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An Empirical Analysis of the Forecast of Corporate Financial Distress in the European Energy Sector

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Introduction

Exploring the causes of corporate financial distress has been a topic of extensive discussion and research in the field of finance. Over the years, scholars and experts have dedicated their efforts to unraveling the intricacies behind financial struggles faced by businesses. The enduring interest in this subject can be attributed to the profound consequences that corporate financial distress can bring.

When a company finds itself in a state of financial distress, it often marks a critical turning point that could lead to insolvency or even bankruptcy. This represents the ultimate failure of the company and has wide-ranging impacts that go beyond its immediate boundaries. Employees are affected by potential job losses, stakeholders face financial losses, connected companies may experience disruptions in their operations, and the overall economy can suffer.

The costs associated with corporate financial distress are substantial and can take different forms. Direct costs include expenses related to legal proceedings, asset liquidation, and settling outstanding debts. Indirect costs can arise from the erosion of the company's reputation, diminished investor confidence, restricted access to credit, and the ripple effect felt throughout the supply chain.

Given the prevalence and far-reaching consequences of corporate financial distress, researchers and experts have delved into the topic with great fervor. Their aim is to develop models, methodologies, and strategies that can help identify early warning signs of financial distress and enable proactive measures to be taken. By doing so, they seek to protect companies from the brink of failure and promote stability and growth in the broader economy.

The study of corporate financial distress has yielded valuable insights into the various factors that contribute to these challenges. Researchers have examined aspects such as poor financial management practices, ineffective governance structures, unfavorable economic conditions, industry-specific challenges, and vulnerabilities unique to individual companies.

Ultimately, the research conducted in this field not only sheds light on the causes and consequences of corporate financial distress but also strives to provide guidance for companies, investors, and policymakers. By understanding the dynamics of financial distress, stakeholders can make informed decisions, implement preventive measures, and contribute to the resilience and success of businesses in the face of adversity.

In the first chapter, the focus is on reviewing the existing literature to gain a better understanding of the concept and terminology related to corporate financial distress, failure, and bankruptcy. This section aims to provide a comprehensive overview of these terms and their definitions within the context of corporate finance.

The chapter also delves into the principal causes of failure, paying particular attention to factors such as the business lifecycle, corporate restructuring, and corporate governance. These factors have a significant influence on the probability of financial distress and are therefore crucial to understanding the dynamics of corporate failure.

Additionally, the chapter explores the importance of predicting corporate financial distress. It discusses the direct and indirect costs associated with financial distress and highlights the significance of accurate prediction in mitigating these costs. The historical background of financial ratios and their importance in predicting financial distress is also briefly discussed in this section.

By organizing the paper in this manner, the reader is provided with a solid foundation of knowledge and understanding before delving into the subsequent chapters, which will focus on specific aspects of financial distress prediction models and the technique of cash flow analysis.

The second chapter of the thesis will focus on reviewing financial distress prediction models. These models can be broadly categorized into three main types: accounting-based models, market-based models, and hybrid models that combine both approaches. Accounting-based models, which rely on information from a company's financial statements, are the most widely used. Within this category, there are several sub-categories, including discriminant analysis models and regression models for specific variables.

In terms of discriminant analysis models, they can be further divided into univariate analysis and multivariate analysis, depending on the number of variables considered. Additionally, modern literature has introduced models based on artificial intelligence, which have shown promise in improving the accuracy of bankruptcy forecasting. However, these AI-based models are currently considered less practical compared to traditional approaches.

Towards the end of the second chapter, I will begin to express my own thoughts on the subject, emphasizing the significance of financial distress prediction studies.

In the third chapter, I'll make financial difficulty predictions based on all previous models . A sample of European businesses will be used to test this approach. The chapter opens by outlining the justification for choosing this particular sample of data. I'll explain why I chose European businesses and go through any unique qualities or elements that make this sample pertinent to the research.

The analysis will be developed step-by-step in the next sections of the chapter. I'll go through the formula for determining the Altman Z-score, X-score, G-score and S-score. To ensure transparency in the study methodology, the data collecting, preparation, and analysis processes will be thoroughly described.

Following the model's development, I will discuss the results of the empirical test. This section will provide an analysis of the predictions made by those models for the sample of European companies. I will evaluate the accuracy and effectiveness of the models in predicting financial distress and highlight any significant findings or trends observed during the analysis.

CHAPTER I

Corporate Financial Distress

1.1 Different Perspectives to Financial Distress

The quality of research in this area may suffer from the lack of a specific and consistent description for the stage of decline that businesses go through when they get into financial troubles. It poses a problem since some insolvent corporations can be incorrectly labeled as non-solvent, while some non-solvent enterprises might be misclassified as solvent. The majority of the previous study on business distress has been on management changes and financial restructurings. Gilson (1989) looked at management turnover; Gilson, John, and Lang (1990), Wruck (1990), and Brown, James, and Mooradian (1992) looked at financial restructurings.

Buttignon (2015) argued that in order to comprehend corporate distress, it is critical to analyze a firm's financial history over a significant amount of time and in sufficient depth to pinpoint the key causes of the value fall. The operational motivators and company-adopted strategies should be included in this research. Also according to Paolone and Pozzoli (2017), all definitions rely on analyzing financial measures from the company's financial records since they are reliable indicators of future failure.

A corporation is in financial distress, according to Carmichael (1972), when it has insufficient liquidity, equity, liquid capital, and debt defaults. According to Foster (1986), distress is characterized as a serious liquidity issue that cannot be remedied without a significant restructure of activities. According to Beaver (1966), this description is based on the cash flow or liquid assets model, which sees a corporation as a reservoir of liquid assets that are fueled by inflows and depleted by outflows. According to Whitaker (1999), businesses with positive cash flows can essentially raise additional money, but those with negative cash flows cannot and may not be able to pay their debts as they mature. Distress is defined by Doumpos et al. (1999) as a negative net asset value, where a company's entire liabilities exceed its total assets from an accounting perspective.

Pindado, Rodrigues, and de la Torre (2008) proposed a technical method to examine the link between a firm's operating profitability and financial commitments in order to ascertain whether a company is in financial distress. According to their methodology, a company is considered to be in distress if EBITDA (Earnings Before Interest, Taxes, Depreciation, and

Amortization) is less than its financial expenses for two years in a row and if its market value has decreased for two years in a row. This technique offers a precise and impartial foundation for locating financially troubled businesses.

Asquith, Gertner, and Scharfstein (1994) used the interest coverage ratio, which is calculated by dividing earnings before interest and taxes (EBIT) by interest costs, to identify financial hardship. If a business has a low interest coverage ratio, it may soon become technically insolvent, which means it may be unable to pay interest or principal on its debt. John, Lang, and Netter (1992) provide a different definition of financial hardship based on a change in stock price or a negative EBIT.

Hofer (1980) centered around businesses that were previously in a healthy financial state but subsequently encountered financial difficulties. In his approach, Hofer places significant importance on the break-even or operational income. By evaluating a corporation's financial health through this lens, Hofer aims to identify the specific challenges and opportunities that arise when a previously thriving business faces financial troubles. Queen and Roll (1987) concurred with Hofer's viewpoint that negative operating profits are a cause for concern regarding a company's long-term viability. They further highlighted that changes in stock prices can serve as indicators of a firm's financial condition. These models offer distinct perspectives on financial distress and can offer valuable insights for researchers and practitioners in the field.

According to Altman and Hotchkiss (2010), bankruptcy, insolvency, failure, distress, and default are commonly used terms to describe the financial difficulties faced by companies. Although these terms are often used interchangeably, they may have distinct formal definitions.

When a company consistently earns a lower rate of return on its invested capital compared to prevailing rates on similar investments, it is referred to as *failure*. This economic condition occurs when the company's revenues are insufficient to cover its costs, and the average return on investment remains below the company's cost of capital. It's important to understand that such situations don't necessarily mean the company will cease to exist or discontinue its operations. A company can experience economic failure for a prolonged period without failing to meet its current obligations, especially if it has minimal or no legally enforceable debt (Altman and Hotchkiss, 2010).

When a company's total obligations exceed a reasonable assessment of its total assets and produce a negative net value, the condition is referred to as *insolvency*. Insolvency circumstances are normally determined only when asset liquidation is being contemplated, hence a thorough value examination is usually necessary. In addition, the term "deepening insolvency" has become a legal notion in more recent times. When a bankrupt corporation is purportedly being kept alive needlessly to the prejudice of the estate and its creditors, this situation is said to exist by (Altman and Hotchkiss, 2010).

When a debtor company breaches a contract with a creditor, it is said to be in *default* and may face legal repercussions. It may take place if the debtor breaks one or more loan covenants relating to dividends, debt obligations, or financial ratios. Technical defaults are infractions that frequently indicate a downturn in the performance of the company and are usually renegotiated. It's critical to realize that technical defaults do not always result in official bankruptcy. If the problem isn't rectified in the grace period, which is often approximately 30 days, in the event of missed interest or principal payments, the security is regarded as being in default. To avoid official bankruptcy procedures, the company may continue to function while seeking to work out a restructure with its creditors (Altman and Hotchkiss, 2010).

Platt and Platt (2006) offer a more thorough explanation of financial distress, describing it as a persistently negative situation that frequently precedes bankruptcy, a legal action that denotes the end of a company's life cycle. They see bankruptcy as a unique occurrence, whereas financial difficulty is seen as a dynamic process that comprises a series of actions. In a similar vein, Foster (1986) cautions that, despite the fact that bankruptcy is a legal procedure largely influenced by creditors and bankers, it is a commonly used benchmark for detecting corporate financial difficulties.

Bankruptcy refers to the formal declaration of a firm's insolvency in a federal district court, accompanied by a petition to either liquidate its assets (Chapter 7) or implement a recovery program (Chapter 11) known as bankruptcy reorganization. However, some experts argue that bankruptcy may not always be the best choice, as it can result in the disruption of businesses that could have potential benefits for the community (Ball and Foster, 1982). In such cases, the concept of reorganization allows struggling corporations to continue operating under the management and control of the debtor, preserving companies that possess greater intrinsic or economic value than their current liquidation value. However, if the firm's assets are more valuable in liquidation than as an ongoing concern, liquidation may be considered the preferable option (Buttignon, 2015).

Whether poor management is the true cause of a company's financial issues is up for debate. According to Aasen (2011), poor managerial skills are the main reason for business problems and likely failure. It's important to keep in mind that the specific source of the distress might affect how effectively management handles issues and improves the performance of financially challenged firms. Sadly, not many attempts have been made to develop financial difficulties prediction models. Among the limited attempts undertaken, Schipper (1977), Lau (1987), and Hill et al. (1996) have made the most significant contributions to this subject.

Therefore, it is crucial to identify financial distress early to prevent the situation from progressing to bankruptcy. Detecting financial distress entails conducting a comprehensive analysis of a company's financial performance, management and strategy, focusing on both historical financial results and non-financial results outlined in a reorganization plan.

1.1.1 Business Failure and Bankruptcy

It's critical to give a precise description of what constitutes a failed firm for (at least) two reasons. It first makes it possible to compare studies. Second, the type of definition used will have an impact on the processes and results that researchers notice. firm failure has been defined in a variety of ways by scholars over the years, with definitions ranging from broad (discontinuity of ownership) to less permissive (discontinuity of the firm) to specific (bankruptcy) definitions.

In previous empirical research, the term "business failure" has typically been used narrowly to refer to bankruptcy, in part because it makes data collecting easier. One ultimately comes to the conclusion that it is practically hard to distinguish between the usage of the terms failure and bankruptcy when trying to pinpoint the reasons why a corporation goes bankrupt. It may be said that bankruptcy is a direct contributor to the reasons of failure, even if only around 10% of all small business failures are officially admitted to bankruptcy.

Shepherd (2005) explored the relationship between trade credit and small business, examining whether it can be a cause of business failures. In a related study, Bradley and Rubach (2002) define failure as the point at which an organization ceases to perform its expected functions. They also reference Shepherd in recognizing bankruptcy as a form of failure, stating that the act of filing for bankruptcy (Chapter 7, 11, or 13) signifies that an organization is no longer functioning properly. Therefore, in most failure prediction studies, the health or risk of failure of a firm has been assessed using bankruptcy models. These models provide either a score (e.g., multiple discriminant analysis models) or a conditional probability of bankruptcy. Additionally, the predictive accuracy of bankruptcy models can vary based on industry characteristics and regional factors. Thus, it is advisable to use multiple bankruptcy models to ensure reliable results (Ooghe & Balcaen, 2007).

In recent years, the majority of innovation in prediction studies has been focused on developing new techniques for calculating bankruptcy; yet, this has not led to an increase in the accuracy of predicting company failure. A company often becomes bankrupt over a period of time that might range from a few years to many decades. According to studies (Argenti, 1976; Hambrick & D'Aveni, 1988; Laitinen, 1991), small to medium-sized businesses are more likely to experience a rapid failure process than huge corporations. Additionally, bankruptcy has been seen as the last phase of the decline process. In recent decades, two lines on business failure have burgeoned which seek to elucidate the causes of business failure: the deterministic and voluntaristic perspectives.

According to the deterministic point of view, there is mounting proof that business failure can be attributed to external organizational factors, such as deregulatory changes, technological advancements, and competition, over which organizational decision-makers have little control (Hager, Galaskiewicz, Bielefeld, & Pins, 1996).

On the other hand, the voluntaristic school suggests that business failures can be attributed to factors within the firm itself, often related to human actions and choices. These factors include mismanagement, corrupt practices among management, poor leadership, and ineffective decision-making processes (Amankwah-Amoah, Boso, & Antwi-Agyei, 2018).

A company's success and survival depend on a mix of internal and external factors. While some challenges can be predicted, unexpected circumstances can lead to failure. Internal factors like poor planning, ineffective management, and financial mismanagement can hinder growth. External factors such as economic downturns, industry disruptions, and intense competition also pose threats. Leaders must monitor and address these factors to ensure organizational success. Innovation, adaptability, and proactive risk management are crucial for navigating challenges and fostering long-term survival.

Internal Factors Lead to Business Failure

A thorough investigation by Argenti (1976) revealed the universal reality that poor management is the main reason behind failure. The age of the company has a considerable influence on the likelihood of bankruptcy, according to Altman (1968). If we analyze the corporate life cycle described in the preceding sentence, firms are more likely to fail in the initial stage and in the decline state, although the chance of bankruptcy is minimal in the intermediate stages (growth and maturity). The likelihood of a new, tiny firm failing within its first three years of operation is higher than it is for an established, larger company. According to a research by Thornhill and Amit (2003), decisions and actions made by people have a big impact on why businesses fail. According to their research, young companies in particular are more likely to file for financial distress because they lack managerial expertise and sound financial management skills. These young businesses frequently struggle with issues including a lack of funding to meet their financial responsibilities or a lack of industry-specific knowledge and skills necessary to build a competitive advantage.

Zhang et al., (2015). asserts that R&D investments have a high possibility of high-uncertain payback, which raises the risk of financial distress. Additionally, for managed businesses and throughout the economic slump, this relationship grew stronger. Additionally, Kane et al. (2005) discovered that organizations with positive employee relations had lower distress risk, which strengthens the company's worth. In general, the risk of distress rises as future business value becomes more unpredictable. Because corporate hedging methods try to minimize the volatility of the firm's value over time, they help to mitigate risk (Stulz et al., 2005).

A basic definition of business failure given by Amankwah-Amoah (2016) is "a situation where the firm ceases operations and/or loses its identity due to inability to respond and adapt to changes in the external environment in a timely manner." A planned or unexpected decline that causes decline or even death might result in a business failure. One indication that a company is about to fail is the depletion of both its financial and human resources.

External Factors Lead to Business Failure

The most frequent causes of corporate bankruptcy in the United States, according to Sullivan et al. (1999), are outside business factors. This result is consistent with past studies carried out by experts such Watson et al. (1998). The overall outcome of business failures is significantly shaped by these non-managerial elements. The status of the national economy (Johnson and Parker, 1996), inflation, unemployment, wage levels, and interest rates are some of the factors that are in play (Hudson, 1997).

The sector in which a firm works is a vital additional consideration. For instance, as new businesses enter the market and older ones leave, competition increases in deregulated industries. During times of high real interest rates, businesses may also experience difficulties. External factors that affect a company's success or failure include local and international rivalry, industry overcapacity, and the possibility for new business growth (Altman & Hotchkiss, 2010).

These studies highlight the importance of specific macroeconomic indicators in assessing the likelihood of firm failure and default rates. Bank credit, inflation, profits, interest rates, business activities, stock market performance, and GDP fluctuations all play crucial roles in understanding and predicting the financial stability and default risks within the economy. In an article by Carling, Jacobson, Lindé, and Roszbach (2007), it was found that the output gap, yield curve, and consumers' expectations contributed significantly to distress models' predictive power. In another study by Giesecke, Longstaff, Schaefer, and Strebulaev (2011), a regime-switching model was employed to analyze default rates. Their findings revealed that stock returns, stock return volatility, and changes in GDP were strong predictors of default rates. Interestingly, credit spreads were not found to have a significant impact on default rates, contrary to expectations. Also, Liu (2009) conducted a study using a vector error correction model and identified several influential factors on firm failure in both the short and long term. They found that bank credit, inflation, profits, interest rates, and business births had a significant impact on the likelihood of firm failure. Monetary policy changes, activities in the financial and real sectors, and shocks originating from major business entities also affected macroeconomic aggregates. Their study emphasized the importance of these macroeconomic indicators in understanding and predicting financial distress.

