (Mahesh et al., 2025). The reliability of the model depends on sample selection and data quality; for example, in a study on hotels in Serbia, statistical significance was confirmed by testing it with pre- and post-pandemic data (Jovancai Stakić et al., 2023; Zmijewski, 1984).

Among the advantages of the Springate S-score is its use as an early warning system for financial distress in small businesses. In emerging markets like India, the model achieved 92.7% accuracy by integrating variables such as the interest expense ratio, current ratio, and leverage (Mahesh et al., 2025; Habib et al., 2020). However, a disadvantage of the model is its sensitivity to external shocks due to its lack of direct macroeconomic factors (Betz et al., 2014; Yazdanfar & Öhman, 2020). Therefore, some studies have improved the model by adding factors such as GDP growth and inflation (ElBannan, 2021; Chen et al., 2020).

In various application areas, the Springate S-score is frequently preferred in credit risk analysis. For example, when used in comparison with the Altman Z-score in Turkish industrial companies, it has been found to exhibit higher discriminatory power through clustering techniques (Gülal et al., 2023; Ohlson, 1980). In measuring the impact of COVID-19 in the hospitality sector, the model has been supported by statistical tests (Wilcoxon signed-rank test) (Jovancai Stakić et al., 2023; in line with the Kolmogorov-Smirnov test). In small businesses, its predictive power increases when combined with variables such as firm age and size (Ciampi et al., 2021; Jones & Wang, 2019).

The theoretical foundations of the Springate S-score evolved from Beaver's univariate model (Beaver, 1966). Its multivariate structure is similar to the work of Taffler (1984). Recent research suggests integrating the model with artificial intelligence (e.g., logit regression) (Mahesh et al., 2025; Barboza et al., 2017).

In comparative analyses, the Springate S-score is practical because it uses fewer ratios than Altman models, but unlike probabilistic models such as the Zmijewski J-score, it has a deterministic structure (Zmijewski, 1984; Jovancai Stakić et al., 2023). In stock market indices (e.g., BIST Industrial Index), combining the model with k-means clustering provides superiority over traditional methods (Gülal et al., 2023). In emerging markets, it is recommended to adapt the model with inflation and GDP (Mahesh et al., 2025; Opler & Titman, 1994).

Consequently, the Springate S-score is an indispensable tool in financial sustainability analysis. Future studies recommend testing the model with more sector and country data, focusing on its adaptability to global crises (Springate, 1978; Li et al., 2020). This model offers opportunities for early intervention for investors and policymakers (Tian & Yu, 2017; Boritz et al., 2007).

3.3. Zmijewski J Model

The Zmijewski model is a logit-based statistical tool developed to predict the risk of financial distress and bankruptcy (Zmijewski, 1984). This model assesses the financial health of companies through three key ratios: net income/total assets (ROA), total liabilities/total assets (leverage ratio), and current assets/current liabilities (current ratio). Its formula is X = 4.3 - 4.5*(Net Income/Total Assets) + 5.7*(Total Liabilities/Total Assets) - 0.004*(Current Assets/Current Liabilities). If the X score is above 0, the company is considered to be at high risk of bankruptcy (Lin, 2009). Designed specifically for US-based companies, the model offers a proactive approach to predicting financial distress and has been tested in emerging markets such as Taiwan (Marsenne et al., 2024; Bilondatu et al., 2019). The Zmijewski model is notable for using fewer variables compared to models such as the Altman Z-score, but shows similar performance in terms of predictive accuracy (Jovancai Stakić et al., 2023; Mahesh et al., 2025).

Variants of the Zmijewski model include the original logit form, as well as versions adapted to various sectors. While the original model (X-score) focused on the manufacturing sector, modified versions have been developed for the service sector (e.g., hotels and airlines) (Gülal et al., 2023; Milić et al., 2021). For example, the Zmijewski J-score, combined with Altman Z", was used to analyze the pandemic impact in luxury hotels in Serbia (Đuričin & Beraha, 2021). These variations increase the flexibility of the model and ensure its applicability in emerging economies (India, Indonesia) by integrating macroeconomic variables (inflation, GDP growth) (Widnyana et al., 2024; Sareen & Sharma, 2022). Zmijewski's hybrid types show higher predictive power in Taiwanese public companies when combined with neural networks (Nugroho & Dewayanto, 2025; Alaka et al., 2018).

