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Altman Z’’-score for predicting bankruptcy: Evidence from the aviation industry

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ABSTRACT:

Bankruptcy prediction has long been a subject of academic interest, as it provides valuable insights for corporate stakeholders, such as investors and creditors. The aviation industry is particularly exposed to external economic shocks and events, including pandemics, intense internation competition and increasing jet fuel prices. As a result, there is a strong demand for reliable tools that enable the early identification of financial distress in this sector. The objective of this thesis is to determine the predictive performance of the Altman Z''-score model in the scope of the global aviation industry. The study aims to assess whether the model can be used as a reliable tool for identifying financially distressed airlines as well as to investigate whether there are any differences in the model's predictive accuracy across different geographical regions and market types. To achieve these objectives, an empirical analysis is conducted based on a data sample of 20 bankrupt and 30 non-bankrupt airlines. In total, a sample of 100 observations from 50 unique airlines is obtained from the Orbis database and annual financial reports for the period from 2005 to 2025. Based on the classification metrics, including overall accuracy, classified accuracy, precision, specificity, sensitivity and F1 score, the study results indicate a moderate overall predictive accuracy rate, with slightly improved performance when excluding grey zone observations from the classified observations. Based on the high sensitivity rate, it can be concluded that the model displays a strong performance in identifying bankrupt airlines. However, a low specificity rate suggests that the model tends to overestimate financial distress by classifying non-bankrupt airlines as financially distressed. In addition, the results of the chi-square test reveal that while the model's performance does not vary significantly between developed and emerging markets, there are statistically significant differences in performance across geographical regions, with considerably lower accuracy observed in the APAC region. Overall, the findings of this study suggest the Altman Z''-score model provides useful insights and can serve as a tool for identifying early warning signals of financial distress, rather than as a precise classifier of bankruptcy in the context of the global aviation industry.

KEYWORDS: Bankruptcy, financial analysis, air transport, financial statements

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1 Introduction

The aim of this chapter is to introduce the reader to the topic of the study by discussing the background, outlining the problem statement and motivation, presenting the research questions and describing the structure of the thesis.

1.1 Background

The aviation industry is highly exposed to global events and economic shocks. Two recent examples that have significantly affected the global aviation industry are the COVID-19 pandemics and the ongoing conflict between Russia and Ukraine. For instance, geopolitical tensions and sanctions forced airlines to reroute the flights between Europe and Asia, which in turn leads to increased fuel consumption and higher operational costs. As the conflict started shortly after the peak of the pandemics, many airlines had insufficient time and resources to recover after the previous losses. The geopolitical tension causes airlines to operate in the environment of uncertainty due to volatile and rising jet fuel prices.

While the above discussed events have significantly impacted financial stability of airlines, the aviation industry has always been vulnerable to economic changes. As discussed by Shi et al. (2024), multiple major airlines have declared bankruptcy over the past decade. For instance, Air Berlin, which was the second largest airline in Germany at a time, went bankrupt after facing significant losses in 2017. In addition, Thomas Cook, the largest airline in the UK, had filed for insolvency in 2019, which led to thousands of tourists being stuck in airports around the globe (Shi et al., 2024).

According to Shi et al. (2024), the aviation industry is closely connected with other industries, such as logistics and tourism. Therefore, an airline filing for bankruptcy might lead to disturbance in logistics and transportation processes, which in turn causes obstacles in foreign trade and increases in prices. Since the aviation industry is interconnected with other industries, the ability to evaluate its financial state is crucial for investors and stakeholders.

1.2 Motivation

The purpose of this thesis is to evaluate the accuracy of the Altman Z''-score model in predicting bankruptcy in the global aviation industry. By analysing financial data from international airlines that filed for bankruptcy during 2005-2025, the study aims to assess the model's reliability and practical relevance in a global context. The research is motivated by the need of evaluating the predictive performance of bankruptcy prediction models, such as the Alman's Z''-score to enhance financial risk management in the volatile aviation sector. Airlines operating model can be characterized by such factors as exposure to external events and shocks, high fixes costs, including aircraft lease and employees' salaries, as well as high level of leverage. Over the past two decades, several major airlines have been forced to file for bankruptcy, while other airlines have managed to recover from financial difficulties through corporate restructuring methods, such as mergers, demergers, or with financial support from the government.

As mentioned in the previous sub-chapter, the ability to predict bankruptcy well in advance can be crucial for businesses and investors, as it provides a possibility to take preventive actions and potentially prevent the insolvency. One of the key stakeholders interested in preventing corporate bankruptcy are financial institutions. Banks seek to minimize credit risk by ensuring that businesses can meet their financial debt obligations (Altman et al., 2017). Therefore, bankers and investment advisors need reliable bankruptcy prediction tools that can support decision-making when constructing investment portfolios that do not include financially distressed companies.

Despite the widespread use of the Altman Z''-score model in academic research and corporate environment, the predictive power of the model might vary across different sectors. Since the aviation industry is characterized by unique business and financial factors that are discussed further in the theory chapter, this study aims to assess how accurately the model can identify bankruptcies specifically in the aviation sector across different geographical regions and market types.

To summarize, this study is motivated by the three following factors:

1. The need to assess the accuracy of Altman Z’’-score in terms of bankruptcy prediction in the global aviation industry.
2. The need to evaluate whether Altman Z’’-score can differentiate financially distressed firms (bankrupt) from financially healthy companies (non-bankrupt).
3. The need to assess if there any differences in the Z’’-score accuracy across different geographical regions and market types.

Conducting a study with a specific industry focus enables to explore the specifics of the aviation industry and provide insights for both theoretical academic research and practical business insights for stakeholders involved in the aviation field.

1.3 Research Question and Hypotheses

The main research question of this study is to examine the extent to which the Altman’s Z’’-score model can predict bankruptcy in the global aviation industry. In addition, the study investigates whether the predictive accuracy of the model varies across different geographical regions and market types.

Based on the literature, the primary hypotheses of this study are formulated:

H1: The Altman Z’’-score model can serve as a reliable tool for predicting bankruptcy in the global aviation industry.

This hypothesis is based on prior research indicating that the Z’’-score model can provide useful insights for capturing early warnings of financial distress, although its overall predictive accuracy is moderate in the context of the aviation industry (Shi et al., 2024; Kroeze et al., 2018).

H2: The predictive accuracy of Altman Z''-score varies across different geographical regions and market types.

The study analyses whether the Altman Z''-score model can demonstrate the same level of predictive accuracy when it comes to different geographical locations and market types. The study includes airlines from both developed and emerging markets, as well as from three business regions including Europe, Middle East and Africa (EMEA), Americas (AMER) and Asia-Pacific (APAC). Therefore, a comparative analysis is conducted to examine whether there are any statistically significant variations in the results. The differences in the model's predictive accuracy can be caused by different accounting principles and reporting standards, economic environments and regulation policies.

1.4 Previous Studies & Research Gap

Due to the aviation industry being highly exposed to external shocks, such as weather shocks, geopolitical tension and fuel price increase, it is important to have reliable tools for observing early signals of financial distress in time. For this reason, there has been a significant academic interest in researching the performance of bankruptcy prediction models, including the Altman Z-score.

For example, in their study, Kroeze et al. (2018), analyse the efficiency of the Alman's Z''-score in comparison to the alternate model. The alternate model used in the study consists of three variables, which include working capital/total assets, retained earnings/total assets, book value of equity/total liabilities variables and error term. Kroeze et al.'s study (2018) focuses on financial data from the major U.S. airlines. In their study, Kroeze et al. (2018) demonstrate that the alternate bankruptcy prediction model tends to have more predictive accuracy compared to the traditional Altman Z''-score model. Upon Kroeze et al.'s (2018) research, the overall accuracy of the Z''-score model is 57.5%, whereas the alternate model achieves a higher accuracy of 80.9%.

In addition, Shi et al. (2024) examine the predictive power of the Z'- and Z''-score models for bankruptcy prediction, with a specific focus on European airlines that went bankrupt during 2009-2020. In their study, Shi et al. (2024) note that liquidity and leverage ratios are critical predictors of distress. As a result of their study, Shi et al. (2024) conclude that Altman Z''-score displays moderate predictive performance when applied to a sample data of airlines belonging to the European aviation sector. The authors also acknowledge the influence of external shocks, such as the COVID-19, on the sample companies, reflecting on the noticeable decrease in the Z''-scores of some airlines in 2020. One important feature observed by Shi et al. (2024), is that flagship carriers, such as Air France-KLM, often receive significant financial support from governments, which helps companies to sustain their operations despite displaying negative Z''-score for years.