However, there are different perspectives on the relationship between general business cycle indicators and aggregate failure rates or default probabilities. Some researchers, like Altman and others such as Hudson or Ilmakunnas and Topi, have found that indicators like GDP growth are negatively associated with failure rates. They suggest that during periods of economic growth, the overall likelihood of business failures decreases.

On the other hand, many researchers conducted a study and found that macroeconomic indicators had an insignificant impact on the probability of default. According to their research, there was no significant relationship between macroeconomic factors and the likelihood of companies defaulting on their obligations.

1.1.2 Cost of Financial Distress

The cost of financial distress refers to the negative economic consequences that arise when a company faces financial difficulties. These costs can be classified as direct or indirect. Direct costs include expenses related to bankruptcy proceedings, such as legal fees and administrative costs. Indirect costs are more intangible and can result from factors like damage to reputation and a decreased ability to conduct business effectively.

Initially, the focus was on direct costs, with studies by Warner (1977) and Weiss (1990) suggesting that these costs are relatively small compared to the total loss suffered by a large firm in bankruptcy. Later, attention shifted towards indirect financial distress costs, which are borne by firms that can no longer meet their financial obligations and may be at risk of bankruptcy, as highlighted by Beaver (1966).

Debt-based indicators have been used to assess the probability of financial distress, assuming that higher leverage increases the likelihood of distress, as noted by Kaplan (1998). However, the relationship between debt and financial distress is complex, as stated by Jensen (1989), and leverage can also have benefits for financially distressed firms.

Altman (1984) measures indirect financial distress costs by comparing a firm's sales performance with that of its industry. In our study, we also utilize sales variables to evaluate financial distress costs, as this measure is less influenced by specific institutional characteristics compared to market values or earnings. We assess the extent of the financial crisis by comparing the growth rate of a firm's sales with that of its sector, following the proposal of Opler and Titman (1994). Insolvent firms tend to lose their position within the sector, even without filing for bankruptcy.

Another aspect is the management of liquid assets by insolvent firms. Opler et al. (1999) demonstrate that insolvent firms often utilize their liquid assets to cover losses instead of allocating them to profitable projects. Holding liquid assets can impose an opportunity cost due to lower returns, as argued by John Opler et al. (1999). The debate continues regarding whether liquid assets serve as a necessary defense against financial distress or contribute to inefficiency by delaying response to the crisis.

In imperfect markets for physical assets, an ideal capital structure emerges if investors disregard risk. Scott (1976) suggests that the value of a non-bankrupt corporation depends on predicted future profits and the asset's liquidation value. The optimal debt level is shown to be influenced by factors such as the asset liquidation value, corporation tax rate, and firm size.

Overall, understanding the costs of financial distress involves considering both direct and indirect consequences, the relationship between debt and distress, the impact on sales performance, the management of liquid assets, and the concept of an ideal capital structure based on market imperfections.

1.1.3 Corporate Lifecycle

Financial distress, default, and bankruptcy are indeed significant stages in the life cycle of companies (Wruck, 1990). The business life cycle typically encompasses four stages: birth, growth, maturity, and decline.

According to the life cycle theory, growing capacity, access to resources, and strategies vary during a firm's life cycle (Anthony and Ramesh 1992). Each stage presents significant differences in terms of situation, organizational strategy, structure, and decision-making style. In particular, distinct lifecycle characteristics influence mainly the restructuring decisions In the earlier stages of their life, firms are typically small, simple and informal in structure, with a centralized power and focus on innovation (Adizes 2004). Logically, the level of uncertainty over the future growth is high and this is reflected in higher book-to-market ratio and firm specific risk . Corporate financial distress in the birth stage is generally associated with weak liquidity level or parallel cash flow difficulty. In the following stage, firms may achieve rapid growth, in this case, corporate financial distress is usually connected to excessive financial leverage because of the apparent necessity to expand capital. Differently, in the maturity stage firms are usually less focused on innovation and on risky strategy than in the previous stages. Indeed, they are interested in stabilising their business in the market. Finally, the life cycle includes a phase of decline, when the company operates under financial distress and its performance worsens for consecutive periods. If the causes are not corrected the decline becomes a crisis and then failures.

According to Koh et al. (2015), distressed firms' choice of restructuring strategies is influenced by their stage in the corporate lifecycle. Early-stage firms tend to reduce employees, while mature firms are more likely to engage in asset restructuring. The impact of the lifecycle is particularly evident in financial restructuring, such as reducing dividends or varying capital structures. Regardless of the lifecycle stage, reducing investments and dividends is associated with recovery, while increasing debt hampers recovery. The interaction of lifecycle and strategy choice also affects recovery, with adopting fewer strategies linked to better outcomes. Shareholder and creditor pressures play a role in prompting corrective measures, constrained by the firm's lifecycle stage.

1.1.4 Corporate Restructuring

When a firm recognizes that it is in danger of financial distress, it is vital that it responds immediately by taking corrective measures to enhance efficiency and control costs. Sudarsanam and Lai (2001) provide four classifications of restructuring: managerial, operational, asset, and financial.

Asset restructuring involves selling underperforming or non-core businesses to realign the firm's focus and refocus the business portfolio on core competencies. This type of restructuring allows companies to redirect resources towards more productive uses, and it is generally considered a value-adding strategy, according to Shleifer and Vishny (1992). Atanassov and Kim (2009) also support the idea that asset restructuring can enhance a firm's performance by optimizing its resource allocation.

Managerial restructuring is a process that involves replacing senior management and/or the Chief Executive Officer (CEO) of a company. It is typically implemented when poor planning or inefficient decision-making by managers contribute to the financial distress of the firm. In such situations, new teams are brought in to assess the situation and implement turnaround strategies, as highlighted by (Koh et al., 2015).

Operational restructuring focuses on restoring profitability by controlling costs and reducing overheads. This may involve selling excess fixed resources, such as assets that require high capital expenditures (CAPEX). By reducing inputs and maximizing outputs, companies aim to generate cash flow and improve overall efficiency, as discussed by Sudarsanam and Lai (2001).

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Financial restructuring refers to changes in a firm's dividend policies or capital structure to address payment pressures during financial distress. Equity-based strategies may involve reducing dividends or issuing new shares to retain or generate funds. Debt-based strategies, on the other hand, involve adjusting interest rates, debt maturity, or the debt/equity ratio. The funds obtained through these strategies are then used to meet debt obligations. DeAngelo and DeAngelo (1990) found that large firms are more likely to respond to financial distress with rapid and aggressive dividend reductions.

Overall, restructuring efforts encompass various aspects, including managerial, operational, asset, and financial restructuring, aiming to address the underlying causes of financial distress and improve the company's financial position and performance.

1.1.5 Effect of Corporate Governance on Financial Distress

The idea of "corporate governance" draws a parallel between how cities, nations, or states are governed and how corporations are managed. Back when textbooks on corporate finance were written, they referred to this idea as "representative government" (Mead, 1928). The term "corporate governance" itself was first used by Richard Eells (1960) to describe the structure and functioning of the corporate system. In simple terms, corporate governance refers to a set of rules, practices, and processes that a company follows to make sure it is managed in the best interests of everyone involved, including shareholders, employees, customers, and suppliers.

Having good corporate governance is vital for a company's long-term success and its ability to sustain itself. The relationship between corporate governance and financial distress is quite complex, with various factors at play. On one hand, effective corporate governance practices can help prevent financial distress by promoting openness, accountability, and making responsible decisions. Good corporate governance is essential in several ways: it helps shape the company's reputation, builds trust among shareholders, and reduces the risk of fraudulent activities OECD (2004). When a company demonstrates strong governance practices that investors believe in, it becomes easier to secure external funding at lower costs Fama & Jensen (1983). Furthermore, implementing robust corporate governance practices ensures that the company adopts the most effective business strategies to maximize its value and mitigate potential risks in the future Fich & Slezak (2008). Ultimately, by prioritizing good corporate governance, a company sets itself up for long-term success and sustainability.

On the other hand, poor corporate governance can seriously harm a company's ability to make money. Imagine a scenario where the people in charge of running the company aren't held responsible for their decisions, there's a lack of proper risk management, and unethical behavior goes unchecked. It fosters a culture in which anything is possible, which can be problematic. In simpler terms, poor corporate governance means there's no one watching over the company's actions and decisions. This lack of oversight can encourage bad behavior and irresponsible choices, ultimately putting the company's financial stability at risk.

In an environment where corporate social responsibility is emphasized, there might be a temptation for companies to take risky actions or engage in fraudulent practices. While these actions may seem beneficial in the short term, they often have negative consequences down the line. Such practices can lead to financial difficulties that are hard to recover from.

To counter these risks, certain components of good corporate governance become crucial. CEO duality, board composition, and management turnover all play significant roles. Independent monitoring, diverse perspectives, and stable leadership contribute to financial stability and long-term success. According to research by Lohrke et al. (2004), when a company is undergoing a turnaround, the composition of the board and the effectiveness of top management become critical factors. The board of directors and top management team are essential in reshaping a company's structure and strategy to overcome challenging times (Porter, 1989).

1.1.5.1 Board Composition

Putting together a company's board of directors is like assembling a dream team. Each board member brings their unique expertise and skills, creating a powerhouse of knowledge that helps the business maintain its financial stability. It's like having a group of trusted advisors who offer valuable insights into the market and guide the company towards success. Just as a sports team benefits from a diverse set of players with different strengths, a well-constructed board brings together individuals with varied backgrounds and perspectives. This collective wisdom provides the company with a solid foundation and a strategic edge in navigating challenges and making informed decisions.

Schiuma et al. (2008) emphasize the importance of having personnel with the necessary abilities and skills. They generate a virtuous loop by creating new ideas and inventive approaches to rejuvenate the company's goods and operations, resulting in enhanced performance. According to research, a diverse board, composed of people with varying experiences and skills, gives diverse viewpoints to the decision-making process. This variety can aid in identifying possible hazards and developing inventive solutions.

According to Adams and Ferreira (2009), having a diverse board that includes both men and women increases monitoring and management efficiency. A lack of gender diversity or domination by a small number of people can impede a board's effectiveness in detecting and addressing financial difficulties, raising the company's risk of collapse. The inclusion of varied viewpoints leads to better decision-making and overall financial stability.

Other research suggests that the relationship between board independence and the advising function is also affected by the firm's unique circumstances. (Duchin, 2010) contends that increasing board independence may have a negative impact on business performance when independent directors find it difficult to obtain information about the firm. According to (Coles, 2008), outside directors contribute to the board advisory function if the firm has multiple business units or extensive relationships with external parties, but inside directors contribute more to the advisory function if the firm's operations are technically more sophisticated and require specialist knowledge. Furthermore, Nguyen and Nielsen (2010) analyze stock price reactions to unexpected fatalities and come to the conclusion that independent directors are often regarded as advantageous to the business.

A board with a solid balance of independent members and financial professionals is more likely to recognize possible financial problems and take necessary preventative steps. According to (Byrd and Hickman, 1992), independent boards are more likely to fire CEOs for bad performance, and (Fich and Slezak, 2008), enterprises with more independent boards are better able to escape insolvency when entering a crisis. Also Hongxia Lie et al. (2008), having a larger share of independent directors is associated with a reduced likelihood of financial trouble. These findings back up researchers, which found that the fraction of independent directors had a considerable negative influence on financial distress.

Fich and Slezak (2008) argued that distressed firms with smaller boards are more likely to avoid financial distress. This suggests that a streamlined and efficient board structure can contribute to the company's survival during challenging times. Previous research (Goodstein et al., 1994), has concentrated on the issues associated with bigger boards, emphasizing that they might encourage opportunistic behavior by the company's management. Many other researches foster that smaller boards with a higher percentage of independent individuals can positively impact a company's performance and reduce the likelihood of financial distress (Jensen, 1993).

Conversely, a larger board can give more resources and knowledge, which is especially useful during times of crisis. A bigger board's pooled skills and experiences can assist in navigating problems and making educated decisions to aid a successful company turnaround. During a business turnaround, the board of directors and senior management are critical in updating a company's structure and strategy. In addition to the previous statement, several studies have found that the makeup of the board of directors has a significant impact on the risk of financial distress. When insiders or family members dominate a board, there is a greater likelihood of hazardous activity or failure to see warning indications of financial troubles.

Overall, the consequences of board composition on financial hardship are complicated and vary according to a number of criteria. However, research shows that in order to reduce the risk of financial difficulty and assure long-term success, organizations should strive for a diverse board that comprises persons with a variety of talents and viewpoints.

1.1.5.2 Management Turnover

Excessive management turnover, on the other hand, can be damaging to a company's financial health. In Japan, Kaplan and Minton, (1994) shows that enterprises with a major banking connection had a greater rate of management turnover in reaction to bad performance than those without and frequent management turnover can be a red flag for investors and stakeholders since it might indicate insecurity and a lack of direction inside the organization. This might cause a loss of trust in the company's leadership and have a detrimental influence on its financial success. Numerous research have been conducted to investigate the influence of management turnover on business performance, and the majority of them agree that the likelihood of management turnover is negatively related with firm performance (Warner et al., 1988). Simply put, when there is a larger likelihood of management change, the overall performance of the organization suffers. Similarly, Kim et al., (1996) shows experimentally that stock returns have a persistently negative influence on turnover likelihood. In badly performing corporations, stock prices tend to react favourably to the news of top management change, and changing underperforming executives can enhance the company's financial performance and avert future financial crises.

According to Schwartz and Menon (1985), 45% of insolvent businesses change CEOs, compared to 19% of control corporations and discover that when financially challenged organizations have their CEOs replaced by outsiders, the chance of bankruptcy more than doubles when compared to a matched sample of solvent enterprises. Parker et al., (2002) found that firms that hire an outsider to replace their CEO are more than twice as likely to fail. As a result, this body of data contends that dismissing CEOs may be indicative of a company's bad financial condition.

(Gilson, 1989) supports the underlying premise that many firms go through a senior management shift when they are in financial trouble. He also shows that the turnover rate for non-financially challenged businesses lowers considerably.

1.1.5.3 Chief Executive Officer Duality

The combining of two functions, the Chief Executive Officer (CEO) and the board chairman, within a single post is referred to as CEO duality. This arrangement balances the board of directors' power dynamics. There are several perspectives on the link between CEO dualism and corporate performance based on agency and stewardship theories. These ideas offer contrasting views on how the merging of the CEO and board chairman responsibilities impacts firm performance. Research has suggested that CEO duality can have both positive and negative effects on a company's financial distress.

Stewardship theorists contend that having a CEO in a dual role improves overall corporate success. Donaldson and Davis (1991) stressed that top managers strive to be responsible stewards of their company's resources. They aim to excel in their dual roles within the organization, aiming to reduce agency costs and increase the profitability of their companies (Beasley, 1996). They also aim to improve the perception of business governance by having CEOs who understand strategic processes and important issues within the company (Jensen and Meckling, 2009).

By taking on both jobs, CEOs gain new abilities and attributes that will assist the firm. The influence of CEO duality on businesses, however, varies (Jensen and Murphy, 1990). According to stewardship theory, CEO duality can boost a company's efficiency by emphasizing maximizing shareholder interests. The promotion of administrative effectiveness, enhanced communication, and flexible management system are all benefits of having a dual-role CEO.

Another aspect of Stewardship theorists is that larger companies have certain advantages over smaller ones. They possess greater resources and enjoy a better reputation in the market (Moeller et al., 2004). This enables them to launch new products and achieve their objectives more effectively. Larger companies are typically more established and structured, allowing them to adapt swiftly to market developments. They are responsive to shareholder pressures and prioritize the interests of the company's stockholders over the personal gain of CEOs. These companies can actively compete in the market and increase their profits due to their abundant resources and well-organized structure (Jensen and Murphy, 1990). The combination of a solid organizational structure, positive brand recognition, and significant market share often leads to better performance when CEOs hold multiple roles.

Contrarily, agency theorists emphasize the negative effects of CEO duality on business performance since the dual nature of the CEO's role may cause them to prioritize personal gain above the success of their company (Fama and Jensen, 1983). Therefore, it stands to reason that CEO duality might result in problems with agency between investors and executives. Additionally, CEO directions allow them to award executive roles to people who are close to them in a weak organization, taking advantage of their dual function . According to these results, CEOs' multiple roles may deteriorate the company monitoring structure and result in a range of firm performance (Krause, 2017). An earlier study that looked into this connection in American sectors found a strong and adverse link between CEO dualism and business company performance.