The Zmijewski model is characterized by its statistical robustness and simplicity. It weights ratios using logit regression and categorizes companies into healthy/distressed groups (Ohlson, 1980; Platt & Platt, 2002). Its leverage- and liquidity-focused structure is superior in detecting short-term risks; however, due to its static nature, it is sensitive to economic fluctuations (Hillegeist et al., 2004; Chava & Jarrow, 2004). When applied to Serbian hotels during the COVID-19 pandemic, the model yielded statistically significant results and captured increased credit risk. However, neural networks offer an advantage when Zmijewski's assumptions are violated (Lin, 2009; Jovancai Stakić et al., 2023). These features make the model more reliable than traditional MDA methods (Beaver, 1966; Deakin, 1972).

The Zmijewski model begins with the collection of financial data. Three ratios are calculated from the balance sheet and income statement data, then inserted into the formula to obtain the X-score (Zmijewski, 1984; Shumway, 2001). Data quality is critical during this process, and 3–5 year timeframes are generally preferred (Altman, 1968; Altman, 1977). For Indonesian airlines (PT Garuda Indonesia), the model achieves 81.25% accuracy by integrating ROA and leverage ratios (Marsenne et al., 2024; Bilondatu et al., 2019). This proactive approach predicts the likelihood of bankruptcy early and demonstrates consistent performance compared to probit in Taiwan (Lin, 2009; Argenti, 1976).

Although the Zmijewski model uses fewer ratios compared to the Altman Z-score, it demonstrates similar discriminatory power when integrated with k-means clustering on the BIST Industrial Index (Gülal et al., 2023; Milić et al., 2021). For example, in Indian small businesses, Zmijewski, when used in conjunction with Springate, predicts financial distress with 92% accuracy (Mahesh et al., 2025; Rajin et al., 2016). This comparison demonstrates that Zmijewski's logit-based framework complements Altman's approach (Altman, 1983; Altman et al., 1995).

At PT Garuda Indonesia, the Zmijewski model analyzes financial distress during the 2020-2022 period by integrating with Taffler and Grover and achieving 81.25% accuracy (Marsenne et al., 2024; Bilondatu et al., 2019). This encourages the use of the model in combination with Altman Z in emerging markets (Widnyana et al., 2024; Đuričin & Beraha, 2021). In the agricultural sector, Zmijewski identifies innovation potential by hybridizing with Altman Z (Burja & Burja, 2013; Sareen & Sharma, 2022).

In the automotive sector, the Zmijewski model analyzes the effects of the GST regime and the financial crisis as an alternative to Springate (Sareen & Sharma, 2022; Nugroho & Dewayanto, 2025). Its integration with panel data increases the robustness of the model (Lin, 2009; Jovancai Stakić et al., 2023). In hotels during the pandemic period, the Zmijewski model yields statistically significant results compared to the Springate S-score (Jovancai Stakić et al., 2023; Mahesh et al., 2025).

The Zmijewski model is used as a reference for statistics- and artificial intelligence-based predictions. In literature reviews, Zmijewski provides 90% accuracy when hybridized with neural networks (Nugroho & Dewayanto, 2025; Alaka et al., 2018). In comparison with the Kralicek DF, Zmijewski provides more robust predictions (Milić et al., 2021; Gülal et al., 2023).

The development of the Zmijewski model began with Beaver's univariate analysis (1966) and evolved into Ohlson's logit model (Ohlson, 1980; Altman, 2013). Over time, compared to probit models, the Zmijewski model demonstrates higher predictive power (Lin, 2009; Taffler, 1983). Its integration with k-means in BIST accelerates development (Gülal et al., 2023; Marsenne et al., 2024).

Limitations of the model are its static nature and industry assumptions; it does not integrate non-financial factors (corporate governance) (Platt & Platt, 2002; Hillegeist et al., 2004). Accuracy is improved in hybrid models (Shumway, 2001;

Chava & Jarrow, 2004). Economic policy uncertainty in India increases the constraints (Mahesh et al., 2025; Bilondatu et al., 2019).

The Zmijewski model provides early detection of global crises. It predicted increased risk in Serbian hotels during COVID-19 (Jovancai Stakić et al., 2023; Widnyana et al., 2024). It captures inflation effects (Lin, 2009; Đuričin & Beraha, 2021). It outperforms k-means during crisis periods in the BIST (Gülal et al., 2023; Sareen & Sharma, 2022).