Golaszewski and Saunders (1992) conduct research analysing not the performance accuracy of Altman Z-score for bankruptcy prediction, but rather for assessing the financial state of the sample of the U.S. airlines. As a result of the study, the authors observe the trend that during the observation period of 1987-1991, the U.S. airlines that have filed for bankruptcy displayed Z-scores ranging from 1.0 to -0.5. They also mentioned that despite getting low Z-scores of close to 1.0., many airlines continue to operate normally, without declaring bankruptcy. The authors state that having low Z-score is a common feature for aviation industry, as it is characterized by having high leverage, operating and fixed-term costs (Golaszewski & Saunders, 1992).

While prior research has explored the Altman Z''-score in regional contexts, for example, the U.S. and European airlines, there is limited research applying the Z''-score model to a diverse group of international airlines. Prior research discussed above highlights the applicability of the Z''-score in specific regional contexts but lack a broader, global perspective. This study addresses this gap by focusing on global airlines across different geographical regions and market types, providing insights into the model's universal applicability and contributing to financial risk management practices in the aviation industry.

1.5 Limitations and assumptions

It is important to acknowledge that this study is a subject to certain limitations. To start with, the sample size of twenty bankrupt and thirty non-bankrupt airlines may restrict the generalizability of findings. The relatively small data size has been influenced by rather low financial data availability when it comes to bankrupt airlines. Many of already bankrupt companies do not have publicly available financial reports, which limited the sample size.

Additionally, the study fully relies on a quantitative approach by analysing financial data from companies' annual accounting reports. What it means in practice is that the study does acknowledge but does not directly incorporate qualitative external factors like fuel price volatility, geopolitical tensions, global pandemic or any unexpected disruptions. Since bankruptcy is a complex outcome of both financial and non-financial factors, relying solely on the Altman Z''-score model might not provide a full picture on the probability of an airline filing for bankruptcy.

Furthermore, the observation period selected for the analysis of this study includes periods of global shocks and geopolitical tensions that have significantly affected the financial stability worldwide and especially the aviation industry. As discussed earlier, the aviation industry is highly vulnerable to external events, so financial ratios might be particularly low during these years which can weaken the predictive accuracy of the Altman Z''-score model. It specifically might be reflected on the Z''-scores of non-bankrupt companies, with short-term distress being captured by the model, which, however, does not necessarily lead to long-term financial issues.

The study assumes access to reliable financial data from public sources, including the Orbis database and companies' annual financial reports.

1.6 Structure of the Thesis

This thesis is structured as follows. Chapter 2 provides a comprehensive overview of the key concepts related to bankruptcy and its prediction. It includes a description of different versions of the Altman Z-score, discusses their limitations and presents a brief overview of alternative bankruptcy prediction models. Chapter 3 describes the structure of the empirical part of the thesis and consists of research design, description of data sources, formulas to be used and statistical methods. In chapter 4, results of the study are presented. Chapter 5 discusses the results mentioned in chapter 4 in more detail. Lastly, chapter 6 summarizes all main observations and results obtained during the study and answers the research questions introduced in chapter 1.

2 Literature Review & Theory

This chapter discusses the key definitions related to the topic of the thesis to provide a more comprehensive understanding and background of the study. The chapter is divided into eight sub-chapters, with each one of them focusing on a specific topic related to bankruptcy, its causes, bankruptcy prediction models and the specifics of the aviation industry.

2.1 Bankruptcy and its causes

When it comes to the U.S. corporate market, historically there have been some certain periods of time when businesses were particularly exposed to bankruptcy. Corporate failure has been become an economic reality for many businesses during the global financial crisis of 2008-2009. One of the most major cases known in the history was the bankruptcy of the Lehman Brothers bank, whose liabilities accounted for 613 billion dollars. The bankruptcy occurred during the global financial crisis of 2008-2009 and remains one of the examples where the government did not provide support that would have prevented the financial failure (Altman et al., 2019).

There are several terms used to describe the state of a company's financial distress. According to Altman et al. (2019), there are four main terms found in academic literature that can sometimes substitute each other, but each still have their own meaning in terms of financial distress.

The first term is insolvency. Altman et al., (2019) define insolvency as a state when a firm's liabilities exceed its assets, and as a result, a company cannot fund its financial obligations when they are due for payment. It is, however, noted that a shortage of assets might result from insufficient cash flow, which can be a temporary condition. However, in case cash flow shortage becomes permanent, it might ultimately lead to insolvency (Altman et al., 2019).

The second term associated with negative economic state of a firm is failure. Failure can be defined as a state when a company's cost of capital is significantly higher than the average return on investment. Failure as an economic term can be also applied to these companies that are forced to terminate their operations, which then leads to significant losses for creditors and unpaid financial obligations (Altman et al., 2019).

The third term is default, which Altman et al., (2019) describe as a state when a borrowing company fails to make a loan instalment, according to the specified schedule and agreement with the lender. If a company does not have enough resources to cover the principal and interest amount of the loan, this indicates a negative financial state of a company, which can be called default (Altman et al., 2019).

Lastly, the fourth term is bankruptcy. According to the U.S. laws, a company can be considered bankrupt once it has declared bankruptcy in the federal bankruptcy court, where it either asked to reorganize its structure or realize its assets (Altman et al., 2019). William H. Beaver (1966) has defined bankruptcy or "failure" as a state when a company is no longer able to pay its financial liabilities by due date. In other words, a company becomes insolvent when its short-term liabilities exceed short-term assets that could be used for repaying its financial obligations.

According to Altman et al. (2019), there are several factors that can contribute to a firm's economic failure. Oftentimes, there is not a single factor that affects the financial stability, but there is rather a combination of these factors. Altman et al. (2019) discussed some of the most common of these reasons.

One of the most common contributors to financial distress is a combination of too high leverage and negative operating performance. Cyclical industries, such as aviation, tend to have poor operating performance. In addition, other elements leading to this factor are increasing commodity prices and high internation competition (Altman et al., 2019).

Another factor is overreliance on credit funding and liquidity risk. Especially during the global financial crisis of 2008-2009, many companies went bankrupt due to the shortage of credit supply and thus their inability to roll over debt (Altman et al., 2019). When a company's current liabilities constantly exceed current assets, the common outcome is that a company faces financial distress and is unable to fulfil its short-term financial obligations.

In addition, another reason for corporate failures, and particularly for bankruptcy in the aviation industry is deregulated environment. According to Altman et al. (2019), the aviation industry was deregulated in the 1970s, which in turn caused the significant increase of bankruptcy cases and the number continues to grow since then. The reason for that is there is a high level of competition in the deregulated environment, where there is a constant flow of companies entering and exiting the market.

Altman et al. (2019) discussed that there are two main outcomes when a company faces bankruptcy. One possible outcome is reorganization and possible continuation of its operations, which can take place in case a firm's liquidation value exceeds its current intrinsic value. However, if a company's total assets are not of much worth, it might a more reasonable idea to liquidate. Corporate reorganization because of financial distress will be discussed further in one the next sub-chapters.

2.2 Theoretical Foundations of Bankruptcy Prediction

The academic interest in researching about bankruptcy prediction tools has grown over the years. One of the earliest contributors to the field was FitzPatrick (1932), who identified key trends and patterns related to financial distress by conducting a comparative study between the financial ratios of bankrupt and non-bankrupt companies. Thirty years later, Beaver (1966) conducted a one variable analysis on financial ratios, after which he concluded that such financial determinants as liquidity and cash flow ratios can help to identify financially distressed from financially stable companies one year prior to bankruptcy. Thanks to these academic studies, there has been established an understanding that with the right use of financial figures and ratios, it can be possible to identify warning signals for potential business failure.

Despite establishing a theoretical framework and contributing to bankruptcy prediction development, one variable model is too isolated to provide a broad picture of financial state of a company. One variable model relies solely on individual financial ratios. Later, this led to the development of multivariable bankruptcy prediction models that include multiple ratios to address the issue of limited results provided by univariate models (Gritta et al., 2006).

There are several theories that describe the factors that lead companies to going bankrupt. To start with, there exists a Gambler's Ruin theory that resolves around the idea of a gambler that bets their money by playing the game, with some chances of gain and loss. In this game, the gambler continues to play until the ultimate loss of all their money. In corporate scenario, a company is viewed as a gambler. Based on this theory, for as long as a company's net worth exceeds zero, it can be viewed as solvent. A company carries on with its operations until it runs out of cash, and at that point a company is forced to claim bankruptcy (Aziz & Dar, 2004).

Another bankruptcy theory is cash management theory. This theory supports the importance of short-term liquidity management. In a scenario where short-term liabilities, such as accounts payable and short-term debt, constantly prevail over short-term assets, including cash, accounts receivables and inventories, a company can find itself in financial distress and in long-term bankruptcy (Aziz & Dar, 2004). Cash management failure can be explained as the state when a company's incoming and outgoing cashflows are not balanced (Laitinen & Laitinen, 1998).