Studies examining performance indicators like return on equity (ROE), return on investment (ROI), stockholder return, and return on assets (ROA) suggest that CEO duality can have a detrimental effect on business performance (Yang and Zhao, 2014). Advocates of agency theory argue that a unified governance structure can mitigate conflicts of interest between company managers and multiple owners, potentially maximizing the positive impact of CEO duality on shareholder interests. The influence of CEO duality on a company's financial troubles varies on a number of variables, including the unique conditions and decisions taken by the leadership team. Businesses must carefully weigh the benefits and dangers of having a dual-role CEO and take the necessary steps to lessen any negative consequences. Having a solid, independent board of directors who can act as a watchdog and guide is a crucial first step. By doing this, choices are made with the company's and its stakeholders' interests in mind. Additionally crucial to preventing any abuse of power and fostering openness is the implementation of checks and balances inside the corporate structure.

1.1.5.4 Corporate Social Responsibility

Back in the 1950s, a new idea started to take hold in the business world—it was called corporate social responsibility (CSR). The main goal of CSR was to focus on improving the well-being of workers, their families, local communities, and society at large. This concept gained momentum both in Europe and the USA, as companies began to realize the importance of getting involved in CSR initiatives. According to the World Business Council for Sustainable Development (2004), CSR covers a wide range of areas, including community development, upholding human rights, taking care of the environment, and treating employees fairly. Initially, CSR was considered as something separate from financial concerns. However, recent research suggests that CSR can actually have a significant impact on a company's financial performance and its ability to weather financial challenges.

In other words, taking social responsibility not only benefits society but also influences a company's bottom line and risk profile. CSR is also essential for assisting businesses in anticipating and reducing risks, such as those associated with environmental legislation and supply chain interruptions, and averting financial difficulties. Companies that proactively participate in CSR activities such as stakeholder management and environmental assessment are better able to foresee and mitigate sources of business risk such labor conflicts, environmental harm, and governmental laws (Wood, 1991). According to Attig et al. (2013), improving a company's relationship with stakeholders through CSR will boost long-term sustainability. Additionally, Kim et al. (2014) found that CSR helps to lower the risk of stock price volatility, which is advantageous for the firm in terms of financial stability. Reputational risks are a significant way in which corporate social responsibility can impact financial distress. During times of crisis, effective management of reputational risk becomes crucial. Gotsi and Wilson (2001) highlight the importance of understanding corporate reputation for efficient reputation risk management. A company's reputation is influenced by various drivers, which evolve over time to align with changes in business and society. It extends on these motivators, adding emotional appeal, social and environmental responsibility, employee treatment, financial success, goods and services, and vision and leadership to the list.

Multinational firms confront extra hazards in the current global economy known as "social risks," which go beyond standard economic, political, and technological concerns. The interconnectedness of industries, global value chains, and the influence of stakeholders who have access to technology all contribute to these concerns (Kytle & Ruggie, 2005). Social hazards include concerns with things like labor laws, environmental policies, and human rights.

These risks result from changes in the business environment, as organizations now work in networks and with numerous partners in various countries. The capacity to influence a company's policies and practices has been made possible by the internet and contemporary technology (Kytle & Ruggie, 2005).

A well-integrated corporate social responsibility (CSR) policy into the company's overall activities would therefore play a crucial role in improving strategic intelligence and the early identification of social issues. This is because the company's skill to recognize the most important stakeholders and their main concerns is what allows it to balance social risks with corporate ambitions.

Godfrey (2005) asserts that corporate social responsibility (CSR) can offer firms something akin to insurance-like protection in the case of catastrophic catastrophes. CSR may have a complex and wide-ranging effect on a company's financial issues. Businesses that put a priority on CSR and proactively deal with social and environmental issues have a higher chance of managing risks successfully, fostering stakeholder trust, and achieving long-term financial success. This can then result in higher sales and general business resilience, higher valuations, and better access to capital.

1.1.5.5 Risk Management

The discovery, assessment, and management of risks that may have an influence on a company's operations or financial performance constitute effective risk management. Risk management reduces financial hardship and unexpected losses by proactively managing risks. Effective risk management is crucial for companies to comply with regulations and avoid legal and reputational risks.

Risk management is an essential component of corporate governance and has a big impact on how vulnerable a firm is to financial trouble. Recent policy texts stress the significance of thorough risk management frameworks together with suggested governance structures. Prioritizing risk management by creating appropriate frameworks is typical advice. This can involve many different actions. According to Kirkpatrick (2009), failures and weaknesses in corporate governance arrangements were significant contributors to the financial crisis. Inadequate risk management can result in fines, legal expenses, and damage to a company's reputation, leading to financial losses and an increased risk of financial distress. Acharya et al. (2009) argue that in modern-day banks, strong and independent risk management is necessary due to the weakening of monitoring incentives by debt holders, as well as the complexity of banking institutions and the challenges faced by supervisors in regulating risks effectively. Therefore, effective risk management is essential in mitigating legal, reputational, and financial risks while ensuring regulatory compliance. When businesses foresee future financial troubles, Smith and Stulz (1985) demonstrate that they would rationally strive to maximize value by purchasing risk management tools. Companies that prioritise risk management and take a proactive approach to identifying and mitigating risks are more likely to be resilient and successful over the long term.

1.2 Emergence and Application of Financial Ratios for Predicting Financial Distress

Ratio analysis has evolved significantly over time, with important advancements occurring in the early 20th century. Initially, analysts began considering a wide range of ratios and recognized the importance of both absolute and relative criteria for assessing financial performance. However, only a small percentage of analysts actually used ratios, with the current ratio being the preferred choice. The du Pont Company introduced a ratio "triangle" approach, emphasizing profit margins, turnovers, and return on investment. Although this concept was initially overlooked, it resurfaced later in the literature. Wall (1919) played a pivotal role by popularizing the use of multiple ratios and empirically determined relative criteria. This led to an increase in papers on ratio analysis and the compilation of industrial ratio data. Wall also developed a ratio index to manage the proliferation of ratios, using weighted averages to represent their importance. The term "scientific ratio analysis" was used to describe the data-gathering process, but there was limited evidence of hypothesis development or testing at the time (Horrigan, 1965).

During the 1920s and 1930s, ratio analysis underwent significant advancements and debates. Bliss introduced a cohesive set of ratios that were connected logically and a priori, viewing ratios as indicators of fundamental business relationships (Bliss, 1923). Concurrently, Foulke's contributions were essential to the growth of ratio analysis, as he developed a strategy based on his expertise in financial statement analysis. The era also witnessed predictive studies, such as Fitzpatrick's examination of ratios as indicators of failure and success in businesses (Horrigan, 1965), as well as Foster's findings that less successful and failing businesses tended to have lower ratios (Horrigan, 1965). In the early 1940s, Merwin's study identified three highly sensitive ratios as predictors of firm discontinuance (Merwin, 1942). Additionally, ratios were utilized in aggregate economic studies, offering insights into their behavior over time and among different groups of firms (Crum, 1939). These developments expanded the empirical base of ratio analysis, shedding light on the potential of ratios as predictive tools and enhancing our understanding of financial statement analysis.

During the 1950s, ratio analysis gained attention and demonstrated its usefulness in management research. With the possibility of an integrated ratio analysis system, the division of return on investment into a profit margin and a capital turnover ratio generated enthusiasm.

Studies during this period revealed that certain financial ratios, when combined with other measures, were inversely correlated with trade credit difficulties (Wojinlower, 1962). Additionally, financial ratios were found to be related to loan criticisms by bank examiners and had a direct impact on credit availability (Wojinlower, 1962). Exploring the connections between financial ratios and a psychological model of "Corporate Personality," researchers discovered that conservative businesses maintained higher liquidity and solvency ratios. Despite challenges in determining appropriate ratios and their desired levels, ratios showed predictive value in anticipating financial troubles. Thus, ratios remained a valuable and straightforward tool for financial analysis, contributing to the empirical foundation of ratio analysis.

Financial ratios can be likened to the heartbeat of an organization, revealing its financial health and stability. Just as a doctor uses a stethoscope to listen to a patient's heart, financial ratios allow us to listen to the story of a company through its financial statements.According to Horrigan (1965), financial ratios are indispensable tools in analyzing accounting data. They provide a way to compare and understand the relationship between different financial elements, all derived from the financial statements of an organization. It is through these ratios that we gain insight into the organization's performance, liquidity, solvency, profitability and efficiency.

1.2.1 Profitability ratio*s*

Profitability ratios are essential for assessing a company's earnings generation capability. Profit represents a key source of funds and liquidity. When a firm experiences negative earnings, it often faces financial distress. Therefore, profit is used as a predictor of such events. This study focuses on three profitability ratios: EBIT margin, return on equity (ROE), and return on assets (ROA). EBIT margin has been found to be significant in predicting financial distress in the automobile supplier industry. Similarly, the survival likelihood of distressed firms is influenced by EBIT margin (Platt and Platt, 2002).

ROE, which measures the return on owners' capital, has also proven to be significant in predicting failure. ROA, specifically EBIT to total assets, is an appropriate measure for studying corporate failure, as insolvency occurs when total liabilities exceed the fair value of a firm's assets determined by their earning power. Previous research consistently found ROA to be a significant factor in explaining financial failure. Overall, profitability ratios play a crucial role in assessing a company's financial health, with each ratio providing valuable insights into different aspects of performance (Altman, 1968).

1.2.2 Liquidity ratios

Liquidity ratios are crucial for assessing a company's ability to meet short-term obligations and avoid financial failure. Higher liquidity levels reduce the risk of bankruptcy. While firms may still be profitable, they often face illiquidity before becoming financially insolvent and eventually bankrupt. The study employs three liquidity ratios: current ratio, quick ratio, and working capital to total assets ratio. These ratios have consistently proven useful in predicting bankruptcy and financial distress in various studies (Beaver, 1966; Platt and Platt, 2002).

The current ratio, which includes cash, marketable securities, accounts receivable, and inventory, has been widely utilized, although some argue that inventory's inclusion impairs its usefulness as inventory is not immediately convertible into cash. In response, the quick ratio was developed, which excludes inventory. The quick ratio has been found to be significant in assessing financial distress and bankruptcy (Beaver, 1968).

Working capital, representing net liquid assets relative to total capitalization, is considered a reliable measure as it cannot be easily manipulated through window dressing practices (Beaver, 1968). Working capital to total assets has been identified as the most valuable ratio in predicting financial distress, compared to quick and current ratios (Altman, 1968). Similar findings were observed by Beaver (1966), highlighting the significance of working capital to total assets in determining survival time and the probability of financial distress.

1.2.3 Leverage ratios

The analysis of financial leverage focuses on a firm's capital structure, examining the origin of funds from external sources that benefit shareholders. Leverage ratios are utilized to assess a firm's long-term solvency and its ability to fulfill long-term liabilities. The debt ratio is employed as a measure of financial leverage and a potential determinant of corporate financial distress. Numerous studies in the financial distress literature have provided evidence of the relationship between financial leverage and a firm's financial distress or failure (Beaver, 1966).

Beaver (1966) identified the debt ratio as one of the top predictors of financial failure based on univariate analysis. This finding was further supported by Beaver (1968), who confirmed that the debt ratio outperforms other ratios in predicting financial failure one, four, and five years before its occurrence. Dambolena and Khoury (1980) incorporated stability measurements of financial ratios with MDA (Multiple Discriminant Analysis) and found that the debt ratio was one of the best predictors in the discriminant function for corporate failure.

Flagg, Giroux, and Wiggins (1991) observed a significantly positive relationship between the debt ratio and the progression towards business failure in firms undergoing potential failure processes. More recent research by Beaver, McNichols, and Rhie (2005) reaffirms the significance of the debt ratio as a variable for predicting bankruptcy, even after combining market-based variables with financial ratios. Importantly, leverage remains significant as market-based variables do not differentiate between volatility caused by business risk and that induced by financial risk.

1.2.4 Efficency Ratios

The activity ratios reflect how effectively a firm utilizes its assets to generate revenue or returns. Efficient asset utilization leads to higher revenue, increased liquidity, and higher net income for the firm. This study focuses on two activity ratios: capital turnover and total assets turnover.

In Laitinen's (1992) failure prediction model, net sales to total capital (capital turnover) was found to be a significant contributor to the discriminant model. However, contrary to expectations, the coefficient for net sales to total capital was negative, indicating that a company with a high capital turnover ratio is more likely to fail.

Total assets turnover, as highlighted by Altman (1968), is a standard financial ratio that measures a firm's ability to generate sales from its assets. It serves as an indicator of management's competency in dealing with competitive conditions. Notably, total assets turnover ranked second in its contribution to the overall discriminant ability in Altman's Z-score model. Overall, activity ratios play a crucial role in assessing how efficiently a firm utilizes its assets to generate sales and contribute to the firm's performance and potential for financial distress.

CHAPTER II

Classification of Financial Distress Models

2.1 Conceptual Framework to Distress Models

Since Beaver's pioneering study in 1966, the empirical literature on financial distress prediction has grown significantly. To develop and evaluate financial hardship and bankruptcy prediction models, researchers have looked at a variety of explanatory factors and methodological approaches.

Altman (1968) extended Beaver's approach by using multiple discriminant analysis (MDA) to identify distress prediction ratios. However, MDA has faced criticism due to its restrictive assumptions regarding multivariate normality and independence of explanatory variables, leading to the exploration of alternative techniques.

Ohlson (1980) proposed a new model based on logit analysis, using a set of nine accounting ratios to overcome the limitations of MDA. This led to the proliferation of studies utilizing logit analysis and an improvement in the predictability of financial distress (Campbell et al., 2008). A three-variable distress prediction model was created by Zmijewski (1984) using probit analysis, and it was afterwards put to the test by other researchers.

Further extensions of financial prediction models have been presented. Researchers criticized static bankruptcy prediction techniques and developed discrete hazard models by incorporating market-based variables. These additions have resulted in increased overall classification accuracy of the models. The models have been tested by researchers such as Campbell et al. (2008). Market-based variables, which take into account both internal and external information, have been underlined as being crucial for improving the predictability of distress prediction models by academics like Agarwal and Taffler (2008). Given the importance of both forms of information in distress prediction, Trujillo-Ponce et al. (2014) proposed that a hybrid model integrating both accounting and market-based factors produces the best results.

The lack of a clear theoretical foundation is a significant disadvantage of prior distress prediction methods. For instance, Altman's well cited paper from 1968 was created with scant data and the proper variables. To address this issue, Blums (2003) proposed the D-score model, which incorporates accounting and market-based variables within a robust conceptual framework.

Additionally, the Springate model, developed by Gordon L.V. Springate in 1978, introduced the S-Score model based on four financial ratios and their respective coefficients that determine the weights.

Overall, the empirical literature has explored various models and techniques for financial distress prediction, aiming to improve predictability and incorporate both accounting and market-based variables. The development of stronger theoretical frameworks and more comprehensive models continues to be a focus of research in this area.

2.2Accounting-Based Models

Accounting-based models, such as those developed by Dimitras et al. (1996), have been widely utilized to assess financial risk and evaluate the financial stability of firms. These models rely on financial and accounting data, incorporating various financial ratios derived from the income statement and balance sheet. The objective, as highlighted by Paolone and Pozzoli (2017), is to compare these financial indicators with benchmark ratios representing sound financial condition. Discriminant analysis and regression models, as discussed by Mousavi et al. (2015), are commonly employed for categorical variables, while survival analysis is another subcategory of accounting-based models used for analyzing time-to-bankruptcy.

One of the major advantages of accounting-based modelsare the ready availability and observability of financial information. Financial statements, containing the necessary data for calculating ratios, are easily accessible. Moreover, the standardized calculation of financial ratios is ensured by the strict regulatory framework governing the presentation of financial statements.

By utilizing accounting-based models, stakeholders and analysts can gain valuable insights into a firm's financial position and assess its risk of facing financial distress. These models provide a systematic and quantitative approach to evaluate the financial stability and viability of a company, aiding in decision-making processes such as investment, lending, and strategic planning.

However, it is important to consider the limitations of accounting-based models. Hillegeist et al. (2004) highlight a notable drawback, which is the heavy reliance on past performance reflected in financial statements. Agarwal and Taffler (2006) argue that historical financial information can still be useful for predicting financial distress when it reflects a prolonged period of negative performance.

Another limitation, as pointed out by Paolone and Pozzoli (2017) and Agarwal and Taffler (2008), arises from the use of book value, which may differ from the actual market value. This disparity can lead to inaccurate assessments of a firm's financial soundness. Therefore, it is important to consider these limitations when interpreting the results of accounting-based models.

However, it's important to acknowledge that distressed firms facing financial difficulties often have a stronger motivation to manipulate their financial records. Such manipulations can create a more favorable image of the company's performance, potentially influencing investors, creditors, and other stakeholders. The literature commonly discusses three types of manipulations: revenue manipulation, expense manipulation, and bad debt manipulation (Peasnell et al., 2000).

Revenue manipulation involves granting clients longer payment periods, artificially inflating sales and accounts receivable to create a perception of higher revenue and better financial performance than the actual situation. Expense manipulation entails delaying the recognition of certain expenses to temporarily inflate reported earnings and portray a healthier financial position. Bad debt manipulation involves underestimating provisions for potential bad debts, reducing reported expenses, inflating net income, and distorting the true financial health of the company.

It is crucial to highlight that these manipulations are unethical and can mislead stakeholders who rely on accurate financial information for decision-making. Detecting and preventing such manipulations is the responsibility of regulators, auditors, and analysts to ensure transparency and trust in financial reporting.