In conclusion, the Zmijewski model is an important tool in financial analysis and its effectiveness increases when used in conjunction with Altman Z (Altman, 2013; Altman & Hotchkiss, 2006).

4. Material and Method

The primary objective of this study is to conduct a comparative analysis by measuring the financial failure and bankruptcy risk of publicly held cement companies operating on the Borsa Istanbul in Turkey using the Altman Z-score method, Springate S-score, and Zmijewski Models. For the study, the 2021-2024 financial data of a total of 13 companies operating in this sector and registered on the Borsa Istanbul were selected. However, due to the unavailability of financial data for Limak East Anatolian Cement, it was excluded from the scope. The financial data used in the study was selected from the relevant companies' balance sheets and income statements. The data used in the study was obtained from the Public Disclosure Platform (KAP). The companies included in the study are shown in the table below.

Table 1. Companies Operating in the Cement Sector in Borsa İstanbul

No	Code	Companies
1	BOBET	Boğaziçi Beton
2	BSOKE	Batı Söke Çimento
3	BTCIM	Batıçim
4	BUCIM	Bursa Çimento
5	CIMSA	Çimsa
6	CMBTN	Çimbeton
7	CMENT	Çimentaş
8	GOLTS	Göltaş Çimento
9	KONYA	Konya Çimento
10	LMKDC	Limak Doğu Anadolu Çimento
11	NIBAS	Niğde Beton Sanayi
12	NUHCM	Nuh Çimento
13	OYAKC	Oyak Çimento
Activity Sector: Cement Production		

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5. Results

In this study, three different models were used to compare the financial failure and bankruptcy risk of companies operating in the cement sector for the years 2021-2024. The comparison results are shown below.

5.1. Altman Z Model

The financial performance of the companies was calculated using the Altman Z method, which is used to measure financial failure and bankruptcy risk. The Altman Z-score model used in the study is Z=1.2X1+1.4X2+3.3X3+0.6X4+0.999X5, and the ratios used in the model are as follows:

X1: Net Working Capital/Total Assets

X2: Retained Earnings/Total Assets

X3: Earnings Before Interest and Taxes/Total Assets

X4: Book Value of Equity/Total Liabilities

X5: Sales/Total Assets (Aslan, 2024).

The results of the Z-scores for the companies included in the study for the years 2021-2024 are calculated and shown below.

Table 2. Z-Scores of Companies Operating in the Cement Sector (2021-2024)

	Companies	**2021**	**2022**	**2023**	**2024**
1	BOBET	1.17	3.47	5.46	2.77
2	BSOKE	-0.67	0.04	0.4	-0.1
3	BTCIM	0,09	1,44	1,49	1,05
4	BUCIM	7.06	9.75	8.28	3.61
5	CIMSA	2.53	1.9	1.99	0.84
6	CMBTN	1.79	2.3	2.25	2.03
7	CMENT	0.99	2.13	2.48	2.66
8	GOLTS	0.87	2.48	4.04	2.66
9	KONYA	1.41	2.21	3.27	1.28
10	NIBAS	0.25	2.44	-0.27	-0.61

11	NUHCM	3.41	4.95	4.70	4.076
12	OYAKC	3.48	5.15	5.42	5.20

Table 2 shows the Z-scores of publicly traded cement companies for the years 2021-2024, shown in different colors. Companies in the safe zone and their years are shown in green, companies with uncertain years are shown in gray, and companies at risk of bankruptcy are shown in red.