2.3 Corporate Restructuring and Financial Distress

Corporate restructuring represents a strategic stage between financial distress and financial bankruptcy in some cases. However, it does not necessarily mean that it will result in financial bankruptcy, as corporate restructuring is intended to increase operating efficiency and improving the firm's value to the owners. There exist several variations of firms' restructuring in the corporate environment.

Financial restructuring refers to adjustments to the right-hand of the balance sheet, while asset restructuring relates to restructuring of the left-hand side. Financial restructuring is aimed at reducing the company's cost of capital, whereas asset restructuring focuses on optimizing operational efficiency and cash flows by redeploying inefficient assets. One of the main benefits of corporate restructuring is an opportunity to proceed with business activities, continue to provide a workplace for a company's employees and fulfil the financial obligations to suppliers and other stakeholders (Altman et al., 2019).

There are two main options of restructuring that distressed firms can face. The first option is to have in-court restructuring, which involves proceedings under the court supervision. The key disadvantage of this option is that in-court restructuring takes a long time and requires more financial resources invested compared to the out-of-court restructuring (Altman et al., 2019). Out-of-court restructuring relates to restructuring processes that are executed without legal court proceedings.

There are several options available for firms that are restructuring their debt out-of-court. Each of these mechanisms is targeted to stabilize a firm's balance sheet and improve liquidity. One of these restructuring options is capital injection, which refers to infusing new capital info a company. New equity is sought from current shareholders or new outside investors. According to Altman et al. (2019), a distressed firm's equity is expected to be positively affected by new capital injection, as strengthened equity capital can provide a chance for a firm to outgrow the financial distress.

Another option available for restructuring companies is debt repurchase, which refers to the process of outstanding debt reacquisition at a discount to face value. By releasing some of their debt at significant discount enables companies to decrease their total liabilities and improve the overall financial situation. Altman et al. (2019) warn that a company should thoroughly structure its debt repurchase proceedings, as it might face sanctions in case the process is later claimed as noncompliant with terms and prices.

When a firm cannot restructure its debt through capital injection or debt repurchase for example, due to lack of cash, there is a third option available, which is known as distressed exchange. This method involves a firm offering its existing debtholders to exchange the existing debt with the new financial securities that could have, for example, more favourable payment terms. New financial securities are provided at the discounted value to the existing debt principal amount. This method can help distressed firms to avoid bankruptcy by reducing their debt and improving liquidity. According to Altman et al. (2019), out-of-court restructuring brings multiple benefits to distressed firms, as this way of restructuring is less damaging to firms' reputation and the time that upper management would otherwise be spending in in-court sessions can be used for negotiations with creditors and setting up a plan of actions.

One of the common legal bankruptcy procedures that distressed businesses can do is filing for Chapter 11. Introduced in 1978 under the U.S. legislation code, Chapter 11 allows financially distressed companies to continue their operations during the reorganization process. This legal procedure provides companies with time for restructuring and stabilizing their financial situation, while also fulfilling some of the debt obligations to critical suppliers and paying salaries to retained employees (Altman et al., 2019).

The sample data of bankrupt companies selected for this study includes some companies that have not ceased to exist but rather have been in such a drastic financial state that they had to file for Chapter 11, after which some of them were able to recover and continue their operations. According to the statistics provided by Altman et al. (2019), the mean number of filings for Chapter 11 when considering firms with liabilities exceeding 100 million dollars was 76 during years 1989-2017. The peak of filing for Chapter 11 occurred during years 2008-2009 due to the consequences of the global financial crisis.

One of the biggest companies that had filed for Chapter 11 during 1989-2017 was Delta Air Lines Inc., a major U.S. airline that needed restructuring, as their liabilities accounted for 28.546 million dollars in 2005 (Altman et al., 2019). Delta Air Line is included in the data sample selected for this study.

2.4 Financial Ratios Used in Bankruptcy Prediction

Financial ratio analysis has been used as a tool for assessing companies' financial performance and stability for many years. In his study, Horrigan (1968) produced an overview on how financial ratios were developed and utilized throughout the history. According to Horrigan (1968), by using financial ratio analysis companies can obtain valuable financial figures and observe a comparison across different companies and time periods.

While analysing financial ratios separately can provide with certain conclusions valuable for a firm's financial state, it has been academically discussed that singles ratios cannot provide a full picture on the probability of financial distress. To increase the predictive power of bankruptcy prediction models, multivariable models were later developed to address this gap. Altman (1968) developed a model that consists of multiple financial ratios, which is discussed later in this thesis.

According to Beaver (1966), some financial ratios can help to predict financial distress up to five years before actual failure. Traditional bankruptcy prediction models, including Altman Z-score, rely on financial data obtained from companies' financial statement, as it is needed for financial ratio calculation. With the help of financial ratios, it is possible to interpret financial data in terms of different indicators, such as liquidity, profitability, leverage and turnover (Gritta et al., 2006).

There exist several ways to evaluate a company's profitability. Profitability ratios are an important part of financial analysis, as they represent how a company can generate profits relative to its resources. In case a company is consistently having negative profitability ratios, it could be a strong indicator of financial distress, as these companies might have difficulties covering their financial obligations as well as reinvesting back into business operations. One widely used profitability ratios is Return on Equity (ROE). ROE is a ratio that measures how a company can generate additional value to the capital invested by shareholders (Yritystutkimus, 2017).

Another important type of financial ratios for bankruptcy prediction is liquidity ratios. Liquidity ratios reflect on a company's ability to generate enough resources to cover its short-term liabilities with short-term assets. Liquidity ratios are widely used for assessing a firm's financial health, as good liquidity ratios indicate that a company has a balance level of short-term assets liabilities, whereas low liquidity ratios mean that a company is struggling to fund its short-term liabilities. In the latter scenario, this might be an early indication of financial distress, which is followed by delays in supplier payments, decreased credit rating and reputation. Despite this, it is important to remember that liquidity should not be used as a single indicator for bankruptcy prediction, as low liquidity ratio can sometimes be caused by a company's business model. According to Yritystutkimus (2017), to obtain a broader picture on a company's financial stability, liquidity ratios should be used together with profitability and solvency ratios.

The current ratio is a one of the liquidity ratios that helps to assess the ability of a company to fund its short-term obligations with its short-terms assets. The current ratio focuses on a slightly longer-term perspective compared to quick ratio. The current ratio is based on the idea that inventory can be also utilized as a short-term asset to cover short-term liabilities. When calculating or interpreting this ratio, it is crucial to consider the difficulty when it comes to inventory value estimation. Current Ratio of between 1 and 2 can be interpreted as satisfactory (Yritystutkimus, 2017).

Another group of financial ratios used for bankruptcy prediction are solvency and leverage ratios. These ratios reflect on how a company's capital is structured, where companies with high leverage are more exposed to interest rate and refinancing risks, particularly when profitability is declining. These ratios evaluate a firm's financial health from a long-term perspective. One of the ratios belonging to this group is Equity ratio. This ratio reflects on how well a company utilizes its equity to fund its assets. Yritystutkimus (2017) categorized an equity ratio of between 20-40% as satisfactory and over 40% as good.

2.5 Altman Bankruptcy Prediction Models

In 1968, Altman introduced the first multiple discriminant model (MDA) that can be used for bankruptcy prediction and is known as the Z-score model. According to Altman (1968), MDA has been previously used mainly in biological and social disciplines. The model represents a multivariable statistical approach for predicting corporate bankruptcy by integrating some key financial ratios into one formula to calculate a final bankruptcy prediction score. Altman (1968) collected the financial data of thirty-three bankrupt and thirty-three non-bankrupt companies. The study reveal that the model can accurately classify bankruptcy with a high rate of 95% one year prior to bankruptcy. In addition, the model can correctly classify bankruptcies with a slightly lower rate of 72% two years prior to bankruptcy (Altman, 1968).

The development of the Z-score model was an important step to shift from a single-ratio financial assessment into a structured, multivariable analysis. Even though the model has been introduced nearly 60 years ago, it is still widely used globally for both theoretical research and practical applications (Altman et al., 2017).

The original Z-score model was created by classifying financial ratios into five main variables: liquidity, profitability, leverage, solvency and activity. Altman (1968) has justified the selection of the mentioned financial categories by their relevance in previous research and possible applicability of them to his own study. One of the main strengths of Altman Z-score models is that they provide transparent and easily interpretable results by relying on accounting-based financial data and main financial ratios.