While accounting statements are prepared on a going-concern basis and may have limited value in forecasting bankruptcy, accounting-based models still dominate the landscape of bankruptcy prediction. Beaver (1966) was one of the first to utilize accounting data for bankruptcy prediction, followed by Altman (1968) who employed multiple discriminant analysis (MDA) and Ohlson (1980) who developed a logit model using accounting data. These models analyze a wide range of financial measures on failed and successful companies to assess the likelihood of failure (Hillegeist et al., 2004).

2.2.1 Discriminant Analysis

Discriminant Analysis (DA), initially proposed by Fisher (1938), is a classification method used to separate observations into different groups by maximizing within-group similarity and minimizing between-group similarity. The goal is to find a linear combination of ratios that effectively discriminates between the groups being classified, such as failed and non-failed firms (Mousavi et al., 2015).

Blum (1974) conducted a study in which he compared 115 failed firms with 115 non-failed firms from 1954 to 1968. These firms were matched based on industry, sales, employees, and fiscal year. Using discriminant analysis and 12 variables, Blum built a financial distress prediction model. The results demonstrated correct classification rates above 70%. Interestingly, Blum identified the cash flow/total debt ratio as the best predictor, which aligned with Beaver's Univariate Analysis. Additionally, Blum found that failing companies experienced a significant decline in inventory, suggesting that excessive inventory accumulation is not a common reason for firm failure based on annual financial reports. Furthermore, the total liabilities of non-failed firms showed a steady increase compared to failed firms, indicating that non-failing firms often used debt as a means to finance growth.

2.2.2 Univariate Model

In 1966, William H. Beaver made significant progress in the field of financial distress prediction. He conducted a study comparing the mean values of 30 ratios from 79 failed firms and 79 non-failed firms across 38 industries during the period of 1954-1964. Beaver aimed to test the individual ratios' predictive abilities in discriminating between bankrupt and non-bankrupt firms.

Beaver's approach, known as univariate analysis, involved analyzing one ratio at a time. He discovered that these ratios were significantly lower for distressed firms compared to sound firms, and the differences became more pronounced as the year of failure approached.

Additionally, his analysis of financial statements led him to conclude that significant differences in ratios between distressed and non-distressed firms could be observed up to 5 years before bankruptcy.

The selection of ratios in Beaver's study (1966) was based on several criteria. Firstly, ratios were chosen based on their popularity and frequent appearance in the literature. This criterion was important because popular ratios are more likely to be manipulated by management in a way that undermines their usefulness.

Table 2.1 Univariate Ratios Explained

Cash-flow ratios	Net-income ratios	Debt to total-asset ratios	Liquid-asset to total-asset ratios	Liquid-asset to current debt ratios	Turnover ratios
1. Cash flow to sales 2. Cash flow to total assets 3. Cash flow to net worth 4. Cash flow to total debt	1. Net income to sales 2. Net income to total assets 3. Net income to net worth 4. Net income to total debt	1. Current liabilities to total assets 2. Long-term liabilities to total assets 3. Current plus long-term liabilities to total assets 4. Current plus long-term plus preferred stock to total assets	1. Cash to total assets 2. Quick assets to total assets 3. Current assets to total assets 4. Working capital to total assets	1. Cash to current liabilities 2. Quick assets to current liabilities 3. Current ratio (current assets to current liabilities)	1. Cash to sales 2. Accounts receivable to sales 3. Inventory to sales 4. Quick assets to sales 5. Current assets to sales 6. Working capital to sales 7. Net worth to sales 8. Total assets to sales 9. Cash interval (cash to fund expenditures for operations) 10. Defensive interval (defensive assets to fund expenditures for operations) 11. No-credit interval (defensive assets minus current liabilities to fund expenditures for operations)

Source: William H. Beaver (1966)

The second criterion was the performance of ratios in previous studies. Ratios that demonstrated good predictive abilities in prior research were included in Beaver's study. This criterion allowed for the examination of consistency and comparison with previous findings.

The third criterion involved ratios that were defined in terms of a "cash-flow" concept. Cash-flow ratios were considered promising for providing a unified framework in ratio analysis, although their effectiveness was untested at that time.

Beaver viewed the firm as a reservoir of liquid assets, which are supplied by inflows and drained by outflows. When the reservoir is depleted and the firm is unable to meet its obligations, it becomes insolvent and may eventually fail. To explain the relationship between ratios and failure, Beaver derived four propositions based on this liquid-assets-flow model:

- The larger the reservoir of liquid assets, the lower the probability of failure.
- The larger the net liquid-asset flow from operations, the lower the probability of failure.
- The larger the amount of debt held, the higher the probability of failure.
- The larger the fund expenditures for operations, the higher the probability of failure.

After computing the 30 ratios for each firm, Beaver observed differences in mean values to demonstrate the lower cash flow and smaller reservoir of liquid assets for failed firms compared to non-failed firms. The results indicated that the ability to predict limited solvency and failure through the analysis of accounting ratios is effective. Furthermore, these differences in mean values could potentially be visible up to 5 years before the actual default occurs.

In Beaver's study (1966), he also discussed the dichotomous test and profile analysis as additional methods for analyzing financial ratios;

The dichotomous test involves predicting the failure status of a firm based solely on its financial ratios. The data is arranged by arranging each ratio in ascending order. A cutoff point is visually determined to minimize incorrect predictions. If a firm's ratio is below the cutoff point, it is classified as failed. If the ratio is above the critical value, the firm is classified as non-failed.

Profile analysis, on the other hand, focuses on computing and comparing the mean financial ratios of failed and non-failed companies at least five years prior to failure. By analyzing the mean values, the behavior of financial ratios leading up to failure can be studied and compared with previous research.

Beaver found that not all ratios predict failure equally well. The cash-flow to total-debt ratio exhibited excellent discriminatory power throughout the five-year period, while the predictive power of liquid asset ratios was weaker. Additionally, ratios did not predict failed and non-failed firms with the same level of accuracy, with non-failed firms being more correctly classified.

The cash-flow to total-debt ratio produced high probability ratios, even five years before collapse, when utilizing financial parameters to evaluate them. Examining the ratio significantly affected how preexisting views changed. The probability ratio and the cash flow to total debt ratio often have a monotone connection. However, there was a minor rise in the probability ratio for high values of the cash-flow ratio in the fifth year before to collapse. This implies that having a very high cash-flow ratio carries more risk than having a lower one, considering most non-failed firms fall within a certain range.

To ensure meaningful comparisons, Beaver emphasized the importance of selecting failed and non-failed firms from the same industry with similar asset sizes. These variables can potentially influence the relationship between ratios and failure, and pairing firms with comparable characteristics allows for a more accurate analysis.

2.2.3 Logit Model

In Ohlson's critique of the Multiple Discriminant Analysis (MDA) model, he specifically highlighted the restrictive statistical requirements imposed by the model (Ohlson, 1980). He focused on the Altman model and its assumptions, which include the normal distribution of explanatory variables and equal variance and covariance of these variables for bankrupt and non-bankrupt firms. Ohlson argued that matching bankrupt and non-bankrupt firms based on criteria like size and industry can be somewhat arbitrary, and variables should be included in the model for predicting bankruptcy rather than for matching purposes. However, it's important to note that this statement is outdated, as recent studies do use size and industry as matching criteria to control for these variables.

Ohlson (1980) calculated the chance of failure for each firm using the logit model and data from US businesses. By applying the logistic cumulative distribution, the logit model attempts to minimise misclassification mistakes by precisely estimating the chance of failure. This method makes it possible to anticipate the likelihood of bankruptcy in a more thorough and accurate manner.

P= (1+ e(-Z)) = (1+ e-(W0+W1X1+…+WnXn))

Where:

P= probability of bankruptcy

Z= linear combination of the independent variables

Wi= coefficient

Xi= independent variables

This logit function maps the value of Z to a probability bounded between 0 and 1. If the company prospers it is the value 1 and if the company declared bankrupt it is the value 0.

Ohlson (1980) identifies four factors that significantly affect the probability of bankruptcy. These are: 1) the size of the company; 2) a measure(s) of the financial structure; 3) a measure(s) of performance; 4) a measure(s) of the current liquidity.

He associated them with 9 financial ratios which are;

- Total Liabilities divided by Total Assets ,
- Working Capital divided by Total Assets,
- Current Liabilities divided by Current Assets,
- If Total Liabilities exceed Total Assets,
- Net Income divided by Total Assets,
- Funds provided by operations (income from operations after depreciation) divided by Total Liabilities,
- if Net Income was negative for the last 2 years,
- Total assets/GNP price-level index,
- (Net Inconme t – Net Inconme t-1) divided by (|Net Inconme t| + |Net Inconme t-1|)

In Ohlson's study (1980), he estimated three models using a dataset consisting of 105 bankrupt firms and 2058 nonbankrupt firms spanning the period between 1970 and 1976. The models were designed to predict bankruptcy within different time frames:

1. Model 1: This model predicts bankruptcy within one year. It focuses on identifying firms that are likely to experience financial distress and fail within the next 12 months.
2. Model 2: Building upon Model 1, this model predicts bankruptcy within two years. It considers firms that did not fail in the first year but may face financial difficulties leading to failure within the subsequent two years.
3. Model 3: This model combines the predictions from both Model 1 and Model 2. It aims to predict bankruptcy within one or two years, covering a broader time frame for assessing financial distress and potential failure.

The overall O-Score function is defined as: □-Score = −1.3 − 0.4□1 + 6.0□2 − 1.4□3 + 0.8□4 − 2.4□5 − 1.8□6 + 0.3□7 − 1.7□8 − 0.5□9 48

The danger of insolvency increases with the O-score. Ohlson discovers that for his estimation sample, a cut-off value of P= 0,038 minimizes the total of type I and type II errors. If the O-Score is below the threshold yet the business is insolvent, there is a type I mistake. This is a Type II mistake if the O-Score is higher than the cutoff point yet the business is not in bankruptcy.

In his study, Ohlson (1980) highlighted two important findings regarding the predictive ability of bankruptcy models:

1. Impact of Information Availability: Ohlson emphasized that the availability and quality of financial information, specifically financial reports, have a significant impact on the predictive ability of bankruptcy models. This suggests that the accuracy of predictions relies heavily on the quality and timeliness of the financial data used as inputs in the models. Earlier research that neglected this factor may have yielded less reliable results.
2. Linear Transformations of Ratios: Ohlson observed that the predictive power of bankruptcy models based on linear transformations of a vector of ratios remained consistent across different (large sample) estimation techniques. This implies that the choice of estimation technique does not significantly affect the model's ability to predict bankruptcy. Instead, Ohlson suggested that incorporating additional predictors beyond ratios could potentially lead to substantial improvements in the predictive accuracy of bankruptcy models.

These findings highlight the importance of reliable and up-to-date financial information in bankruptcy prediction models and suggest that the inclusion of additional predictors beyond ratios could enhance the models' performance.

2.2.4 Probit Model

Zmijewski (1984) introduced probit analysis as an alternative technique in the field of financial distress prediction. Similar to the logit model, Zmijewski's probit model aims to estimate the probability of a firm going bankrupt. The key difference lies in the requirement of non-linear estimation.

Zmijewski's research draws attention to the issue of sample selection in financial distress prediction models. He points out that many studies utilize nonrandom samples, leading to biased parameter and probability estimates. Zmijewski identifies two types of biases resulting from sample selection: choice-based sample bias and complete data criterion bias.

Choice-based sample bias occurs when the likelihood of a firm being included in the sample depends on its observed financial distress attributes. This violates the assumption of random sampling and introduces biases into parameter and probability estimates. Zmijewski demonstrates the presence of this bias and shows that it diminishes as the sample composition approaches that of the population, using probit estimation techniques.
Complete data criterion bias arises from the assumption of having complete data for model estimation. The computed model will be skewed if the likelihood of distress for complete data considerably differs from that for partial data. Zmijewski finds that this bias increases with the disparity between sample selection probability and population probability.

Despite the existence of sample selection biases in many tests, Zmijewski concludes that these biases do not have a significant impact on overall classification and prediction rates or the qualitative results of financial distress models. He emphasizes the importance of accounting for biases and ensuring that the sample composition is representative of the population.

Zmijewski further investigates the effect of choice-based sample selection on model estimation and compares classifications and predictions using different techniques and sample designs. He notices that biases decrease and classifications and forecasts become more comparable when the sample selection probability becomes closer to the population probability.

In conclusion, Zmijewski's analysis underscores the importance of addressing sample selection biases in financial distress prediction models. Adjustments can mitigate biases, and using representative samples leads to reliable classification and prediction rates. These findings have significant implications for future research in the field of financial distress prediction models.

The equation for the function of the Zmijewski model is as follows:

$$\text{X-Score} = -4.3 - 4.5X1 + 5.7X2 - 0.004X3$$

Where:

X1 = Net Income / Total Assets

X2 = Total Liabilities / Total Assets

X3 = Current Assets / Current Liabilities

Zmijewski model categories, namely:

a. If X> 0 the company is predicted to go bankrupt,

b. If X <0 the company is predicted not to go bankrupt.

Shumway (2001) expressed skepticism about the predictive power of the probit model, primarily due to the high correlation between variables. According to Platt and Platt (2002),Because he only conducted one regression for each sample size, Zmijewski's (1984) empirical test to address choice-based sample bias was ineffective because it did not provide for a direct evaluation of bias against the population parameter. More common tests of bias were performed by Platt and Platt (2002) by comparing the mean estimated coefficient to the population parameter.

They argued that the number of studies using probit analysis was relatively small, likely because the technique requires more computations compared to other methods.

The probit function, similar to the logit function, maps values between 0 and 1. However, Zmijewski (1984) classified firms differently from Ohlson. Firms with probabilities greater than or equal to 0.5 were classified as bankrupt or having complete data, while firms with probabilities less than 0.5 were classified as non-bankrupt or having incomplete data.

Grice and Dugan (2001) conducted research to examine the generalizability of Zmijewski's (1984) and Ohlson's (1980) bankruptcy prediction models. They found that the probit model was significantly more accurate than the logit model. Additionally, they observed that Ohlson's model was highly sensitive to industry classification. Ultimately, Grice and Dugan (2001) concluded that both logit and probit analyses were generally useful for identifying financially distressed firms, not just those on the brink of bankruptcy.

2.2.5 Springate Model

The Springate model, developed by Gordon L.V. Springate in 1978, is a method used to predict the survival of a company by combining several financial ratios with different weights. The model selects four financial ratios from the Altman Z-Score model and assigns coefficients to determine their weights. These ratios, multiplied by their respective weights, are used to calculate the Springate S-Score (Hussein et al, ,2015).

The Springate S-Score model was tested on a sample of 40 companies and achieved an accuracy rate of 92.5%. It provides a measure that indicates the likelihood of a company's survival based on its financial ratios and their weighted contributions. The specific financial ratios and coefficients used in the Springate model may vary depending on the study or application (Hussein et al, ,2015).

By considering multiple financial ratios and their relative importance, the Springate model aims to provide a comprehensive assessment of a company's financial health and potential for survival.

The formula used in the Springate Score model for different types of companies is;

S-Score = 1.03A + 3.07B + 0.66C + 0.4D

Where;
A = working capital / total assets
B = net profit before interest and taxes / total assets
C = net profit before taxes / current liabilities
D = sales / total assets

The study by Hutabarat and Manurung (2016) focused on analyzing the financial instruments of Indonesian stock exchange infrastructure enterprises using the S-score model, specifically the Springate method. The results of their analysis indicated that two companies, META and JSMR, were categorized as being at risk of bankruptcy in 2014.
In a separate study by Büyükarıkan et al, (2014) in Turkey, bankruptcy prediction models were employed to investigate financial failures in the information sector between 2008 and 2013. The study utilized both the Altman Z-Score and Springate S-Score models and found that these models produced similar results in determining financial failure.

Bozkurt (2014) conducted a study in Turkey to examine the effects of bankruptcy prospects on firms' systematic risks. The research revealed that a higher probability of bankruptcy increased systematic risk, and it identified the Altman-Z, Ohlson-O, and Springate-S bankruptcy models as effective models for the Istanbul Stock Exchange (ISE), particularly in explaining changes in systematic risks.

Overall, these studies highlight the applicability and effectiveness of bankruptcy prediction models, such as the Springate S-Score model, in assessing the financial health and potential risks of companies in different contexts, including the Indonesian and Turkish markets.

2.2.6 Grover Model

Grover's model is a way for assessing a company's financial health and predicting the likelihood of financial disaster. It considers the following four crucial financial ratios: working capital as a percentage of total assets, retained profits as a percentage of total assets, total assets as a percentage of book value of equity, and sales as a percentage of total assets.

These ratios provide insights into various aspects of the company's financial situation, such as its liquidity, profitability, asset utilization, and financial leverage. By combining these ratios using logistic regression, which is a statistical technique, the model calculates the likelihood of the company experiencing financial distress.