GRAY: UNCERTAIN 1.80 < Z < 2.99

GREEN: SECURE Z > 2.99

RED: BANKRUPTCY Z < 1.80

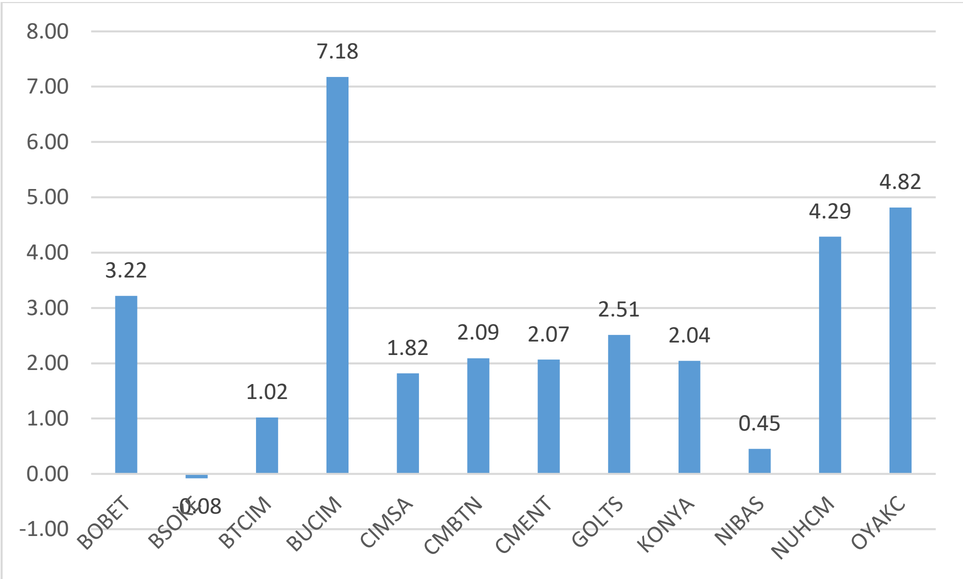

Figure 1. 4-Year Average Z-Scores of Companies

An examination of the Z-scores of companies operating on Borsa Istanbul for the 2021-2024 period reveals that BSOKE and BTCIM experienced financial distress and faced the risk of bankruptcy in all periods under review. Conversely, NUHCM, OYAKC, and BUCIM were financially sound and stable throughout all periods. The CMBTN, CMENT, and GOLTS companies examined in the study were found to be in the gray area and experiencing financial uncertainty between 2022 and 2024. The other companies included in the study were found to be at risk of financial bankruptcy in certain periods, while in the uncertain zone or experiencing successful financial performance during other periods. According to the results obtained, the companies included in the study, based on the Altman Z-score method, generally did not exhibit significant financial success between 2021 and 2024.

5.2. Springate S Model

Another model for identifying financial failure and bankruptcy risk in businesses is the Springate S model, developed by Gordon LV Springate. The model developed by Springate and used to calculate bankruptcy risk is as follows:

$$S = (1.3X1) + (3.07X2) + (0.66X3) + (0.4X4)$$

X1: Net Working Capital/Total Assets

X2: Profit Before Interest and Taxes/Total Assets

X3: Profit Before Taxes/Short-Term Liabilities

X4: Net Sales/Total Assets

As a result of the analysis, if a business's S score is <0.862, the business is at risk of bankruptcy (Aslan, 2024). The results of the S scores for the companies included in the study for the years 2021-2024 are calculated and shown below.

Table 3. S-Scores of Companies Operating in the Cement Sector (2021-2024)

	Companies	**2021**	**2022**	**2023**	**2024**
1	BOBET	0.47	1.48	2.26	1.11
2	BSOKE	-0.36	0.04	0.03	-0.15
3	BTCIM	0.02	0.67	0.50	0.35
4	BUCIM	2.69	3.39	2.60	1.23
5	CIMSA	1.03	0.89	0.82	0.33
6	CMBTN	0.74	0.95	0.77	0.70
7	CMENT	0.31	0.81	0.95	1.00
8	GOLTS	0.41	1.12	1.37	0.94
9	KONYA	0.68	1.19	1.31	0.50
10	NIBAS	-0.03	0.38	-0.11	-0.18
11	NUHCM	1.40	2.06	1.55	1.50
12	OYAKC	1.54	2.20	1.98	1.88

Table 3 shows the S scores of publicly traded cement companies for the years 2021-2024 in different colors. Companies in the safe zone and their years are shown in green, while companies at risk of bankruptcy are shown in red, along with their years.