The original Alman’s Z-score model (1968) is calculated as follows:

$$Z = 0{,}012 * X1 + 0{,}014 * X2 + 0{,}033 * X3 + 0{,}006 * X4 + 0{,}999 * X5, \qquad (1)$$

Where:

X1 = Working Capital/Total Assets

X2 = Retained Earnings/Total Assets

X3 = Earnings before Interest and Taxes/Total Assets

X4 = Market Value of Equity/Book Value of Total Liabilities

X5 = Sales/Total Assets

Z = Overall Index.

Altman (1968) categorized the Z-score results into three distinct groups, with each group indicating a different risk of bankruptcy and level of financial stability. Companies that have Z-scores of under 1.88 are classified as high-risk companies that are in the distress zone. It was concluded that these companies typically demonstrate troubles with profitability, liquidity and efficiency of deployed capital. These factors indicate potential financial distress and bankruptcy. Companies that have Z-scores in between 1.81 and 2.99 are classified in the grey zone, meaning that these companies are not in significant financial distress but neither they are completely in the zone of financial stability. Firms that are placed in this zone need to stay alert as they might potentially face financial distress if the dynamics do not improve. Finally, companies that have Z-scores of higher than 2.99 are categorized in the safe zone, which suggests that the risk of financial distress is low. Safe zone companies tend to have good liquidity and profitability, as well as high efficiency of operational productivity (Altman, 1968).

The traditional Z-score model (1968) is applicable only for publicly traded manufacturing companies (Altman et al., 2017). In 1983, Altman developed a new version of the bankruptcy prediction model, which was called Z'-score model. The expanded Z'-score model was designed to account for private manufacturing companies. Therefore, in this version of the model, Altman has left all variables unchanged, except for X4. In Z'-score model, X4 factor is estimated as Book value of equity divided by Book value of total liabilities to account for absence of market value of equity values for private firms. Z'-score model was intended to be relevant for both manufacturing and non-manufacturing companies, as well as both publicly traded and private companies.

The model has undergone another change to increase its applicability also for non-manufacturing and international firms. Altman has further refined the model by removing the X5 variable, which comprised of Sales/Total Assets ratio. In 1968, Altman discovered that the X5 variable did not demonstrate a significant between bankrupt and non-bankrupt groups opposed to the other four variables. The updated Z''-score model is also applicable to companies belonging to emerging markets, which increases the relevancy of the model.

The updated Z''-score model is considered to be better suited for international and non-manufacturing firms, such as airlines, and is defined as:

$$Z'' = 6.56 * X1 + 3.26 * X2 + 6.72 * X3 + 1.05 * X4, \quad (2)$$

Where:

X1 = Working Capital/Total Assets (liquidity ratio)

X2 = Retained Earnings/Total Assets (profitability ratio)

X3 = Earnings Before Interest and Taxes/Total Assets (operating performance ratio)

X4 = Book Value of Equity/Book Value of Total Liabilities (solvency ratio).

Altman Z-score model is still widely used despite being having been designed over fifty years ago. According to Altman (2018), there exist multiple applications for Z-score model. These implications can be divided into two groups: internal and external. When it comes to internal applications, Z-score is used by internal stakeholders to address a firm's strengths and weaknesses as well as to formulate plan of actions to correct the financial state of a company. As for external application, there are several parties that can use Z-score for various purposes. For example, credit lenders use the model to assess the lending risk for corporate and consumer parties. With the requirements of Basel II and Basel III standards, the role of bankruptcy prediction models has strengthened (Altman, 2018).

2.6 Criticism of Altman Model

Altman Z-score model has been a subject to academic discussion and even criticism for several reasons. Due to the original Z-score model being designed specifically for manufacturing companies, it has been questioned whether the model is relevant for non-manufacturing companies from industries and geographical locations.

One of the major concerns regarding Altman Z-score is its long-term predictive power. Begley et al. (1996) have questioned whether Altman Z-score (1968) and Ohlson's O-score (1980) can provide accurate results when using current financial data. While the criticism is applicable to Altman Z-score, it is important to remember that Altman has further developed the model by removing one of the variables and adjusting the coefficients.

Braunsberger and Aschauer (2025) conducted research, which focused on analysing how and why traditional bankruptcy prediction models, including Altman Z-score and more modern machine learning models can be utilized in the corporate environment by companies and analysts. The research highlights some of the strengths of the Z-score model. For example, the researchers mentioned that Z-score model is transparent, as users can easily comprehend how the final Z-score index is affected by changes in individual financial ratios. In addition, the Z-score is rather simple to use, as financial data needed for calculations can be extracted from publicly available annual reports and databases (Braunsberger & Aschauer, 2025).

However, the research has identified certain weaknesses of the model as well. For instance, according to Braunsberger and Aschauer (2025), Z-score results rely solely on accounting data and do not incorporate other external factors and macroeconomic indicators, which might not provide as broad picture as with the use of machine learning models.

In conclusion of their research (Braunsberger and Aschauer, 2025), the authors summarized that traditional bankruptcy prediction models, such as Altman Z-score are still relevant and applicable for practical purposes, especially when transparency and simple interpretability of the results is needed. However, it is also important to note that with the rapid development of technology, machine learning bankruptcy prediction models can perform better than the traditional ones, as they can offer relatively higher predictive accuracy, particularly when analysing large datasets.

2.7 Alternative Bankruptcy Prediction Models

In addition to Altman Z-score models, there exist some other alternative bankruptcy prediction models. Since 1968, when Altman introduced the Z-score bankruptcy prediction model, other methods that utilize multivariate discriminant analysis and probit analysis have been designed.

In addition, since early 2000 machine learning techniques started gaining popularity as means for bankruptcy prediction. This chapter analyses academic literature and reviews some of these frameworks.

Table 1 displays a comparison of Altman's bankruptcy prediction models to other traditional models and more modern models such as machine learning, which will be introduced in more detail in this chapter.

Model	Authors	Year	Methodology	Output	Main variables

Z''-score	Altman	1995	Discriminant analysis	Score	Solvency, profitability, capital structure
O-score	Ohlson	1980	Logistic regression	Probability	Firm size, liquidity, leverage
Machine learning methods	Multiple (Support vector machines, boosting, random forest)	2000->	Machine learning & pattern recognition	Classification	Multivariable

Table 1. Comparison of main bankruptcy prediction models.

One of the most well-known bankruptcy prediction models and an alternative to Altman Z-score model is Ohlson's O-score, which was developed by J. A. Ohlson in 1980 and can be utilized to predict bankruptcy two years prior to bankruptcy filing. In his study, Ohlson (1980) identified that there are factors that meaningfully impact on the probability of bankruptcy within a period of one year. These factors are a company's size and measures of financial structure, financial performance and current liquidity.

The core difference between this model and Z-score lies in the approach taken to estimate the risk of financial distress. Ohlson modelled bankruptcy as probability by applying logistic regression to assess the probability of corporate bankruptcy, while the Z-score model relies on the discriminant analysis. The O-score is considered to be well-suited to be utilized across different sectors. However, one of the limitations of the O-score model is that the results are more difficult to interpret and the model includes a larger number of variables compared to Z-score. As shown in Table 2, nine independent accounting-based variables have been included in the O-score model.

	Variable	Brief explanation
1	SIZE	A firm's size; Log (Total assets/GNP price-level index)
2	TLTA	Leverage; Total liabilities/Total assets; suggested as positive coefficient
3	WCTA	Liquidity; Working capital/Total assets; suggested as negative coefficient
4	CLCA	Current liabilities/Current assets; suggested as positive coefficient
5	OENEG	Indeterminate coefficient: in case TL > TA: 1, other case: 0
6	NITA	Performance measure; Net income/total assets; suggested as negative coefficient
7	FUTL	Funds provided by operations/Total liabilities; suggested as negative coefficient
8	INTWO	Net income was negative for the past two years: 1, otherwise: 0; suggested as positive coefficient
9	CHIN	Used to measure changes in net income; suggested as negative coefficient

Table 2. Ohlson's (1980) bankruptcy prediction model variables.

One of the most modern trends used for bankruptcy prediction is machine learning. Unlike the traditional bankruptcy prediction models which rely solely on accounting data, machine learning aims to capture trends and patterns that differentiate from the group and can lead to financial distress. Barboza et al. (2017), conducted a comparative study on traditional bankruptcy prediction models with five modern machine learning techniques by using sample data of American companies for a period of 1985-2013.

There exist many various techniques applied in machine learning. In their study, Barboza et al. (2017), have focused on five machine learning mechanisms: support vector machines, boosting, bagging, random forest and artificial neural networks. According to Barboza et al. (2017), machine learning techniques achieve 10% more accurate results compared to the traditional models when it comes to bankruptcy prediction. The most effective machine learning method identified in this study is random forest, which displayed 87% accuracy rate in bankruptcy prediction.