The formula used in the Grover Score model for different types of companies is;

□-score = G = 1,650 X1 + 3,404 X2 + 0.016 ROA

If G-score < –0.02, it is the sign of bankrupt

X1 = Working capital/Total assets

X2 = EBIT/Total assets

ROA = net income/total assets

One study conducted by Husein and Pambekti (2015) indicates that Grover's model achieved a 100% accuracy rate when applied to companies in the food and beverage sector. This implies that the model was able to accurately predict financial distress in all the analyzed cases within this specific industry.

However, other studies, such as those by Prasandri (2018), KÜRKLÜ and Zeynep (2017), concluded that Altman's Z-Score model and Springate's model were more accurate than Grover's or Zmijewski's models. Although the specific accuracy rates were not provided, it

suggests that these models were better at identifying companies that were experiencing or likely to experience financial distress.
Additionally, Yuliastary and Wirakusuma (2014) found that Zmijewski's and Grover's models were the most accurate in detecting unhealthy or potentially bankrupt conditions. However, the exact accuracy rates were not mentioned.

It's important to note that the accuracy of a bankruptcy prediction model can vary depending on factors such as the dataset used, the industry being analyzed, and the specific context of the study. Therefore, it is crucial to consider the individual findings and conclusions of each study when evaluating the accuracy and effectiveness of these models in predicting financial distress.

2.2.7 Z Score Models of Altman

The Z-Score model has become an influential prototype for many similar models in the financial industry. It has garnered significant attention from asset managers and investors who rely on reliable tools to select suitable companies for their portfolios. Financial distress can have a detrimental impact on investor returns, but it can also present opportunities for high returns through short-sale strategies. Rating agencies play a crucial role in assessing the risk associated with entities and securities issues, making it essential for them to have a tool that can predict the likelihood of default.

In 1983, Altman suggested that the Z-Score model could be utilized by the management of distressed firms as a guide for achieving financial turnaround. Over time, the approach to bankruptcy prediction has evolved. In the initial stages, Beaver (1966, 1968) employed univariate analysis by examining selected ratios and discovered that some ratios possessed strong predictive power. Altman (1968) made significant advancements by developing a multiple discriminant analysis model known as the Z-Score model.

Despite being developed more than 45 years ago and the existence of alternative failure prediction models, the Z-Score model continues to be widely used worldwide as a primary or supporting tool for predicting bankruptcy or financial distress. This holds true for both research and practical applications.The emphasis is mostly on accounting-based Z-Score models, which do not rely on market data yet may occasionally exceed them despite being occasionally surpassed by other models.

One of the reasons for the continued use of the Z-Score model is that many businesses, particularly privately held firms, operate without readily available market data such as stock prices. Banks, who must evaluate these companies' creditworthiness and keep tabs on their performance, frequently provide financing for these businesses. Regulatory requirements call for the employment of a single model for economic capital calculation, provisioning, and distress prediction in the case of globally operating banks.

Accounting data is more readily accessible for these private firms, making accounting-based models like the Z-Score model particularly relevant and practical. The model's reliance on accounting information allows banks and other financial institutions to evaluate the creditworthiness and financial health of these privately held firms without relying on market data.

Beaver (1966, 1968) followed a similar approach to Beaver (1966) by collecting the financial statements of the firms under study. He identified 22 potentially useful ratios, which were categorized into five main groups: liquidity, profitability, leverage, solvency, and activity ratios.

To select the most relevant ratios, Beaver considered several factors:

Observation of statistical significance: He examined the statistical significance of different functions and determined the relative contributions of each independent variable. This analysis helped identify the ratios that had a significant impact on predicting financial distress.

Evaluation of inter-correlations: Beaver also assessed the inter-correlations between the relevant variables. This step aimed to identify any strong relationships or dependencies between the ratios, as highly correlated variables may provide redundant information.

Observation of predictive accuracy: Beaver analyzed the predictive accuracy of various ratio profiles. This involved assessing how well each ratio or combination of ratios predicted financial distress. The ratios that demonstrated higher predictive accuracy were given more importance.

Judgement of the analyst: Lastly, Beaver utilized the judgement of the analyst. This subjective evaluation considered the expertise and experience of the researcher in selecting the most relevant ratios. The analyst's judgement played a role in the final selection process.

The initial Z-score provided by Beaver is:

$$Z = A1\ X1 + A2X2 + A3X3 + A4X4 + A5X5$$

Where:

Z is the score that is used to categorize or forecast the business into one of the groups.

A1, A2, ..., An are the discriminant coefficients.

X1, X2, ..., Xn are the set of predictors .

The final function completed with the Z-score was like:

$$Z = 0.012X1 + 0.014X2 + 0.033X3 + 0.006X4 + 0.999X5$$

Here's a breakdown of each ratio and its significance:

- Working capital/total assets (X1): This ratio measures the firm's liquidity by comparing its working capital (current assets minus current liabilities) to its total assets. A higher ratio indicates better liquidity and the ability to meet short-term obligations. A consistently negative working capital may suggest financial difficulties and an increased risk of default.
- Retained earnings/total assets (X2): This ratio evaluates the firm's ability to reinvest earnings and self-finance its operations. It reflects the proportion of retained earnings (accumulated profits not distributed as dividends) in relation to total assets. Younger firms with a shorter history of profitability may have lower retained earnings, indicating higher bankruptcy risk.
- Earnings before interest and taxes/total assets (X3): This ratio assesses the productivity of the firm's assets without considering tax or leverage effects. It indicates the profitability of the firm's assets and provides insight into the fair value of the assets. A higher ratio suggests greater profitability and efficiency in asset utilization.
- Market value of equity/book value of total debt (X4): This ratio compares the market value of a firm's equity (market capitalization) to the book value of its total debt. It measures the decline in asset value (market value of equity plus debt) that a firm can withstand before liabilities exceed assets, highlighting the risk of insolvency. A lower ratio indicates a higher risk of bankruptcy.

- Sales/total assets (X5): This ratio evaluates the efficiency of asset utilization by measuring the ability of assets to generate sales. It reflects management's effectiveness in handling competition and gaining market share. A higher ratio suggests better sales generation and operational performance.

These ratios, when combined using a specific formula, provide a Z-Score that indicates the likelihood of financial distress or bankruptcy. The Z-Score model has been widely used due to its reliance on accounting data, making it applicable to both public and privately held firms without relying on market data.

In 1983, Altman made modifications to the original Z-Score model to make it applicable to both publicly traded and privately held firms. These adjustments were based on the recognition that the market value of equity may not be available for private companies. Altman advocated for substituting the market value of equity with the book value of equity in the model.

The revised Z-Score model, known as Z'-Score, is as follows:

$$Z' = 0.717X1 + 0.847X2 + 3.107X3 + 0.420X4 + 0.998X5$$

The key adjustment is the use of the book value of equity in the X4 ratio, which is the ratio of the book value of equity to the book value of total liabilities. The other variables remain the same as in the original 1968 Z-Score model.

Due to the unavailability of a comprehensive database of private enterprises, Altman did not test the Z'-Score model on a secondary sample of private firms. However, he analyzed a four-variable version of the model, called Z''-Score, by excluding the X5 ratio (Sales/Total assets) due to potential industry-specific effects that can arise when including industry-sensitive variables. The Z''-Score model is:

$$Z'' = 6.56X1 + 3.26X2 + 6.72X3 + 1.05X4$$

In this iteration of the model, Altman discovered that the X3 ratio (EBIT/Total assets) contributed most to the discriminating power. The new five-variable Z'Score model and the Z'Score model's classification results were found to be similar.

In the revised model, the zones stress that if the company is in financially distressed:

Z < 1.23 (+3,25) → A company is financially distressed.

1.23 < Z < 2.90 (+3,25) → A company should be careful.

Z > 2.90 (+3,25)→ A company is in a healthy position.

Table 2.2 Revised Z-score Threshold

	Rating	Z" - Score Threshold	Rating	Z" - Score Threshold	
Safe Area	AAA	>8.15	BB+	5.65	Grey area
	AA+	8.15	BB	5.25	
	AA	7.60	BB-	4.95	
	AA-	7.30	B+	4.75	
	A+	7.00	B	4.40	Distress Area
	A	6.85	B-	4.15	
	A-	6.65	CCC+	3.75	
	BBB+	6.40	CCC+	3.20	
	BBB+	6.25	CCC-	2.50	
	BBB-	5.85	D	<1.75	

Source: Altman and Hotchkiss (2010)

In the context of computing the Z"-Score for emerging countries, Altman, Hartzell, and Peck proposed the addition of a constant value of +3.25. This modification was made to normalize the findings and make scores of 0 or below represent the default state. With this modification, the Z"-Score model will be adjusted to account for the unique traits and dangers of emerging economies.

When analyzing credits in emerging markets, a similar approach to that used for traditional analysis of U.S. corporates can be initially applied. This involves quantitative risk assessment using models like the Z"-Score. Once a quantitative risk assessment has been conducted, analysts can then incorporate qualitative factors to further refine the assessment. These qualitative factors may include considerations such as currency and industry risk, industry characteristics, and the firm's competitive position within the industry. By incorporating both quantitative and qualitative assessments, a more comprehensive analysis of the credit risk in emerging markets can be achieved.

By creating a connection between the Z"-Score and the ratings given by Standard & Poor's, Altman and Hotchkiss (2010) extended the use of the score. This mapping allows for a better understanding of the credit quality implied by the Z"-Score and facilitates comparisons with established rating systems used by credit rating agencies.

2.3 Market-Based Models

Market-based models in assessing the risk of a firm rely on market information, particularly stock prices, to evaluate the likelihood of default. These models originated from the groundbreaking work of Black and Scholes (1973) and Merton (1974) using option pricing methods. Here are the key characteristics and advantages of market-based models:

- Sound theoretical model: Market-based models provide a robust theoretical framework for understanding firm bankruptcy. They incorporate option pricing techniques that have a strong foundation in financial theory.
- Efficiency of market information: In efficient markets, stock prices reflect all the information contained in accounting statements and also capture additional information that may not be explicitly stated in financial documents. Thus, market-based models benefit from the efficiency of market prices in aggregating available information.
- Independence from accounting policies: Market variables, such as stock prices, are less likely to be influenced by firm-specific accounting policies. This reduces the potential biases or limitations that can arise from varying accounting practices.
- Forward-looking nature: Market prices are forward-looking and reflect market participants' expectations of future cash flows. As such, they provide valuable insights for bankruptcy prediction as they capture expectations about a firm's future performance.
- Time and sample independence: Market-based models are not dependent on specific time periods or samples. They provide real-time information and can be applied consistently across different time periods and companies.

The fundamental concept of market-based models is to compare the market value of a firm's assets with the book value of its liabilities, known as the default point. When the market value falls below the book value of liabilities, it signals a potential default risk. This approach has been instrumental in the development of credit risk models like Moody's KMV.

According to Beaver (2005), market-based models are valuable for predicting bankruptcy because they capture not only the information present in financial statements but also additional market-driven factors. Market prices are continuously updated and reflect market participants' collective expectations, providing a more dynamic and comprehensive assessment of a firm's financial health and default risk. Additionally, market variables allow for the estimation of volatility, which serves as a significant risk indicator in these models.

While market-based models offer advantages in predicting financial distress, it's important to acknowledge the limitations of the Merton model, which is a prominent structural model used in this context. The Merton model makes certain assumptions that may impact its applicability and accuracy.

Firstly, the Merton model assumes that the natural logarithms of stock prices follow a normal distribution. However, in reality, stock price movements can exhibit non-normal behavior, such as fat tails or skewness, which may affect the model's predictions for financial distress.

Secondly, the Merton model assumes a simplified debt structure consisting of non-differentiated zero-coupon bonds with a one-year maturity. This assumption may not fully capture the complexities of real-world debt structures, which often involve various types of debts with different maturities and characteristics.

These presumptions are the reason why there is conflicting empirical data about how well market-based models work in foretelling financial disaster. Some studies suggest that market-based models outperform traditional accounting-based methods in predicting financial distress, highlighting the additional information captured by market-based models. However, other studies indicate that market-based models have limited predictive power when controlling for other variables or that accounting-based measures are more relevant for short-term financial distress prediction.

For example, studies by Hillegeist et al. (2004) suggest that market-based models provide superior information compared to accounting-based methods, with Hillegeist et al. (2004) finding them to be up to 14 times more informative about the probability of financial distress.

2.4 Hybrid Models

Hybrid models, such as the one proposed by Shumway (2001), aim to enhance bankruptcy prediction by combining both accounting ratio and market-driven variables. Shumway's "hazard model" incorporates two accounting ratios (net income to total assets and total liabilities to total assets) previously used by Altman (1968) and Zmijewski (1984), along with three market variables (market size, past stock returns, and the idiosyncratic standard deviation of stock returns) to identify firms at risk of bankruptcy.

Other researchers have also contributed to the development of hybrid models in this area. Campbell et al. (2008), Li and Miu (2010), have explored the benefits of combining different bankruptcy prediction models, showing that such combinations improve default prediction compared to using a single measure.

However, Agarwal and Taffler (2008) have criticized market-based models and argue that there is not enough evidence to support their superior performance over accounting-based techniques. They suggest that the accounting-based approach produces significant economic benefits compared to the market-based approach. Traditional approaches, including accounting-based models, still dominate risk assessment practices in the industry.

Paolone and Pozzoli (2017) provide further support for the dominance of accounting-based models, citing Altman's (1968) model as an example. They state that the accuracy rate of Altman's model was 79%, while no market-based model has achieved this level of accuracy.

2.4.1 D-Score Model

The D-Score is a model used to predict financial distress for middle market publicly traded companies. It employs a forward selection process and draws on the concepts of the Gambler's Ruin and Merton models.

Blum (2003) conducted a study using a dataset consisting of 44 distressed companies and 1342 non-distressed observations. As part of the validation process, the author randomly set aside 126 observations (approximately 10% of all firms) as a hold-out sample and estimated the D-Score model using the remaining 1260 observations (about 90% of the sample).

The D-Score incorporates 10 inputs or ratios to assess financial distress, including Current Liabilities, 3-year Sales growth, Net Income, 6-month stock price change, Sales (4 years), Current Liabilities/Total Assets, Stock price (6 months prior and at the time of evaluation), Net Income/Total Assets, Total Assets, Total Debt/Total Equity, and Total Equity/Total Assets.

D-Score provides an objective measure to evaluate the probability of financial distress for companies. With only 10 inputs required for computation, it offers a more streamlined approach compared to other models such as Moody's RiskCalc TM, which utilizes 17 inputs. While the empirical performance of the D-Score model has shown promise, further validation is needed through testing on larger samples of companies not included in the initial model estimation.

2.4.2 Hazard Model

Shumway (2001) suggests the utilization of hazard models in predicting financial distress probabilities, emphasizing the importance of specifying them as duration-dependent models with time-varying covariates. He criticizes static and single-period models for their potential to deliver incorrect and biased coefficient estimations of financial distress probability, as they do not consider the dynamic nature of firms over time. Shumway highlights three reasons why hazard models should be preferred over static models: (i) the failure of static models to account for each firm's time at risk, (ii) the incorporation of time-varying explanatory variables, and (iii) the higher predictive power of hazard models in out-of-sample tests for financial distress prediction.

Additionally, Beck, Katz, and Tucker (1998) demonstrate that the standard errors of static models may be understated. In line with this suggestion, Hillegeist et al. (2004) develop a discrete-time hazard model, which they believe is best suited for analyzing data that consists of binary, time-series, and cross-sectional observations, such as financial distress data.

Shumway (2001) finds that about half of the accounting ratios used in previous models are not statistically significant for predicting financial distress. On the other hand, market size, past stock returns, and idiosyncratic return variability are strongly related to financial distress. Shumway proposes a model that combines both accounting ratios and market-driven variables to produce out-of-sample forecasts that are more accurate in predicting financial distress compared to alternative models.

2.5 Other Prediction Techniques

Financial distress prediction plays a vital role in assessing and managing the financial stability of businesses and individuals. The application of machine learning algorithms has greatly improved the accuracy and efficiency of these prediction models. This abstract explores the use of machine learning techniques in predicting financial distress.

Machine learning algorithms have the capability to analyze large volumes of historical financial data and identify patterns and relationships that indicate financial distress. By training on diverse features such as financial ratios, market indicators, and relevant variables, these algorithms can effectively classify entities as financially distressed or solvent.

Machine learning techniques for financial distress prediction offer advantages such as processing large and diverse datasets, automating the prediction process, and adapting to changing market dynamics. Decision-makers can gain timely insights into potential financial risks and take proactive measures to mitigate and manage distress situations.
However, challenges exist in applying machine learning to financial distress prediction. Issues like overfitting, feature selection, and class imbalance require careful consideration. Interpreting machine learning models is also important for understanding the factors contributing to distress predictions and gaining stakeholder trust.

In conclusion, machine learning techniques have revolutionized financial distress prediction. By utilizing algorithms such as decision trees, random forests, support vector machines, and neural networks, accurate predictions can be made based on historical financial data. Further research should focus on addressing challenges, refining algorithms, and integrating machine learning with other financial analysis approaches to enhance the effectiveness of financial distress prediction models.

2.5.1 Artificial Neural Network(ANN)

Artificial neural networks (ANNs), also known as neural networks, are mathematical models inspired by biological neural networks. They emulate the functioning of the human brain and are utilized as data mining techniques for classification tasks. ANNs are designed to learn and generalize from data and experience, making them suitable for modeling functions with unknown mathematical expressions.