GREEN: SAFE S>0.862

RED: BANKRUPTCY S<0.862

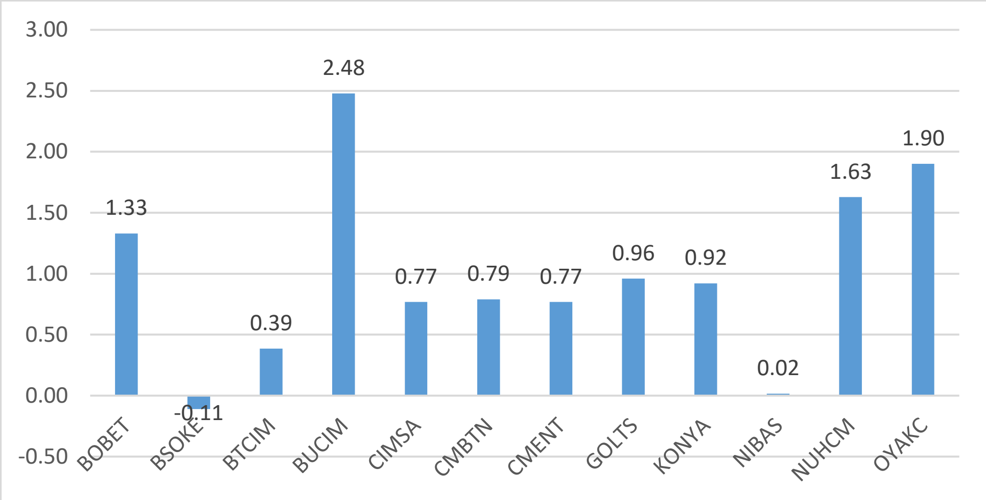

Figure 2. 4-Year Average S-Scores of Companies

An examination of the S values of companies operating on Borsa Istanbul for the 2021-2024 period reveals that BSOKE, BTCIM, and NIBAS experienced financial distress and faced the risk of bankruptcy in all periods under review. NUHCM was financially sound in all periods except 2024, while OYAKC and BUCIM were financially sound and stable in all periods. The other companies included in the study were at risk of financial bankruptcy in certain periods and performed well financially in other periods. According to the results obtained, the companies included in the study, based on the Springate S score method, generally did not appear to have performed particularly well financially between 2021-2024.

5.3. Zmijewski J Model

Another model for determining the risk of financial failure and bankruptcy in businesses is the Zmijewski model. The model used to calculate bankruptcy risk in companies is as follows:

J=4.3- 4.5*X1 + 5.7X2- 0.004X3

X1: Net Income/Total Assets

X2: Total Liabilities/Total Assets

X3: Current Assets/Short-Term Liabilities

As a result of the analysis, if a company's J score is >0, the company is at risk of bankruptcy. If the J score is <0, the company is considered financially sound and stable. The results of the J scores of the companies included in the study for the years 2021-2024 are calculated and shown below.

Table 4. J Scores of Companies Operating in the Cement Sector (2021-2024)

	Companies	**2021**	**2022**	**2023**	**2024**
1	BOBET	-2.33	-3.11	-3.37	-2.74
2	BSOKE	2.64	2.27	-1.51	-2.06
3	BTCIM	0.74	0.44	-2.58	-2.59
4	BUCIM	-4.31	-4.77	-4.22	-3.18
5	CIMSA	-2.52	-2.97	-2.49	-1.51
6	CMBTN	0.56	0.39	-0.59	-0.02
7	CMENT	-2.16	-2.79	-3.09	-3.02
8	GOLTS	-0.11	-2.00	-3.96	-3.21
9	KONYA	-1.82	-0.82	-3.34	-2.38
10	NIBAS	3.89	-5.26	-3.71	-3.29
11	NUHCM	-2.99	-4.05	-3.14	-3.52
12	OYAKC	-2.76	-4.05	-3.91	-3.75

Table 4 shows the J scores of publicly traded cement companies for the years 2021-2024 in different colors. Companies in the safe zone and their years are shown in green, while companies at risk of bankruptcy are shown in red, along with their years.