In addition, Shetty et al. (2022), conducted a study on predicting bankruptcy by applying comprehensive machine learning techniques on a sample set of Belgian small and medium-sized companies using the data from years 2002-2012. With the help of machine learning techniques, such as boosting, deep neural network and support vendor machine, the authors were able to predict bankruptcy with a high accuracy rate of 82-83%, despite using only three financial ratios. The financial ratios included in the study were the returns on assets, current ratio and solvency ratio (Shetty et al., 2022).

There also exist some airline-specific developed models for bankruptcy prediction. One of these models is Airscore, which is the model using multiple discriminant analysis approach like Altman prediction models, but is tailored to the aviation industry. The model was designed in 1991 by Chow et al. and reported the overall accuracy rate of 83%. One of the main characteristics of the model is a strong emphasis on debt, leverage and asset efficiency ratios to account for the specifics of the aviation industry. Three ratios included in the final formula are interest/total liabilities, operating revenue per air mile and shareholders' equity/total liabilities (Chow et al., 1991). According to Grita et al. (2006), the model is to some extent more biased towards larger airlines included in the data sample.

2.8 Aviation Industry Specifics

The aim of this sub-chapter is to review previous academic research on financial distress in aviation industry to understand the specific characteristics of the business models of those companies operating in aviation.

Academic research shows that aviation companies are one of the most financially exposed and vulnerable sectors. Aviation companies are highly sensitive to changes in economic conditions as they operations are characterized by small operating margins and high fixed costs which include employee salary and other expenses, aircraft fuel and maintenance and plane leasing. According to Golaszewski & Saunders (1992), financial statements of airlines often display high long-term and total liabilities, as one of the main characteristics of the aviation industry is heavy reliance on aircraft leasing. This is an important feature to keep in mind, as the Altman Z''-score model includes total liabilities variable.

Airlines have a common feature of having high leverage ratios due their operating models, which indicates their reliance on debt financing. One of the studies related to this subject is the research by Kasim Kirasi (2021). In his study, Kirasi (2021) analysed the financial data of a sample of 35 airlines to examine which variables affect the probability of financial distress the most by applying Altman Z-score model amongst other models. As a result of the study (Kirasi, 2021), it was concluded that firm size, leverage, profitability and liquidity have the most significant impact on financial distress in the aviation industry. From these observations, it can be concluded that Z-score bankruptcy prediction model can capture most significant determinants of financial distress applicable to airline companies.

Another main characteristic of the aviation industry is its vulnerability to external factors such as geopolitical tensions, increasing fuel prices and changes in regulatory and environmental policies. In their study, Shi et al., (2024) discuss that economic instability and pandemic events are the factors that have significant influence on aviation industry. The authors note that despite European airlines having a good profit on the industry level, there have been cases of major airlines filing for bankruptcy in the past decade (Shi et al., 2024).

In conclusion, the aviation industry can be characterized as a turbulent and highly exposed to external events and factors industry, with the operating business model of high level of leverage, capital intensity and cyclicity. These factors make airlines more easily exposed to financial distress. In the context of this thesis, Z''-score can be considered a relevant tool for predicting bankruptcy in the aviation sector, as the factors described above align closely with the financial indicators estimated by the Z''-score model. However, it is still worth mentioning that the Z''-score model results should be thoroughly studied before making final conclusions, as the model does not incorporate external factors described above, but that do have an impact on a financial state of an airline.

3 Methodology

This chapter outlines how the empirical part of the thesis is conducted, including the research design, data sources, variable construction and statistical methods.

3.1 Research Design

This study adopts a quantitative research approach to assess the predictive accuracy of the Altman Z’’-score model in predicting bankruptcy in the global aviation industry. The Z’’-score model is applied to secondary financial data from international airlines that filed for bankruptcy during 2005-2025. Statistical techniques are used to assess the model’s performance across different market types and business regions.

The data sample for this study includes both bankrupt and non-bankrupt airlines, as it allows to evaluate the model’s predictive power from different aspects. Including only bankrupt airlines into the sample would limit the relevance of findings, as testing how well the model is able to correctly identify financially healthy airlines would not be possible.

The inclusion of both classes is important for assessing main performance statistical measures, such as accuracy, precision, recall, sensitivity and specificity. All these metrics rely on the presence of both bankrupt and non-bankrupt observations. In addition, having two distinct classes in the data sample enables to measure classification errors, including false positives and false negatives, which helps to critically evaluate the predictive performance of the Z’’-score model.

In this thesis, the sample of companies selected as bankrupt companies is selected according to the criteria of filing for bankruptcy during the observation period. This means that not all airlines selected for this study as bankrupt have completely ceased their operations and existence. This choice is also consistent with the original research by Altman (1968), who included airlines into the bankrupt sample based on the principle of them filing for bankruptcy petition under Chapter 10. Therefore, some of the companies selected for the sample have not entirely ceased to exist, but rather have filed for bankruptcy protection, including filing for Chapter 11, which was introduced in the theory chapter.

In addition, the choice is methodologically justified, as bankruptcy prediction models are design to capture the signals and early warning of financial distress which lead to legal insolvency, and not the complete cessation of operations. This choice is also supported by the previous academic research. For example, Golaszewski and Saunders (1992) included three airlines into their data bankrupt companies' sample that at the time of the research have been undergoing a restructuring process under Chapter 11.

As discussed in the previous chapter, even though the model was designed decades ago, it still retains practical value and can be used for academic research. Despite the new technological advances and design of modern machine learning models, the Z''-score is relevant to use for this study, as it provides transparent and easily interpretable results. The research aims at examining the predictive power of Z''-score model by comparing the Z''-scores of a sample size of twenty bankrupt and thirty non-bankrupt companies. Focusing on a single industry enhances the generalizability of findings, as structural differences can provide limited results when it comes to analysing companies from different industries. All aviation companies have quite similar operating model and characteristics which increases the validity of the study findings.

The model's formula, as outlined in the literature review, is used to calculate Z''-scores based on four financial ratios (X1 to X4). The approach is retrospective, analysing financial data from one and two years prior to each airline's filing for bankruptcy to determine if the model identified distress signals ($Z'' < 1.10$). Data and statistical analysis are done using Excel to compute Z''-scores and assess statistical trends in financial ratios. The Orbis database is selected as a source of financial data as it provides standardized financial information of over thirty million firms around the world.

Since the financial data needed for calculation of Z-score is not fully available in the Bureau van Dijk's Orbis database, some of the financial figures are, therefore, extracted from the sample companies' annual financial reports. The data is collected to the Excel file, where the calculations of the Z''-score are made.

In this study, each observation accounts for one firm-year. The sample consists of 50 unique airlines, out which twenty are classified as bankrupt companies and thirty as non-bankrupt companies. In total, there are 100 observations, as there are two observations for each firm. For non-bankrupt firms, the observations are collected for financial years 2018 and 2019. When it comes to bankrupt companies, the observations are collected one- and two years prior to bankruptcy filing. Financial reports of airlines Flybe Group Limited and Air Poland SP Z.O.O. are not publicly available for one year prior to them filing for bankruptcy. Therefore, financial data from two and three years before bankruptcy is analysed for these two companies.

3.2 Data Sources

Financial data is collected from publicly available annual reports and the Orbis database for international airlines that filed for bankruptcy in the past decade. The data covers one and two years prior to each airline's bankruptcy declaration to ensure relevance and consistency. Key financial metrics required for the Z''-score calculation (current assets, current liabilities, retained earnings, EBIT, total assets, book value of equity, and total liabilities) are extracted. The selection criteria for airlines include:

1. Official bankruptcy declaration/filing for chapter 11 during years 2005-2025
2. Availability of reliable financial data
3. Representation of diverse geographical regions to ensure global coverage

To have a more complete picture of the predictive power of Altman Z''-score, the data from airlines that are not bankrupt is analysed as well. In total, financial data of a sample of twenty bankrupt and thirty non-bankrupt companies is collected to calculate the Z′′-score and assess whether the Alman model's reliability varies between bankrupt and financially healthy companies.

3.3 Variable Construction

This study uses Alman Z′′-score model for conducting the practical part and answer the research questions introduced in the chapter one. The reason for selecting Altman Z′′-score over Z- and Z′-scores can be justified by the specific sector of this study. Since the study focuses on analysing the predictive performance of the bankruptcy prediction model in the global aviation industry, Z′′-score is the most relevant for this study, as it can be applied to non-manufacturing companies and emerging markets. The Altman Z′′-score is constructed of a set of financial ratios that can help to assess financial state of a company. Every ratio focuses on a particular financial dimension, such as leverage, liquidity and profitability. As described in the previous chapter, the Altman Z′′-score is estimated as follows:

$$Z'' = 6.56 * X1 + 3.26 * X2 + 6.72 * X3 + 1.05 * X4, \tag{3}$$

The X variables are defined as follows:

X1 = Working Capital / Total Assets
X2 = Retained Earnings / Total Assets
X3 = Earnings before interest and taxes (EBIT) / Total Assets
X4 = Book Value of Equity / Total Liabilities.