Similar to other statistical models, ANNs require the estimation of parameters (arc weights) before they can be used for prediction purposes. This process, known as training, plays a critical role in the utilization of neural networks. In classification problems, network training is typically supervised, meaning that the desired or target response for each input pattern is known in advance (Zhang et al., 1999).

Neural networks have demonstrated considerable success in various business applications compared to traditional regression analysis. Wilson and Sharda (1994) conducted a study comparing the performance of neural network models with discriminant analysis. Their findings revealed that neural networks outperformed discriminant analysis in terms of prediction accuracy, particularly in the challenging task of predicting bankrupt firms, which is both difficult and of great importance. This suggests that neural networks are more adept at handling complex classification problems.

Furthermore, more studies have shown that neural networks are capable of better capturing complex relationships among variables compared to logistic regression analysis. This indicates that neural networks are particularly suitable for modeling non-linear and intricate interactions between variables.

2.5.2 Decision Trees (DT)

The decision tree (DT) model is a recursive procedure that divides a set of statistical units into sub-groups, aiming to reduce impurity and maximize homogeneity in each group. DT models have several advantages:

- No statistical assumptions: Unlike parametric methods, DT does not require specific distribution assumptions, making it suitable for real-world situations (Zmijewski, 1984).
- Data exploration and modeling: DT facilitates exploring data and identifying relationships between variables, making it a powerful tool for model construction (Woods et al., 1997).
- Interpretable and meaningful representation: DT provides human-readable "if-then" rules, offering a clear understanding of the acquired knowledge (Kumar & Ravi, 2007).
- Additionally, Shaw and Gentry (1990) found that inductive learning methods, such as DT, outperformed probit or logit analysis in risk classification applications, likely due to their freedom from parametric and structural assumptions associated with statistical methods.

2.5.3 Support Vector Machine

Support Vector Machines (SVMs) are a popular supervised learning method used for classification. They separate data points into distinct categories by drawing a line or hyperplane that maximizes the distance to the closest points from each group. SVMs have demonstrated improved performance in various applications, including pattern recognition, regression estimation, financial time-series forecasting, marketing, and medical diagnosis.

SVMs utilize mathematical techniques to transform input data into a higher-dimensional space, enabling the creation of a linear model for estimating the decision function and determining non-linear class boundaries based on support vectors. Support vectors are the training points closest to the separating hyperplane, playing a crucial role in defining class boundaries.

In cases where data is not linearly separable, SVMs employ non-linear machines to find a hyperplane that minimizes errors on the training set. SVMs have been used to assess the probability of financial distress, with studies demonstrating their superiority over other methods such as multiple discriminant analysis, logit models, and neural networks in terms of prediction accuracy (Shin et al., 2005). However, it's important to note that not all studies have reached the same conclusions.

2.5.4 Random Forest

The Random Forest (RF) method has gained popularity in classification problems, and its success has been demonstrated in various studies. Breiman (2001) who has applied RF successfully. RF is an ensemble learning method that combines the concepts of aggregation, bagging, and decision trees.

Sharma (2012) conducted a study on creditworthiness prediction and found that Random Forests outperformed Logistic Regression in terms of accuracy. This was particularly evident when dealing with variables that exhibited multicollinearity and complex inter-relationships. Sharma (2012) concluded that Random Forests provide a powerful tool for obtaining more robust findings and enable researchers to assess the importance and meaning of variables. Other study by Arora & Kaur (2020), also supported the higher accuracy of Random Forests in creditworthiness assessment compared to alternative techniques.

2.6 Cash Flow-Based Analysis on Financial Distress

The significance of cash flow ratios in forecasting financial difficulty has been stressed by several scholars. According to them, reviewing cash flow statements, which include inflows and outflows of cash from operating, investing, and financing activities, can provide valuable insights into a company's financial health. According to Handari and Iyer (2013), the cash flow from operations is a precisely calculated, clearly defined amount that is always provided as part of the cash flow statement.

One of the early pioneers in this area was Beaver (1966), who recognized that cash flow ratios had a lower probability of error compared to other ratios based on accrual accounting. However, when Sharma (2001) reviewed studies on cash flow information and its predictive ability for corporate failure, the results were mixed. Some studies supported the effectiveness of cash flow ratios as predictors of financial distress, while others like Casey and Bartczak (1985) did not find them to be significant.

Ward (1994) specifically examined the usefulness of cash flow ratios in predicting financial distress in mining, oil, and gas companies. They found that cash flow from investing activities to total liabilities was the most effective predictor in these industries, while cash flow from operating activities to total liabilities worked best in other sectors. In a study focused on corporate failure prediction in India, Murty and Misra (2004) identified several significant predictors, including cash flow from operating activities to total assets, total liabilities, current assets, current liabilities, and capital employed.

The ratio of cash flow from operational operations to total liabilities was also found to be a significant predictor of financial hardship by Ong et al. (2011) in their study of Malaysian public listed corporations. Using logistic regression analysis, they attained a remarkable overall correct prediction rate of 91.5%. They discovered that the ratio of operating cash flow to total debt is a very reliable indicator of financial difficulty in Malaysia.

Aharony et al. (2006) conducted a comparative study that further supports the enhanced value relevance of cash flows compared to accrual accounting information items. Their research findings suggest that cash flow ratios are particularly effective in predicting the performance of firms during their growth periods. They also found that cash flow information more accurately reflects the market value of a firm. The study by Aharony et al. highlights the importance of cash flow information in evaluating a firm's financial performance and market value. By emphasizing the predictive power of cash flow ratios, especially during growth phases, their research contributes to the understanding of the relevance and usefulness of cash flow information in financial analysis and valuation.

In their study, Bhandari and Iyer (2013) emphasize the importance of cash in business operations. They argue that cash is essential for purchasing goods, paying wages and salaries, servicing debt, and compensating stockholders. Furthermore, they highlight that cash generation is highly correlated with profit generation. Based on these insights, Bhandari and Iyer suggest that information regarding cash should be given more consideration compared to accounting income.

To support their conclusion, Bhandari and Iyer conducted an analysis using a sample of 50 failed firms from various industries spanning the period of 2008-2010. They employed seven predictor variables, of which six were based on cash flow. By applying their model, they were able to correctly classify 83.3 percent of the firms.

Cash flow from operating activities to total liabilities showed a significant difference between distressed and non-distressed companies in a different study by Wan Adibah et al. (2005), but was not a reliable predictor of financial distress. This study used logistic regression analysis to predict financial distress up to five years in advance.

Overall, the research findings on cash flow-based analysis for financial distress prediction are diverse, with some studies supporting the effectiveness of cash flow ratios as predictors, while others do not find them to be significant in this regard.

Chapter III

Empirical Analysis

In this discourse, the efficacy of select financial models – namely the Zmijewski, Grover, Altman Revised Z-Score, and Springate – in prognosticating financial distress will be rigorously examined. To facilitate this examination, an assumption-driven approach will be adopted: companies will first be demarcated into categories of distress based on extant literature, subsequent to which the capacity of these models, in tandem with binary logistic regression, to execute this classification will be evaluated. A salient aspect of this study will be discerning which among the employed ratios provide statistically significant results.

While the Altman and Zmijewski models have been prolifically interrogated in the literature, the Grover and Springate models appear to be relatively underexplored. The analytical value of this study is heightened by the incorporation of these less-studied models, as they introduce varied financial dimensions, thereby enriching the diversity of the analysis.

To elucidate the distinct perspectives:

The Grover Model: This model is predicated on assessing the profitability and efficiency of firms. By evaluating metrics such as net income juxtaposed against net sales, the Grover Model provides insights into the operational efficacy in translating activities to profit.

The Springate Model: A more comprehensive model, Springate integrates aspects of liquidity, profitability, and efficiency. This provides a multi-dimensional view of a firm's current and prospective financial health.

The Altman Revised Score: An advanced iteration of its precursor, this model amalgamates considerations of liquidity, profitability, leverage, and market valuation. By leveraging a nuanced set of metrics, it aims to provide a holistic understanding of a firm's financial resilience. It's noteworthy that Altman et al. (1977) and subsequent scholarship have underscored that leveraging solely debt variables may be less elucidative of financial distress compared to metrics that encapsulate financial expenditure.

The Zmijewski Score: By homing in on key financial pillars such as profitability, leverage, and liquidity, the Zmijewski Model serves as a rapid assessment tool for evaluating a company's solvency and its aptitude to service its debt commitments.

In summation, whilst each model presents a unique analytical lens, their collective objective remains consistent: to decipher and elucidate the multifaceted financial realities of companies, thus providing stakeholders with invaluable insights into prospective financial trajectories.

3.1 Sample Data

A firm is considered to have entered the failure process if during the period 2022-2020 it had an negative net profit following at least two consecutive years within the period. Profitability is defined as net income greater than zero. The two years of profitable income restriction (Chen et al, ,2010) was applied in order to assure that selected firms were reasonably "healthy" at the outset and not already in some stage of the distress process. All samples must comply with the broad requirements, which include the following:

1. The Companies have continuously released their financial accounts for five years. (income statement, balance sheet, and cash flow)
2. Companies are engaged in the energy sector that includes: Renewable energy and equipment & services , Oil related services , Coal and Gas related services.
3. Companies that are all in the eurozone area and they are publicly-traded companies.

I have decided to aim for the Energy sector since there are few examples that specifically foster the literature on financial distress or bankruptcy. Also the sector itself is highly demanded. I assume that financial approaches in that sector will explode in the near future. Even though I have an intention to write my thesis on that sector, there are not many public firms and some of them have reliable financial information. *Thomson Reuters Eikon™* has been used as a database to collect data of the firm's financials. *European Countries* that consist of 27 countries were aimed. In the beginning, there were *177* companies listed and many of them had some problems with the absence of data, unpublished financial statements or old-dated data. For that reason 65 of them had to be eliminated and my total sample size decreased to *112* which consists of 74 non distressed and 38 distressed firms. Ward et al. (1999) found that logistic regression is a decent predictive tool if there is imbalance between the groups.

Since we have two cases, noted as “distressed” and “non-distressed” our goal is to understand if the models, which are, the below-mentioned ratios, contribute in the determination of the different status, and it will be tested for at lag t-1 and t-2. Therefore, the significance level is particularly important for our study because it tells us that what is observed is hardly due to chance. The significance level in a statistical test is given by the P-value and it is used in order to determine the relative contribution of each independent variable. A variable is significant when the P-value is below 0,05 because generally, the ratio 5/100 is small enough to conclude that it is "unlikely" that the observed difference is due to the simple case.

3.2 Definition of Variables

A dummy variable serves as the dependent variable. The dependent variable is undoubtedly a qualitative variable. As previously mentioned, there are several meanings of financial difficulty. To offer properties for the dependent variable, dummy variables are employed. organizations in financial crisis should be given the characteristic 0 while organizations doing well should be given the attribute 1. On the other hand, the factors that have been included in the bankruptcy prediction model are the independent variables. The variables are generated from the equation as follows:

Altman revised Z-score = 6.56X1 + 3.26X2 + 6.72X3 + 1.05X4
X1 = Working capital /Total assets
X2 = Retained Earnings /Total assets
X3 = EBIT /Total assets
X4 = Book value of Equity / Book value of Total Liabilities
(Distressed < 1.10 < Healthy)

Zmijewski Score = -4.3 – 4.5X1 + 5.7X2 – 0.004X3
X1 = After-tax earnings/Total assets
X2 = Total debt/Total assets
X3 = Current assets/ Current liabilities
(Healthy < 0 < Distressed)

Grover Score = G = 1,650 X1 + 3,404 X2 + 0.016 X3
X1 = Working Capital/Total Assets
X2 = Earnings before interest and taxes/Total Assets
X3 = Net income/Total Assets
(Distressed < -0.02 < Healthy)

Springate Score = 1.03X1 + 3.07X2 + 0.66X3 + 0.4X4
X1 = Working capital/Total assets
X2 =EBIT /Total Assets
X3 = EBT / Current Liabilities
X4 = Sales / Total Assets
(Distressed < 1.062 < Healthy)

3.3 Analysis

This study was carried out to predict the financial distress of publicly traded energy companies in Europe. Financial distress forecasts for 2022 were created by examining the energy sector financial data for the years 2020-2021 in depth. The analysis process was carried out using four different models: Altman, Springate, Zmijewski and Grover. The selection of these models is based on their potential to effectively analyze the financial status and structures of companies in the energy sector.

During the examination of the data set, visualization of the data was performed with the boxplot method and potential outliers were detected. These detected outliers were removed from the analysis by the "trimming" method to make the data set more homogeneous. Then, binary logistic regression analysis was applied on the adjusted dataset; this analysis was essential in assessing the ability of energy firms to predict financial distress situations.

In particular, the stratified bias corrected bootstrap method was used to eliminate potential problems caused by imbalance in the data set. This method has a critical importance in order to minimize the bias that the unbalanced data set can create and to make the model results more reliable. Hesterberg, back in 2011, chimed in on this method. He believed that using 1000 of these mini datasets was a good enough approach for rough estimates. But he also gave us a heads-up: when working with small original datasets, this bootstrap method might exaggerate the variability of our estimates a bit. However, between the bootstrap method and another popular method called the robust variance estimator, he found the bootstrap method came closer to the real deal. Finally, the prediction success of each model was analyzed in detail based on the classification results.

3.3.1 Outliers Detection and Trimming

Table 3.1 Descriptive Statistics & Normality Test Results

	N	Min Statistic	Max Statistic	Mean	Standard Deviation	Skewness	Kurtosis	K&S Lilliefors	Shapiro & Wilk
Altman Z Score									
T-1	112	-22,54	35,45	2,89	6,23	,56	8,90	<0,001	<0,001
T-2	112	-20,30	32,71	2,90	6,75	,13	5,44	<0,001	<0,001
Springate S Score									
T-1	112	-3,40	11,81	,67	1,67	2,56	17,60	<0,001	<0,001
T-2	112	-5,45	7,63	,46	1,54	,17	6,45	<0,001	<0,001
Zmijewski X Score									
T-1	112	-4,43	8,03	-,97	1,87	1,16	4,14	0,007	<0,001
T-2	112	-4,88	9,30	-,80	2,17	1,33	4,26	<0,001	<0,001
Grover G Score									
T-1	112	-1,88	11,48	,43	1,33	5,31	43,04	<0,001	<0,001
T-2	112	-3,88	7,44	,34	1,08	2,33	19,00	<0,001	<0,001

According to the test results of all models, the scores are not normally distributed; this is confirmed by p values of "<0.001" from both the K&S Lilliefors and Shapiro & Wilk tests.

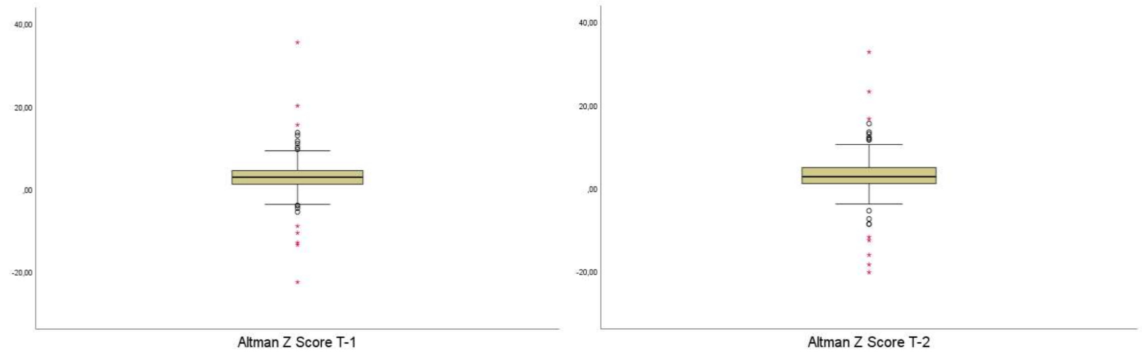
Skewness tells us where most of our data leans in a dataset. Imagine it as the tilt of a see-saw; if it's perfectly balanced (skewness is 0), our data is evenly spread out. A high skewness means our see-saw is tilting more to one side, showing that our data is bunched up on that side. Kurtosis, on the other hand, is about the shape of our data's distribution. Think of it like the peak of a mountain. If it's sharp and pointy (leptokurtic), most data is gathered at the peak. If it's a gentle slope (mesokurtic), it's a standard distribution, and if it's more of a hill than a mountain (platikurtic), our data is spread out more broadly. In numbers, a kurtosis less than 3 means it's spread out, equal to 3 is standard, and greater than 3 means most data is at the peak (Husein et al., 2015).

Numerous research have investigated various methods for identifying outliers. Simple residuals, which are modified by the projected values, and standardized residuals versus the actual values are used in regression analysis to identify outliers (Gentlemen et al., 1975).