RED: BANKRUPTCY J>0

GREEN: SAFE J<0

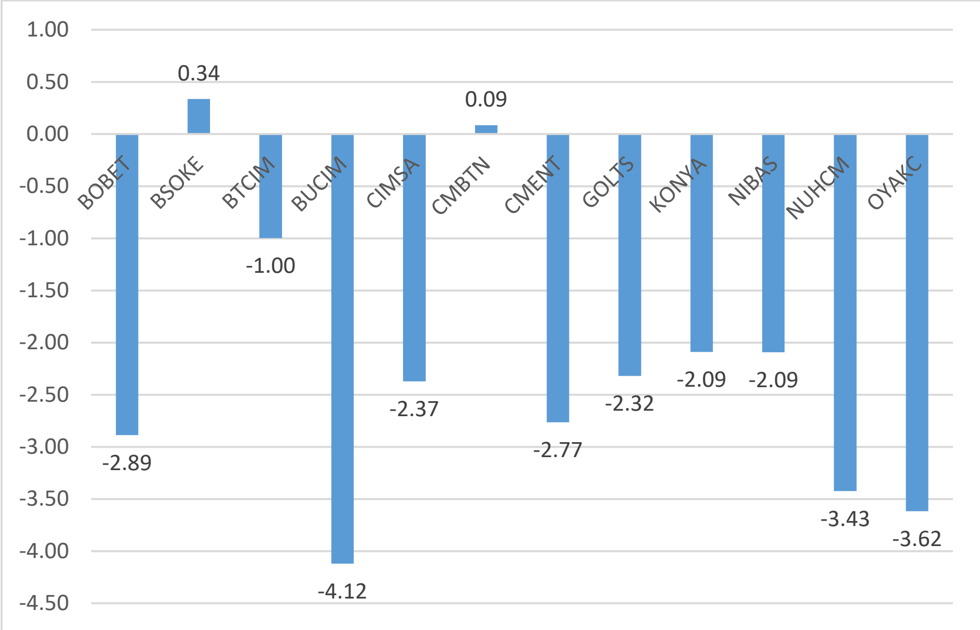

Figure 3. 4-Year Average J-Scores of Companies

An examination of the J values of companies operating on the Borsa Istanbul for the 2021-2024 period reveals that BSOKE, BTCIM, and CMBTN experienced financial difficulties only in the 2021-2022 period and were not at financial risk in other periods. NIBAS, however, was at risk of bankruptcy in 2021 and was financially sound in the other periods examined. All other companies in the study were financially sound in all periods.

6. Conclusion and Evaluation

A company's growth and sustainability depend on its competitiveness compared to other companies operating in the same sector. A company's ability to maintain continuity and grow depends on its profitability. Maximizing profitability requires profit-driven companies to utilize their resources effectively and efficiently.

Companies can experience a decline in financial performance and become exposed to the risk of bankruptcy due to various internal and external factors. Financial risk, or financial failure, stems from a variety of factors. Generally, financial distress, or bankruptcy risk, refers to a situation where a company's cash assets are insufficient to pay its current liabilities. When a company's current assets are insufficient to pay its liabilities, it faces the risk of bankruptcy. While companies can continue operating for a certain period even at a loss, disruptions in cash flow can put them at risk of bankruptcy.

In this study, the financial risk status of companies operating in the cement sector, registered on the Borsa Istanbul, and whose shares are publicly traded was estimated using the Altman Z, Springate S, and Zmijewski J-Score models. The study examined 48 periods between 2021 and 2024, collected four years of financial data, and calculated the ratios necessary to estimate the companies' financial failure.

At the end of the study, a prediction was made regarding whether firms are exposed to bankruptcy risk using the Altman Z-score, Springate S, and Zmijewski J methods. Based on financial risk (bankruptcy) and financial soundness studies conducted using three different models, it was found that BSOKE and BTCIM firms were at risk of bankruptcy for all periods studied using the Altman Z-score and Springate S methods, and for the 2021-2022 periods according to the Zmijewski J model. Similarly, in the same models, NUHCM, OYAKC, and BISCIM firms were concluded to be financially sound in all three models. The analysis results show that the methods used to calculate the firm's bankruptcy risk yield similar results. Over the 4 years and 48 periods covered in the study, it was concluded that 0.62 of the firms were financially sound according to the Altman Z-score method, 0.50 according to the Springate S method, and 0.85 according to the Zmijewski J method and were not at risk of bankruptcy. The research reveals that the Altman Z-score and Springate S methods yield similar results, but there is a slight difference in the Zmijewski J method. This is primarily due to the lower bankruptcy rates used in this model compared to others. However, it should be noted that estimating a company's bankruptcy risk solely based on its financial statements is not an accurate assessment. The company's current economic climate, weak market conditions, poor management, inappropriate location, and incorrect management strategies also contribute to bankruptcy risk.

As a result, the Altman Z-score, Springate S-score, and Zmijewski J-score methods indicate that firms not at risk of bankruptcy are generally similar, while those at risk of bankruptcy are similar when calculated using the same models. Academic studies also indicate that these models yield similar results in measuring bankruptcy risk and financial strength.

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