The first ratio included in the Altman Z′′-score is Working Capital/Total Assets. Working capital can be defined as the difference between a company's current assets and current liabilities. Working capital represents a company's operating liquidity and its ability to cover the short-term financial obligations (Shi et al., 2024). Negative WC/TA ratio can be an early indicator of financial distress, as it reflects on how current assets and insufficient to cover current liabilities. In capital-intense companies, such as the aviation industry, sufficient cash flow at the right time is crucial. Altman (1968) claimed that this ratio is the most valuable out of all ratios included in the bankruptcy prediction model.

$$WC/TA = (Current\ Assets - Current\ Liabilities) \div Total\ Assets, \tag{4}$$

The second ratio of the Z''-score model is Retained Earnings/Total Assets. Retained earnings are the cumulative earnings that have been reinvested back into business, instead of distributing them to shareholders as dividends. According to Altman (1968), relatively new firms are likely to have low retained earnings due to the lack of time for accumulating profits. Altman (1968) also acknowledges that this factor might influence the total Z-score of a company, but it is acceptable, as younger firms are more inclined to failure compared to older firms. This ratio provides an insight into a company's ability to generate profits and retain them in the business over time. High RE/TA ratios can indicate strong financial performance compared to lower value ratios, as the latter can mean consistent negative profitability.

$$RE/TA = Retained\ Earnings \div Total\ Assets, \tag{5}$$

The third ratio included in the Altman Z''-score is EBIT/Total Assets. EBIT stands for Earnings Before Interest and Taxes and represents a company's operating result before deducting taxes and interest expenses. EBIT is a useful measure for assessing a company's operating performance based on its core business operations. This ratio reflects on how well a company is using its assets to generate earnings without the weight of tax expenses (Shi et al., 2024). It is an important measure for bankruptcy prediction, as companies that are not efficient using their assets for operating earnings, tend to have financial struggles.

$$EBIT/TA = Earnings\ Before\ Interest\ and\ Tax\ \div\ Total\ Assets, \tag{6}$$

The fourth financial ratios included in the Z''-score is Book Value of Equity/Total Liabilities. According to Bărbuță-Mișu and Madaleno (2020), this ratio is used to measure a company's solvency, as it represents by how much a company's total assets value can decrease before liabilities exceed them, and the company faces insolvency.

$$BV\ of\ Equity/TL = Book\ Value\ of\ Equity \div Total\ Liabilities, \qquad (7)$$

The zones of discrimination of Z''-score model are categorized as follows:

Z'' > 2.60: Safe zone (very low bankruptcy probability)
1.10 < Z''< 2.60: Grey zone (potential risk)
Z'' < 1.10: Distress zone (high bankruptcy probability)

3.4 Statistical Methods

The total number of observations refers to the full dataset of 100 observations collected from the financial statements of 50 unique airlines. However, not all observations can be categorized as classified observations. Non-classified observations refer to those observations that fall into neither safe zone nor in distress zone. In this study, grey zone observations are excluded from the classification accuracy calculations and are treated as non-classified observations. This choice is justified by the need for clear and distinct class labels, specifically distress and safe, to enable the application of binary classification metrics in the analysis.

The empirical analysis is divided into several stages. First, the sample airlines are classified into bankrupt and non-bankrupt groups. Second, financial data and annual reports are examined, and key financial figures are extracted and added to the Excel dataset. Finally, Z''-scores are calculated for each company. For bankrupt companies, the Z''-scores are computed for one and two years prior to bankruptcy filing, while for non-bankrupt airlines, the scores are calculated for the selected period of 2018-2019.

The choice of the years 2018-2019 for analysis of non-bankrupt financial performance can be justified, as these two years represent the period of macroeconomic stability before the world had faced the COVID-19 pandemics in 2020. By choosing these two years for the analysis the aim was to obtain financial figures that are driven by firms' own financial performance under regular market conditions. As discussed earlier in this study, aviation industry is highly vulnerable to external shocks, therefore, selecting the years 2018-2019 for the analysis provides an opportunity to increase the validity of findings, as the sample firms have not been significantly affected by systemic shocks and volatile crisis environment during that time.

After the Z''-score calculations are completed, a comparative analysis is conducted by dividing the sample into subgroups. This is done to address H2 of the study, which examines how the Altman Z''-score performs across different geographical regions and market types when applied to companies in the aviation industry. The first sub-group consists of bankrupt versus non-bankrupt airlines. The second subgroup is based on market classification, distinguishing between developed and emerging markets. The third sub-group is based on the geographic business regions. In this study, there are three business geographic regions are included: Europe, Middle East and Africa (EMEA), the Americas (AMER) and the Asia-Pacific (APAC) regions.

Observations are assigned to binary outcomes to calculate the model's predictive power. Binary classification refers to the assignment of observations into one of two classes. According to Sokolova & Lapalme (2009), classes can be defined, ambiguous or a combination of both. In this study, the binary classification consists of bankrupt and non-bankrupt classes.

The assessment metrics used in this thesis are based on confusion matrix, which includes True Positives (TP), True Negatives (TN), False Positives (FP) and False Negatives (FN). These performance measures are widely applied in classification research, for example, in the study by Sokolova and Lapalme conducted in 2009. True Positives represent the number of correctly classified observations, while True Negatives indicate the number of correctly classified negative observations. In addition, False Positives refer to the observations that are incorrectly assigned to the positive class, whereas False Negatives represent observations that have not been correctly identified by the model but belong to the positive class (Sokolova & Lapalme, 2009).

To answer H1 of this study that investigates the predictive power of the Altman Z''-score, overall accuracy rate is calculated based on the observations discussed above. According to Sokolova & Lapalme (2009), accuracy rate demonstrates the overall effectiveness of a model. Overall accuracy is calculated as follows:

$$Overall\ Accuracy = (TP + TN) \div (TP + FN + FP + TN), \qquad (8)$$

In addition to overall accuracy, this study also uses classified accuracy rate to assess the predictive power of the Altman Z''-score. What differs classified accuracy from overall accuracy is that it only includes classified observations (CO) into the consideration. In terms of this study, classified observations are considered as those observations that are classified either in the safe zone or in the distress zone, meaning that observations belonging to the grey zone are excluded from the classified sample. Grey zone observations are not considered as classified observations, as definitive predictions on bankruptcy cannot be made based on these observations, placing them in the uncertainty zone between the safe and distress zones. Classified accuracy is calculated as follows:

$$Classified\ Accuracy = (TP + TN) \div CO, \qquad (9)$$

In addition to overall accuracy assessment, this study also implements other performance evaluation metrics, such as recall, precision, specificity and F1 score to evaluate the predictive power and classification performance of Altman Z''-score by evaluating different aspects of the model's performance.

Recall or sensitivity rate indicates how well the model can correctly identify bankruptcies, making it an important performance measure in this study. The sensitivity rate is calculated as follows:

$$Sensitivity\,rate\;=\;TP\;\div\;(TP+FN), \tag{10}$$

In binary classification, the precision rate presents how many of distressed predictions are correct, in this study meaning how many of airlines categorizes as distressed are actually bankrupt. The rate is calculated as follows in this study (Sokolova & Lapalme, 2009):

$$Precision\,rate\;=\;TP\;\div\;(TP+\;FP), \tag{11}$$

In contrast to the sensitivity rate, the specificity rate is used to evaluate how well a model identifies negative cases, which in this study refers to non-bankrupt airlines (Sokolova & Lapalme, 2009). In the context of this study, the specificity rate indicates how effectively the Altman Z''-score model can correctly classify non-bankrupt airlines without falsely labelling them as distressed. The rate is calculated as follows:

$$Specificity\,rate\;=\;TN\;\div\;(FP\;+\;TN), \tag{12}$$

Type I error rate is calculated to assess how many false alarms (non-bankrupt airlines) are classified by the bankruptcy predictions model as distressed. Furthermore, type II error rate is calculated to evaluate how many actual bankruptcies are missed by the model.

In addition, Chi-test is conducted to assess whether there is a statistical difference between the predictive performance of Altman Z''-score model across different business regions and market types.

Furthermore, temporal analysis is conducted in this study to test how well the Altman Z''-score model can capture the early warnings of financial distress. The calculations are made for one year and two years prior to bankruptcy filing.