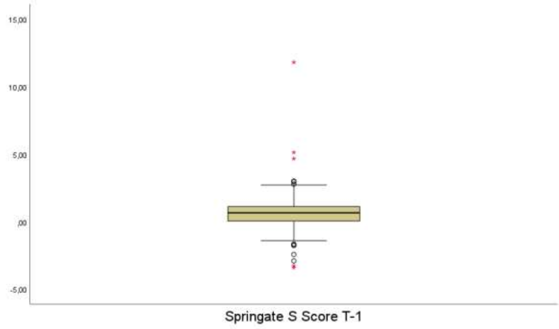
The boxplot, developed by Tukey (1977), is one of the most used graphical methods for examining a univariate data set. A box plot shows the dispersion of the data graphically. Along with the median, the lower quartile (Q1) and upper quartile (Q3) are shown in the graph. The data's 50th percentile is represented by the median. The 25th percentile represents the lower quartile, while the 75th percentile represents the upper quartile. The interquartile range (Q3-Q1) is often placed at a preset distance between the upper and lower gates. The upper and lower gates should be set at 1.5 times the interquartile range. Outside of these gates, any observation is likely to be an anomaly. Because a box plot relies on the median and not the mean of the data, it may be utilized even when the data are not regularly distributed (Walfish, 2006).

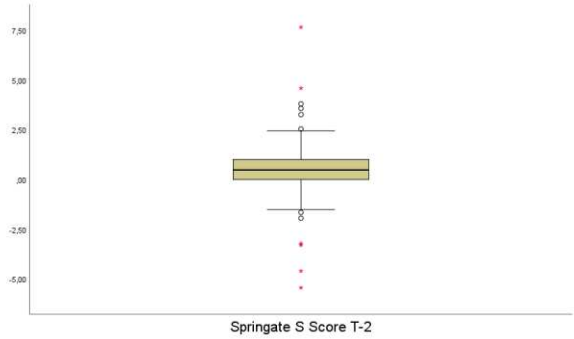
Boxplot with extreme values. By 1.5 times the difference between the 3rd and 1st quartiles, the upper and lower fences, respectively, depict values that are greater and less than the 75th and 25th percentiles (3rd and 1st quartiles). The value above or below the upper or lower fences is referred to be an outlier (Kwak and Kim, 2017).

Overall, a straightforward boxplot approach will be helpful for identifying outliers in univariate data. Since an analysis with a single independent and dependent variable was to be performed, univariate outliers were examined via box plox. Outliers are shown with a red (*) sign in the box plots of the models examined.

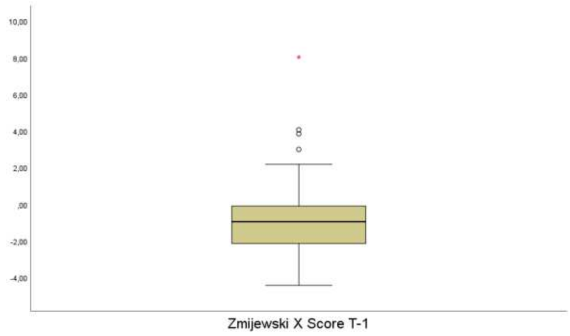


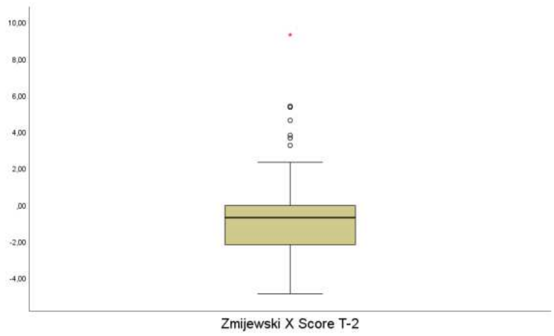
As emphasized in the statistics above, Altman Z Score does not have a normal distribution at either time. Considering the K&S and Shapiro&Wilk tests, a significance is observed. This is an indication that the data does not have a normal distribution. For the Altman Z score, a boxplot was examined in the T-1 and T-2 lagoons and 8 outliers were determined. Afterwards, when the data was extracted and examined again, 1 more outlier was identified and removed.



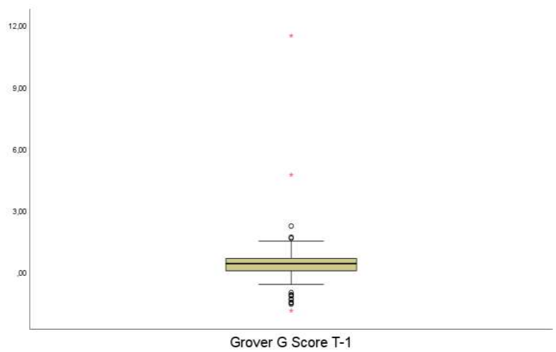


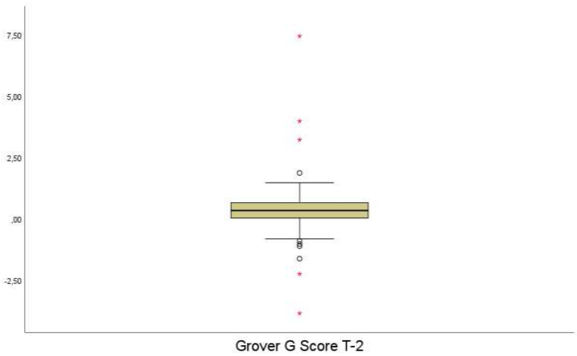
When the Springate S Model was also examined, outliers were detected. Again, looking at the normal distribution tests, it was an indication of the existence of outliers that did not meet the normal distribution. When viewed for the first time, 5 outliers were detected in the T-1 lag, and when viewed for the second time, 3 outliers were detected and removed. In the T-2 lagoon, 6 outliers were detected and removed when looked at for the first time and 2 outliers when looked at for the second time.





The Zmijewski model managed to pass the K&S test in the T-1 lagoon, but could not pass the Shapiro&Wilk test. Again, two years were examined via boxplot, and 1 outlier was detected in both years in the first time. When this outlier was removed and looked for the second time, 1 more was found and removed.





The situation is no different in the Grover model. According to the test results, boxplot was used. In the first time, 3 outliers were detected in the T-1 lag and in the second time, 5 outliers were detected. For T-2 lag, the situation was the opposite. When examined for the first time, 5 outliers were found, and when examined for the second time, 3 outliers were found and all of them were removed.

When the data extracted was examined, it was found that the same companies were mostly outliers for all models. These types of companies are outliers for 2 or 3 models. When examined in depth, the companies excluded from the analysis in the T-1 and T-2 lags of each model are the same.

Table 3.2 Descriptive Statistics after Trimming

	N	Min Statistic	Max Statistic	Mean	Standard Deviation	Skewness	Kurtosis
Altman Z Score							
T-1	103	-5,6	13,0	2,99	3,42	,22	,82
T-2	103	-8,7	13,4	3,07	3,96	,03	1,78
Springate S Score							
T-1	104	-2,4	3,0	,55	,97	-,29	,93
T-2	104	-2,0	3,2	,47	,91	,07	,94
Zmijewski X Score							
T-1	110	-4,4	4,1	-1,09	1,61	,23	,27
T-2	110	-4,9	5,3	-,95	1,86	,56	1,26
Grover G Score							
T-1	104	-1,5	-1,1	,31	,59	-,84	1,30
T-2	104	1,6	1,5	,27	,50	-,30	,63

After removing the outliers from the boxplot, descriptive analysis was performed again after trimming. At the end of the trimming, all models fit the normal distribution. Also, significant changes were observed in Skewness and Kurtosis. While Skewness values approached 0, Kurtosis values decreased below the 3.0 limit. However, when we look at the general distribution on the boxplot, there are many points between the maximum and minimum inspection points and the fences. Even though these points are not considered outliers by boxplox, they can increase the variance and therefore the standard error. As a result, they have an impact on the parameter estimate.

3.3.2 Logistic Regression Test Results of The Models

	Binary Logistic Regression								***Bias Corrected Stratified Bootstrap***				
	N	**Omnibus Step,Block,Model**	**Hosmer Lemeshow**	**B**	**S.E**	**Wald**	**df**	**Significance**	**Bias**	**S.E**	**Significance (2-tailed)**	**BCa Confidence Intervals**	
Altman Z Score													
T-1	**103**	**<,001**	**,09**	**-,43**	**,10**	**16,07**	**1**	**<,001*** **	**-,54**	**,19**	**,007**	**-,77**	**-,24**
T-2	**103**	**0,14**	**,65**	**-,14**	**,06**	**5,23**	**1**	**,022** **	**-,008**	**,07**	**,042**	**-,30**	**-,16**
Springate S Score													
T-1	**104**	**<,001**	**,48**	**-3,14**	**,66**	**22,42**	**1**	**<,001*** **	**-,22**	**,97**	**<,001**	**-4,96**	**-2,19**
T-2	**104**	**<,001**	**,37**	**-1,56**	**,38**	**16,19**	**1**	**<,001*** **	**-,09**	**,46**	**,002**	**-2,50**	**-1,01**
Zmijewski X Score													
T-1	**110**	**<,001**	**,05**	**,72**	**,18**	**16,09**	**1**	**<,001*** **	**,02**	**,18**	**<,001**	**,42**	**1,22**
T-2	**110**	**,005**	**,67**	**,32**	**,12**	**7,05**	**1**	**,008** **	**,01**	**,13**	**,007**	**,07**	**,63**
Grover G Score													
T-1	**104**	**<,001**	**,07**	**-2,73**	**,63**	**18,50**	**1**	**<,001*** **	**-,13**	**,73**	**,002**	**-4,28**	**-1,76**
T-2	**104**	**<,001**	**,47**	**-1,71**	**,51**	**11,01**	**1**	**<,001*** **	**-,05**	**,53**	**<,001**	**-2,75**	**-,90**

Table 3.3 Statistical Test Results

In the binary logistic regression, each output was examined. Considering the class distribution inequality, the analysis was supported on the precision and reliability of the results obtained with the stratified bias corrected stratified bootstrap method. In order to evaluate the results in detail, it would be better to first interpret each finding step by step and finally combine it with a general idea. In addition, making separate evaluations for each model is important for the intelligibility of the analysis.

3.3.2.1 Altman Z Score: The omnibus test is a test that evaluates how well the independent variables of your regression model explain the dependent variable. In general, if the p-value of this test is low (usually less than 0.05), we can say that the independent variables in the model significantly affect the dependent variable in total.

According to the result, Omnibus test results for Altman Z Score at T-1 and T-2 periods are less than 0.001. This shows that the independent variables in the model (in this case the Altman Z-Score and its associated lags) affect the dependent variable (financial distress status) in a statistically significant way. In other words, we can say that the Altman Z-Score and related lags are important variables in predicting financial distress. This result confirms that the Altman Z-Score and associated lags are appropriate for this type of analysis.

A high Hosmer & Lemeshow p-value (usually greater than 0.05) indicates that the model fits the data well because it means that there is no significant difference between the model's actual events and forecasts. Having a low p-value may indicate that the model does not fit the data well.

Looking at the results you provided, the Hosmer-Lemeshow test result for the Altman Z Score in the T-1 period is 0.09, which is a borderline value indicating that the model fits the data well. On the other hand, a p-value of 0.65 for the T-2 period indicates that the model fits the data well.

These results show that the Altman Z score fits the logistic regression model well. Especially in T-2, there is a harmony between the model prediction and the occurrence of the event.

Logistic regression results for Altman Z-Score at T-1 period indicate that the effect of the independent variable is -0.43. This effect is quite significant with a value of 16.07 with the Wald test. However, uncertainty about the magnitude of this effect is expressed with a standard error of 0.10, meaning there is some uncertainty in the estimates. In the T-2 period, while the effect of the independent variable decreases to -0.14, the Wald value also decreases to 5.23, indicating that the effect is less significant than in T-1. But in the T-2 period, the standard error drops to 0.06, which indicates that the forecast in this period is more accurate than in the T-1 period. The standard error measures the precision of an estimate; therefore the estimation is more accurate in T-2 than in T-1 period. However, we should consider that the effect was significant in both periods. A greater effect, but a higher uncertainty, in T-1; T-2 has a lower impact but a more precise estimate.

While the value of B in the original model at the T-1 period was -0.43, the bias in the bootstrap results was -0.54. This suggests that the model's prediction of financial distress shows a slight bias. The standard error goes up to 0.19 with bootstrap. This shows that the standard errors of the original model (0.10) are lower than the bootstrap result. So bootstrap states that there is more performance in the model's predictions.

In period T-2, the value of B is -0.14. Bootstrap bias is only -0.008. This shows that the model makes pretty good predictions for this period. While the standard error increased to 0.07 with bootstrap, it was 0.06 in the original model. That is, in the T-2 period, bootstrap shows a slight increase in uncertainty in the model predictions, but this increase is less pronounced compared to T-1.

As a result, the Altman Z-Score is an invaluable tool for measuring financial distress risk. According to the data I have presented, this score is statistically significant in the T-1 period and the Omnibus Test supports the significance of this model. The Hosmer-Lemeshow test shows that the model fits the data well, while the Wald statistic confirms the importance of the independent variable. However, the bootstrap results show that the standard error has changed. This implies that the model may have some precision and results may vary with different samplings. Considering that the classification success of the Altman Score decreased especially in the T-2 period, it should be noted that the model may yield different results in different time periods.

3.3.2.2 Springate S Score: When we look for the Springate S Score, the results of the Omnibus test are quite significant. This indicates that the independent variables used by the model are important in estimating the dependent variable. In particular, the p-value of the Omnibus test indicates that the null hypothesis of the model should be rejected and that these independent variables have a significant effect on the dependent variable. This result confirms the necessity of including the variables used by the Springate S Score to predict the risk of financial distress in the model.

The Hosmer-Lemeshow test result for the T-1 period shows a high p-value (0.48). This indicates that our model fits the data well. In other words, the probabilities predicted by the model have a good agreement with the observed rates.

For the T-2 period, the p-value was recorded as 0.37. This value shows that the model fits the data. However, it shows a slight decrease compared to the T-1. This indicates that there may be some variation in the fit of the model over the T-2 period, but this change does not indicate a significant non-fit.

In conclusion, the Hosmer-Lemeshow test shows that the model generally fits the data well in both periods for the Springate S Score. However, attention should be paid to the small changes that occur over time in the fit of the model.

When we look at the T-1 period of the Springate S Score, the regression coefficient of -3.14 indicates that one unit change in the independent variable causes a -3.14 unit change in the distress estimation. This means a large probability change in the target variable. However, we need to look at the Wald test to be sure if this coefficient is correct. The Wald value (22,42) is high, indicating that the coefficient is significant. On the other hand, the standard error (S.E) value is a measure of how accurate the estimation of the coefficient is. A value of 0.66 indicates uncertainty around the coefficient, but this uncertainty is within an acceptable range.

At the T-2 period, the regression coefficient of -1.56 indicates that there is still a negative relationship, but this relationship weakens compared to the T-1 period. A Wald value of 16.19 confirms that this coefficient is still statistically significant. However, the standard error falling to 0.38 indicates that the model's estimation is somewhat more precise during this period. This may suggest that the model may be more stable and reliable in the T-2 period than T-1.

In conclusion, it seems that Springate S Score has a significant effect in both periods, but we can observe that its effect weakens a little in the T-2 period and the model makes some more precise predictions in this period. However, high Wald values in both periods show that the model is meaningful and carries important information in both periods.

While the regression coefficient for the Springate S Score was -3.14 in the T-1 period, the bias value obtained by the bootstrap method was calculated as -0.22. This shows that the regression coefficient has a very close value with the bootstrap method, that is, the model is stable. There is a similar situation between standard error values; The standard error of 0.66 for regression increases to 0.97 for bootstrap. This increase may indicate that the bootstrap method takes a more conservative approach to the generalizability of the model, especially without being influenced by extreme values or class imbalances in the dataset.

For the T-2 period, the regression coefficient is -1.56, while the bootstrap bias value is only -0.09. This indicates that the model's regression estimates for this period show less deviation with the bootstrap method. The standard error also increased from 0.38 for the regression to 0.46 for the bootstrap. This again shows that bootstrap is more conservative when assessing the generalizability of the model.

As a result, the bootstrap results show values close to the regression results, but usually with higher standard errors. This suggests that the bootstrap method takes a more cautious approach to the generalizability of the model. However, the Springate score seems to be a very powerful tool in predicting financial distress. Both the initial regression analysis results and the bootstrap validated results confirm the potential of this score as a valuable and reliable estimator. This highlights the importance of using Springate score effectively in real world applications.

3.3.2.3 Zmijewski X Score: The result of the Omnibus test for the Zmijewski score shows that the model is significant. This indicates that the independent variable (Zmijewski score) makes a significant contribution to estimating the dependent variable (financial distress classification). We observe that the p-value is quite low, confirming that the model makes a better prediction than a fixed model (based on the cut-off value only).

On the other hand, the result of the Hosmer-Lemeshow test shows that the fit of the model is reasonable. This test evaluates how well the predicted probabilities match the observed probabilities. Ideally, we want the p-value of this test to be high because it indicates that the model's predictions fit well with the observed values. Based on the information you provided, the Hosmer-Lemeshow test has a high p-value, indicating that the model generally fits the data well.