4 Results

The companies included in this study are identified using the Orbis database. Filters were applied to separately search for bankrupt and non-bankrupt airlines. Firstly, the search was restricted based on industry classification by selecting relevant NACE and SIC codes. The NACE codes used were 51 (Air transport), 512 (Freight air transport and space transport) and 5121 (Freight air transport). In addition, the US SIC codes included were 4512 (Air transportation, scheduled), 4513 (Air courier services) and 4522 (Air transportation, non-scheduled). Only primary codes were selected for this study to ensure that companies whose primary operations are not related to aviation are excluded from the sample.

Secondly, aviation companies were further restricted based on status criteria. For this study, both active and inactive companies were included in the search. When it comes to inactive companies, the status filter was refined to include companies with status ”Bankruptcy”,”Dissolved (bankruptcy)”, “Dissolved” and “Dissolved (liquidation)”. In addition, a ”Change date” filter was applied, with valid a range starting from 01.01.2005 to ensure that only airlines that filed for bankruptcy during the last 20 years. For non-bankrupt companies, the same industry filters were applied, however, the status filter was limited to ”Active companies” only.

Out of the filtered airlines, a sample size of twenty bankrupt and thirty non-bankrupt companies were selected manually from the available list of companies. The approach was applied with an aim of constructing a balanced sample of bankrupt and non-bankrupt airlines.

Region	Bankrupt airlines	Non-bankrupt airlines	Total
EMEA	8	10	18
AMER	10	6	16

APAC	2	14	16

Table 3. Geographic distribution of sample companies.

As discussed in the introduction chapter, there is limited research on the predictive accuracy of Altman Z''-score in the global aviation. Therefore, this thesis is not limited to a particular geographical region. Instead, the selected companies are categorized by their geographical regions, as is presented in the Table 3. This is done to align with H2 and with an aim of assessment of potential regional differences in the Z''-score model predictive accuracy.

Out of twenty non-bankrupt companies, 8 are geographically located in EMEA region, 10 companies are located in AMER region, with the remaining 2 are based in APAC business region. The aim of this study is to observe the patterns in the Z''-scores of airlines geographically located across various continents, so this split is in line with the objective of the study. For this study, the companies have been divided into two groups according to their geographical location. The first group account for developed and emerging markets. In total, there are 64 observations from developed countries and 36 observations from emerging countries. The second group is created based on the geographical region. In total, there are 36 observations from Europe, Middle East & Africa (EMEA) region, 32 observations from the Americas (AMER) region and 32 observations from the Asia-Pacific (APAC) region.

Table 4 presents the descriptive statistics of Z''-score based on the overall data sample used in this study. As can be seen from the table, the overall mean Z''-score of the 100 observations is -0.27. This indicates that an average airline is placed in the distress zone, according to Altman classification where Z''-scores under 1.10 indicate financial distress. The overall minimum Z''-score is -16.34, which was scored by Air Poland SP Z.O.O in 2010, before it officially went bankrupt in 2012. On the opposite side, the overall maximum Z''-score is 6.90, which was scored by Abu Dhabi Aviation PJSC in 2019, confidently placing the airline in the safe zone.

Metric	Overall
n	100
Mean	−0.27
Median	0.22
Std. Deviation	3.84
Minimum	−16.34
Maximum	6.90

Table 4. Overall descriptive statistics of Z’’-scores.

When comparing the descriptive statistics between the two groups of bankrupt and non-bankrupt companies presented in Table 5, there is a clear distinction between the mean Z’’-scores. The mean Z’’-score of bankrupt companies’ sample is -2.96, while the Z’’-score of non-bankrupt companies is 1.53. While the mean Z’’-score of non-bankrupt companies is significantly higher than the Z’’-score of the bankrupt companies, it is still not high enough to place an average non-bankrupt airline into safe zone, which according to Altman is classified when a Z’’-score exceeds 2.60. These observations confirm the assumption that the aviation industry is structurally distressed according to Altman’s classifications.

Metric	Bankrupt	Non-Bankrupt
n	40	60
Mean	−2.96	1.53
Median	−1.12	1.36
Std. Deviation	4.34	2.01

Metric	Bankrupt	Non-Bankrupt
Minimum	−16.34	−1.25
Maximum	1.67	6.90

Table 5. Descriptive statistics by class.

Table 6 presents the descriptive statistics of Z′′-score divided into three groups according to the geographical regions: EMEA, AMER and APAC. Out of 100 observations, 36 belong to EMEA market, 32 observations come from AMER region, and the remaining 32 observations belong to APAC business region, meaning that the data sample is well-balanced and provides relatively similar number of observations for each region.

The mean Z′′-scores of all three business regions fall in the distress zone, as they do not exceed the score of 1.1. EMEA and AMER regions both have negative mean Z′′-scores of -0.77 and -0.61 respectively, while the mean Z′′-score of APAC business region is a positive value of 0.64, meaning that the airlines that belong to this region display better average financial performance compared to EMEA and AMER business regions.

However, when looking at the medium values presented in Table 6, it can be noticed that the medium Z′′-scores of EMEA and AMER regions are positive values despite their mean Z′′-scores being negative. This indicates that while many airlines are not severely financially distressed, there are some airlines in the data sample that are very financial distressed. This in turn contributes to negative mean Z′′-scores. On the other side, the medium Z′′-score of APAC region is slightly lower than the mean value, demonstrating a moderately skewed distribution.

The observations regarding several EMEA and AMER airlines facing significant financial distress, which were discussed in the previous paragraph are supported by the minimum values presented in Table 6. The lowest Z′′-score observed in EMEA region is -16.34, scored by Air Poland SP. Z.O.O in 2010. Similarly, the minimal value of Z′′-score observed in AMER region is also relatively low and equals to -9.44, which was scored by Gol Linhas Aereas Inteligentes S.A. in 2022. On the contrary, the minimum value of APAC region Z''-score is -2.33, which is considerably lower compared to the other two regions. The lowest Z''-score was displayed by Kingfisher Airlines Ltd in 2010.

As it can be seen from Table 6, standard deviation varies between the regions. EMEA region has a high standard deviation of 5.34, meaning that the sample airlines' financial performance is spread out, with some airlines performing better, and some are very financially distressed. AMER region sample presents a medium standard deviation of 3.17, meaning that airlines still perform on different levels, but the variation is lower compared to EMEA region. On the contrary, APAC region sample displays a low standard variation of 1.88, meaning that the average sample airlines financial performance is relatively similar. Overall, while the descriptive statistic values of the APAC region are relatively higher, the financial distress is present across all three business regions.

Metric	**EMEA**	**AMER**	**APAC**
n	36	32	32
Mean	−0.77	−0.61	0.64
Median	0.59	0.24	0.05
Std. Deviation	5.34	3.17	1.88
Minimum	−16.34	−9.44	−2.33
Maximum	6.90	3.26	4.41

Table 6. Descriptive statistics of Z''-scores by business region.

Table 7 displays the confusion matrix of predicted bankruptcies versus actual classifications. Out of total 40 bankrupt observations, the model was able to correctly classify 37 observations as distressed, while 3 observations were placed in the grey zone. When it comes to 60 non-bankrupt observations, the Altman Z''-score model classified 28 observations as distressed, 17 observations as grey zone and 15 observations as safe zone. This means that the model was able to identify only 25% of non-bankrupt companies as financially healthy and safe from distress.

		Predicted Classification		
		Distress	**Grey Zone**	**Safe**
Actual Classification	Bankrupt (n = 40)	37	3	0
	Non-Bankrupt (n = 60)	28	17	15
Predicted total		65	20	15

Table 7. Confusion matrix: predicted vs. actual classification.

Table 8 presents the results of the Z''-score performance metrics based on the classification outcomes. As it can be seen from the table, out the total of 100 observations, the model was able to correctly classify 37 observations as distressed (true positives), as well as it correctly identified 15 observations as financially safe (true negatives). On the other hand, the Z''-score model incorrectly classified 28 observations of financially healthy companies as distressed (false positives) and 3 financially distressed observations were missed by the model (false negatives).

The classified sample consists of 83 observations, since as is shown in Table 8, 17 observations were classified within the grey uncertainty zone. For this reason, these observations are excluded from binary classification metrics.

Across 83 classified observations, the classified accuracy rate of Altman Z''-score model in the aviation industry equals to 62.7%. The classified rate shows the proportion of correctly identified observations within the observations belonging to either distress or safe zone. When applied to the total set of 100 observations, the overall accuracy rate of the model declines to 52%. These results highlight the fact that while the model performs well in classifying bankrupt companies correctly as distressed, it also tends to misclassify the observations, especially when it comes to non-bankrupt airlines, with 28 observations of non-bankrupt airlines incorrectly captured as distressed.

Furthermore, Table 8 presents the error rates of the Altman Z''-score model. The type I Error equals to 65.1%, which signals that a high number of financially healthy airlines are misclassified as distressed. On the other hand, a relatively low type II error rate of 7.5% indicates that only a small number of bankrupt airlines are incorrectly categorized as non-distressed. It is worth mentioning that three observations that contributed to the 7.5% type II error rate are classified as grey or uncertainty zone, and not as safe zone airlines.