When we examine the T-1 and T-2 lag periods for the Zmijewski score, we can see that these scores are important predictors of financial distress. First, when we look at the B coefficients for both periods, we can see that these values are non-zero and significant. The positive B coefficient reveals how each unit increase in the Zmijewski score increases the probability of financial distress. The Wald statistic tests the significance of the B coefficient, and high Wald values strongly confirm that the coefficient is nonzero. Especially in the T-1 period, we see a very high Wald value, which indicates that the coefficient of this period is significantly different from zero. However, when we look at the values of the standard errors (S.E.) for both periods, it helps us to understand that there is an uncertainty in the estimation of the coefficients. This uncertainty can affect the accuracy of the model's predictions. The fact that the Wald value is lower in T-2 compared to T-1 and the B coefficient is smaller may indicate that the model may be slightly less sensitive for this period than for the previous period. This may suggest that T-2 may be less informative than T-1 in estimating financial distress. However, the significance values for both periods conclusively confirm that the coefficients are different from zero and that the model is effective in estimating financial distress.

When we compare the results from the regression analysis for the Zmijewski score and the bootstrap results, we see interesting differences and similarities. First of all, the regression results reveal that the Zmijewski score is a significant predictor of financial distress. However, the bootstrap results indicate an uncertainty in the estimation of these coefficients.

Moreover, we look at the B coefficients, we can see that the values in the regression analysis and the bootstrap values are generally compatible. However, the bootstrap results show that the coefficients are generally somewhat more conservative and the confidence intervals are wider. This suggests that the bootstrap method takes a more cautious approach on the generalizability of the model, especially due to unbalanced sampling.

The values of standard errors (S.E.) also support this idea. The standard errors obtained in the regression analysis are generally lower than the bootstrap standard errors. This indicates that the bootstrap method indicates potentially greater uncertainty in the accuracy of model predictions.

In conclusion, when we look at the results obtained with the bootstrap method, we see that this technique is used to test the robustness and durability of the model. Bootstrap results generally agree with regression analysis results, although there are some uncertainties. We can say that the findings obtained using bootstrap results provide a more realistic and careful approach, especially in cases of unbalanced samples. This is important to give a more accurate idea of how the model will perform in the real world.

3.3.2.4 Grover G Score: The impressiveness of the Grover model on financial distress forecasts is very promising for both lag times. According to the omnibus test results, the model establishes a strong relationship between the independent variables and the dependent variable for both lag times; This shows that the model successfully provides information on this subject.

For the T-1 latency, although the Hosmer-Lemeshow test indicates that the model does not fit well in some subgroups, this does not overshadow the overall performance of the model. In fact, this slight deviation may indicate that the model may need additional adjustments to handle more specific situations.

For the T-2 latency, the model shows an outstanding fit to the data. The results of the Hosmer-Lemeshow test indicate that the model is extremely reliable for this delay time. This marks an overall success in the Grover model's T-2 latency, which highlights the model's usefulness in this area.

When we look more specifically at the regression analysis results of the Grover model; The B coefficient for the T-1 delay was -2.73. This indicates that the effect on the dependent variable is negative. Wald statistics shows that this coefficient is 18.50 and with this value the significance of the variable is high. Significance level <0.001, confirming that this variable has a significant effect on the model. Besides, the standard error (S.E.) is set to be 0.63, this value provides information on how accurate the estimation of the coefficient is, and in this case, it indicates a reasonable uncertainty in the estimation of the coefficient. For T-2 lag, the B coefficient is -1.71 and the standard error is 0.51, again showing a negative effect, while Wald statistics supports the significance of this variable with 11.01. Significance value is <0.001. Based on these results, we can say that the Grover model can be used as an effective tool for estimating financial distress for T-1 and T-2 delays.

Also, we saw that the B coefficient for T-1 lag was -2.73. Looking at the bootstrap results, the bias value is -0.13. This shows that the bootstrap results are pretty close to the original regression results. However, the standard error is 0.73 with bootstrap. This indicates that the standard error (0.63) in the original regression model slightly increased with bootstrap. This increase indicates that we should be more cautious about the generalizability of the model.

The B coefficient for T-2 delay is -1.71, while the bootstrap bias value is -0.05. This again states that the bootstrap results are close to the original regression results. However, the standard error here also increases slightly with bootstrap (0.53 vs. 0.51).

In general, we can say that the bootstrap results are quite close to the regression results. However, the observed increase in standard errors indicates that the performance of the model on real-world data may be somewhat more uncertain. This is something to consider before applying the model. Because the Bootstrap method allows us to more realistically assess the model's ability to generalize, we must consider these results when using the model.

3.3.3 Classification Results of The Models

3.3.3.1 Confusion Matrix

		Predicted	
		Non-Distressed	**Distressed**
Actual	**Non-Distressed**		*Type II Error*
	Distressed	*Type I Error*	

Imagine a doctor diagnosing diseases. A Type 1 error is like the doctor is not diagnosing someone who is actually sick as a patient. This may cause the person to not receive necessary treatment or medication. Type 2 error, on the other hand, is to diagnose a healthy person as sick. This can result in the person getting the unnecessary treatment or use wrong medication.

The effects of these mistakes in the financial world can be huge. If we think a company is in financial distress but it is not, this could increase the company's credit costs, lower its stock price, or cause the company to unnecessarily adopt risk-aversion strategies. So, labeling an actually solid company as risky can have serious financial consequences.

On the other hand, judging a company that is in real financial trouble as sound can also cause problems. However, in the financial field, we can observe that a false belief that a company is sound creates greater risks and costs than the opposite. Therefore, minimizing the Type 1 error is often the main goal in financial distress forecasting models.

3.3.3.2 Altman Model Classification Results

T-1

Classification Table[a]

Observed			Predicted Y ,0	Predicted Y 1,0	Percentage Correct
Step 1	Y	,0	69	2	97,2
		1,0	17	15	46,9
	Overall Percentage				81,6

a. The cut value is ,500

T-2

Classification Table[a]

Observed			Predicted Y ,0	Predicted Y 1,0	Percentage Correct
Step 1	Y	,0	70	0	100,0
		1,0	27	6	18,2
	Overall Percentage				73,8

a. The cut value is ,500

When we look at the T-1 lag results with the Altman Z score, we see that the model does a pretty good job of identifying companies that are financially sound. It correctly predicts almost 97 out of every 100 companies. However, this very high success may be due to the fact that there were many more companies in this category from the beginning. When it tries to find companies in financial distress, it can correctly predict approximately 47 out of every 100 companies. Not bad, but we have to keep in mind that there is a high probability of being wrong here.

When it comes to the T-2 lag, the model seems to detect companies that are financially stable perfectly. But this perfection is a bit doubtful; perhaps it enjoys an advantage simply because of the number of companies in this category. The real challenge is identifying distressed companies, where it can only correctly predict 18 out of every 100 companies. This suggests that the probability of mistaken for this delay may be quite high.

As a result, we can say that the Altman Z score has a high success rate at T-1 lag for companies that are not in financial distress and a reasonable success rate for companies that are in distress. For the T-2 lag, we find that the model perfectly classifies companies that are not in financial distress, but has serious difficulties for companies that are in distress. It is crucial to consider this class imbalance and the risk of Type 1 error when making decisions based on model results.

3.3.3.3 Springate Classification Results

T-1 ***T-2***

Classification Table[a] (T-1)

Observed			Predicted Y ,0	Predicted Y 1,0	Percentage Correct
Step 1	Y	,0	66	5	93,0
		1,0	10	23	69,7
	Overall Percentage				85,6

a. The cut value is ,500

Classification Table[a] (T-2)

Observed			Predicted Y ,0	Predicted Y 1,0	Percentage Correct
Step 1	Y	,0	67	4	94,4
		1,0	21	12	36,4
	Overall Percentage				76,0

a. The cut value is ,500

When we look at the T-1 lag results of the Springate model, we see that it classifies companies that are not in financial distress (0) with 93% accuracy. This shows that the model is quite successful in predicting this large class. However, this high accuracy may be due to class imbalance. On the other hand, it is noteworthy that companies in financial distress are classified as (1) with 69.7%. This shows that the model also predicts a small number of classes, namely firms in financial distress, quite well. However, in this case, the risk of Type 1 error should not be ignored.

For the T-2 lag, firms that were not in financial distress were classified with 94.4% accuracy, indicating consistent success of the model in this class. However, only 36.4% of firms in financial distress were classified correctly. This represents a significant drop in this class relative to the T-1 lag and indicates that the model has difficulty predicting firms in financial distress at this lag. This means that the Type 1 error may increase for this delay.

As a result, we can say that the Springate model performs reasonably well in both classes at T-1 latency. However, it should be noted that for the T-2 lag, the model has difficulty classifying firms in financial distress, and these difficulties are most likely due to class imbalance. Therefore, it is very important to consider class imbalance, especially for T-2 latency, when making decisions based on the results of the model.

3.3.3.4 Zmijewski Classification Results

T-1

Classification Table[a]

Observed			Predicted Y ,0	Predicted Y 1,0	Percentage Correct
Step 1	Y	,0	69	5	93,2
		1,0	20	16	44,4
	Overall Percentage				77,3

a. The cut value is ,500

T-2

Classification Table[a]

Observed			Predicted Y ,0	Predicted Y 1,0	Percentage Correct
Step 1	Y	,0	72	2	97,3
		1,0	31	5	13,9
	Overall Percentage				70,0

a. The cut value is ,500

When we look at the model for the T-1 lag, it classifies companies that are not in financial distress with 93.2% accuracy. This high success rate may be due to the fact that there are so many companies in this large group. On the other hand, it can predict companies in financial distress with only 44.4% accuracy. This shows that the model has difficulty correctly predicting the small number of such companies. In other words, the model may make the mistake of portraying a company that is in financial distress as not being in distress, but this error may be due to the unbalanced number of companies.

A similar situation applies to the T-2 delay. It predicts companies that are not in financial distress with 97.3% accuracy. However, this high accuracy rate may again be due to class imbalance. It can predict companies in financial distress with only 13.4% accuracy. This suggests that the model has great difficulty predicting these small numbers of companies.

In summary, the classification results of the Zmijewski score clearly show the effects of class imbalance. Difficulties in classifying companies, especially those in financial distress, indicate that the model is sensitive to the problem of class imbalance. Therefore, it is very important to consider this imbalance when making decisions based on the model's results.

3.3.3.5 Grover Model Classification Results

T-1 ***T-2***

Classification Table[a]

Observed			Predicted Y ,0	Predicted Y 1,0	Percentage Correct
Step 1	Y	,0	69	2	97,2
		1,0	15	18	54,5
	Overall Percentage				83,7

a. The cut value is ,500

Classification Table[a]

Observed			Predicted Y ,0	Predicted Y 1,0	Percentage Correct
Step 1	Y	,0	67	4	94,4
		1,0	23	10	30,3
	Overall Percentage				74,0

a. The cut value is ,500

When we look at the T-1 lag results, we observe that companies that are not in financial distress (0) are classified with an accuracy of 97.2%. This high success rate indicates that the model is effective in this class. However, it should be taken into account that this success rate may be due to the uneven distribution in the sample. On the other hand, the classification of firms in financial distress (1) with 54.5% accuracy indicates that the model also predicts this minority class quite well. However, the model's risk of Type 1 error may be relatively high for this lag.

For T-2 lag results, it is seen that companies that are not in financial distress are classified with 94.4% accuracy. This ratio shows that the model is quite successful in this class. However, we see that only 30.3% of companies in financial distress are classified correctly. This indicates that the model has difficulty in accurately predicting firms that are financially distressed in T-2 lag. This may indicate increased Type 1 error specifically for this lag.

In conclusion, the Grover model appears to have achieved reasonable success in T-1 lag for both classes. For T-2 lag, while the model classifies firms that are not in financial distress quite successfully, we see that this success decreases for firms in distress. It is important to consider this class imbalance and risk of Type 1 error for decisions to be made based on the model's results.

According to the model success rates, Springate shows the highest success with 85.6% in the T-1 lag in financial distress predictions, while Zmijewski shows the lowest success with 77.3%. In the T-2 lag, Springate is again the leader and gives the best results with 76%, while Zmijewski is the least successful model with 70%.

The performance gap between these models needs to be evaluated more comprehensively, especially basing it on data imbalances and statistical results. First, unbalanced datasets can increase the propensity of models to correctly classify non-stressed firms. This may be a critical factor, especially for the poor performance of the Zmijewski model observed in the T-2 lag. The Springate model shows the strongest overall performance based on the data, while the Zmijewski model offers weaker results at certain lags.

3.4 Summary of Empirical Results

Within the scope of this thesis, the financial data of publicly traded energy companies in Europe between the years 2020-2021 were examined in detail and in the light of this information, financial distress forecasts for 2022 were made. The four main models used - Altman Z-Score, Springate, Zmijewski and Grover - shed light on the various financial positions and structures of companies in the energy sector. However, the success of these models has varied due to several factors.

First of all, Altman Z-Score and Springate models showed very high classification success in 2021. The robust structure of these models may indicate a detailed analysis capacity over a wide range of financial data. While Grover showed similar success in the 2021, it experienced some decline in the 2020 lag, which may indicate the sensitivity of the model to financial indicators that change over time. However, the Zmijewski model showed lower classification success than all models. It can be thought that the predictive power of the model is more limited than others.

When performing these analyses, it would be a huge mistake to ignore the potential effects of imbalance in the data set. The fact that firms that do not experience distress (marked as 0) outnumber those that experience distress (marked as 1) can have a serious misleading effect on the accuracy rates of the models. In particular, the economic consequences of misclassifications can be large; therefore, it is important to consider the potential effects of both types of errors (Type 1 and Type 2). Type 1 error, in particular, represents false positive results, and an incorrect prediction that a firm is in economic distress can lead to serious financial losses for investors and creditors.

Furthermore, standard error (SE) is an important factor to consider during model evaluations. The standard error is an indication of how accurate the estimator is. For example, while the Grover model has a lower classification success in the 2020, it should be taken into consideration that this result may be due to a high standard error. On the other hand, although Altman Z-Score and Springate models have higher classification success in 2021 and 2020, it is necessary to consider how this success affects the standard error values. High standard errors indicate that the model is sensitive to certain predictors and could potentially show higher variance. Therefore, choosing a model by taking into account both classification success and standard error will help us reach more general and consistent results.

Consequently, The years 2020 and 2021 were a period of significant changes and uncertainties for the energy sector. These uncertainties may be one of the main factors affecting the success of financial distress forecasting models. To ensure the accuracy of this type of analysis, the quality, balance and scope of the data set feeding the model are critical, as is the structure of the model used. The selection of the most appropriate model may vary depending on the characteristics of the data set, the acceptable margin of error, and especially how companies' financial indicators change over time.

3.5 Limitations

So, diving into my study, I did face a few hurdles that are important to share.

1. Data Availability: I started off with data from 177 companies that are publicly traded. That might sound like a lot, but here's the catch: once we dug deeper and tried to select the most complete and relevant records, I could only use 112 of these companies. The rest didn't have enough data for our purposes. Additionally, I found a significant imbalance in our sample. It's kind of like wanting to compare apples to oranges, but finding out you have a basket full of apples and just a few oranges.

2. Incomplete Financial Data: My second hiccup was in the details. I had a clear idea of what financial markers we wanted to look at, but the database sometimes fell short. Imagine wanting to bake a cake with specific ingredients, but realizing halfway that you don’t have everything you need. That meant leaving out some company records because they didn’t give us the full picture we needed for our analysis.

3. Literature Challenges: Now, when it comes to financial distress studies, things get a bit murky. There isn't a universally accepted yardstick to measure how well a model works. I decided to compare models using terms like AUC, sensitivity, and specificity. But there's a twist. Many scholars and studies have concentrated on predicting bankruptcy, which is a clear-cut event. It's like predicting rain—either it rains or it doesn't. Financial distress, on the other hand, is more like predicting cloudiness; it's a bit more subjective and varies based on definitions. My benchmark was based on a pattern of negative net profit. But if you look back in past research, others have picked different benchmarks, such as EBIT, EBITDA, or debt ratios. Lastly, I found something intriguing: a couple of the popular models used in bankruptcy predictions didn't hold up when we applied them to the energy sector. It's a bit like using a roadmap for one city and finding it doesn't work for another.

3.6 Future Research

This study focuses on financial distress prediction with Altman , Springate, Zmijewski and Grover models on European publicly traded energy companies. However, it was observed that the results obtained were affected by factors such as data imbalance and standard error. It is recommended that future research test these models in broader or more niche subsectors, taking into account the specific dynamics and political and economic fluctuations of the European energy sector. In particular, examining how model success varies across specific subcategories, such as renewable energy or energy companies based on fossil fuels, can help us understand whether the model is adaptive and how it can be optimized within the industry.

Exploring the potential of artificial intelligence and machine learning algorithms in financial distress prediction in the energy sector will be one of the important research topics of the future. The complexity of the energy sector has the potential to improve model success by leveraging advanced algorithms to address the issue of data imbalance.

Additionally, investigating how these models synergize with financial ratios or macroeconomic indicators specific to the energy sector can help create more holistic and comprehensive forecasting models. Finally, in the light of the ever-changing regulations and policies of the European energy market, studies examining the adaptation and updating of these forecasting models over time are also needed.

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