Metric	**Value**	**Interpretation**
Classification counts		
True Positives (TP)	37	Bankruptcies correctly identified as distressed
True Negatives (TN)	15	Healthy airlines correctly classified as safe
False Positives (FP)	28	Healthy airlines wrongly flagged as distressed
False Negatives (FN)	3	Bankruptcies missed by the model
Grey Zone non-bankrupt (GZNB)	17	Healthy airlines in uncertain zone (excluded from binary metrics)
Accuracy		
Classified Accuracy	62.7%	Accuracy across 83 classified observations
Overall Accuracy	52.0%	Accuracy across all 100 observations, grey zone observations are treated as unclassified
Error rates		
Type I Error Rate	65.1%	Proportion of healthy airlines misclassified as distressed

Metric	Value	Interpretation
Type II Error Rate	7.5%	Missed bankruptcies as a share of all bankrupt airlines
Sensitivity and specificity		
Sensitivity (Recall)	92.5%	Proportion of actual bankruptcies correctly detected
Specificity	34.9%	Proportion of healthy airlines correctly cleared
Precision and F1		
Precision	56.9%	Share of distress predictions that were correct
F1 Score	70.5%	Harmonic mean of precision and recall

Table 8. Z′′-score model performance metrics.

In addition, Table 8 shows a high sensitivity rate of 92.5%, indicating that the Altman Z′′-score model can correctly identify a large proportion of actual bankruptcies. On the other hand, the specificity rate of 34.9% signals that the model has a limited ability to correctly classify non-bankrupt airlines as financially healthy. A moderate precision rate of 56.9% displayed in Table 8 suggests that nearly 57% of all observations classified as distressed in this study are actually bankrupt airlines. F1 score, which combines precision and recall, equals to 70.5%.

Table 9 presents the results of chi-square test conducted to examine H2, which relates to the geographical predictive accuracy of the Altman Z′′-score. More specifically, the test was performed to assess whether the performance of the Altman Z′′-score model is influenced by the market type (developed versus emerging countries), as well as by geographical region (EMEA versus AMER versus APAC). Overall, EMEA and AMER business regions display similar accuracy rates of 63.9% and 62.5% respectively. However, APAC region shows significantly lower predictive performance of 28.1%.

When it comes to the market type comparison including developed and emerging countries, it can be concluded that there is no statistically significant relationship between airline market type and the predictive accuracy of the Z''-score model. As can be seen from table 4, the P-value is 0.594, indicating that the model performs relatively similarly across both emerging and developed markets.

In contrast, Table 9 shows that there is a statistically significant relationship between the geographical region of an airline and the predictive performance of the Z''-score model. P-value equals to 0.005. This indicates that the model's performance varies across three geographical regions, which include EMEA, AMER and APAC regions.

Test	**Comparison**	**χ^2**	**df**	**p-value**	**Result**
Market Type	Developed vs. Emerging	0.285	1	0.594	Not significant
Business Region	EMEA vs. AMER vs. APAC	10.760	2	0.005	Significant

Table 9. Chi-square test results: H2 geographical predictive accuracy.

Two companies did not have financial reports available for 1 year prior to bankruptcy. Therefore, the observations for t-3 have been excluded from the data for temporal analysis, as its goal is to measure the Altman model sensitivity for t-1 and t-2. The overall sensitivity of the model is 92.1%, with three misclassifications observed due to Z''-score placing in grey zone. As it can be seen from table 10, there is an increase in the model's sensitivity from t-2 to t-1, indicating deteriorating financial performance closer to the bankruptcy declaration. With 90% sensitivity rate two years prior to bankruptcy and 94.4% sensitivity rate one year prior to bankruptcy, the model displays consistency and reliability in providing early warning signals of financial distress two years prior to bankruptcy in the aviation sector.

Years Before Bankruptcy	n	Distress	Grey Zone	Safe	Sensitivity
1 year prior	18	17	1	0	94.4%
2 years prior	20	18	2	0	90.0%
Total	38	35	3	0	92.1%

Table 10. Temporal analysis - Z′′-score sensitivity by years before bankruptcy.

5 Discussion

The aim of this chapter is to comprehensively discuss the main results and observations of the study. The chapter includes the interpretation of the results presented in the previous chapter, the analysis of the implications for airlines stakeholders, the limitations of the study as well as introduces suggestions for future research that could be conducted based on this study.

5.1 Interpretation of the results

The confusion matrix presented in Table 7 provide an overview of the Altman Z''-score model classification power. The table shows a comparison between predicted and actual results. Out of 40 bankrupt observations, the model can correctly classify 37 of them as distressed. The remaining 3 observations are misclassified to uncertainty zone. No observations from bankrupt data sample are classified as financially safe, which indicates a strong predictive power in identifying financially distressed airlines.

When it comes to 60 non-bankrupt observations, the model can correctly identify 15 non-bankrupt observations as financially safe. The remaining 75% of non-bankrupt observations are split between misclassifications to grey zone (17 observations) and distressed zone (28 observations). Overall, 65 out of 100 total observations, meaning the majority of observations, are classified as distressed.

As discussed throughout this thesis, this can be explained by the specifics of the aviation industry, where even big and well-known airlines display negative working capitals and high leverage, which in turn contributes to low Z''-scores and classification as distressed companies. These observations are consistent with findings about type I and type II error rates discussed further in this chapter.

The descriptive statistics of the overall data sample reveal that the mean Z''-score of 100 observations equals to -0.27. According to Altman classification, the mean score of this study is placed within the distress zone (Z′′-score < 1.1), meaning that an average airline included in the data sample is considered as financially distressed. These findings are in line with the previous research by Shi et al., (2024), where it was discussed that the aviation sector displays lower Z′′-scores compared to other sectors.

A relatively high standard deviation of 3.84 indicate that financial performance of the airlines included in this study's data sample varies significantly, with some airlines being in deep financial distress according to the Z′′-score classification, while other airlines display more financially stable performance. Extreme negative values, such as the minimal Z′′-score of this study of -16.34 scored by Air Poland in 2010, as well as extreme positive values, such as the maximum Z′′-score of 6.90 obtained by Abu Dhabi Aviation in 2019, can skew the distribution of the data and negatively affect the overall accuracy of the Z′′-score model.

Some interesting patterns can be observed when comparing the Z′′-score metrics of bankrupt and non-bankrupt airlines. There is a clear distinction between the mean Z′′-score of bankrupt airlines (-2.96) and non-bankrupt airlines (1.53). However, while non-bankrupt airlines display higher Z′′-scores, their mean score of 1.53 still falls into the grey zone rather than safe zone. This indicates that despite being non-bankrupt, the sample airlines do not display sufficiently high financial ratios to be classified as financially healthy, according to Altman Z′′-score classification thresholds.

The results presented in Table 8 demonstrate that the Altman Z′′-score model can serve as a reliable tool for identifying early warning signs for distressed companies. Table 8 shows that the model correctly identified 37 bankrupt observations (true positives) as distressed, with only three observations missed as false negatives. On the other hand, the model did not display a strong ability to correctly classify non-bankrupt airlines as financially healthy airlines in the safe zone.

When applied to a total of 100 observations, the model incorrectly classified 28 non-bankrupt observations (false positives) as distressed. These factors contributed to a moderate classified accuracy rate of 62.7%, which includes only the 83 classified observations. When including all 100 observations, the overall accuracy rate decreased to 52%.

The performance metrics display interesting observations when it comes to the predictive power of the Altman Z''-score model. On one hand, a high sensitivity rate of 92.5% indicates that only a few bankrupt airlines are wrongly classified as non-distressed, meaning the model shows a strong performance in identifying bankrupt airlines. Based on these findings, it can be concluded that the model can provide valuable insights for stakeholders in detecting financial distress.

On the other hand, the strong ability to identify early warnings of financial distress is also followed by high type I error rate and low specificity. As presented in Table 8, the study results indicate a high Type I error rate of 65.1 %. A high type I error rate implies that the Altman Z''-score model incorrectly classifies non-bankrupt companies into the distress zone. From a practical perspective, this can lead to overly cautious decision-making, where investors might avoid airlines that in fact are financially stable.

The high false positive rate implies that the model has its limitations in the scope of the aviation industry, as it cannot take into consideration the specific characteristics of aviation business model. Aviation industry is characterized by firms having high leverage and high fixed costs (Golaszewski & Saunders, 1992). These observations can be explained by the specifics of the aviation sector, which have been discussed in more details in the theory chapter. The low specificity rate of 34.9% suggests that the model can be biased towards classifying airlines as financially distressed.

On the other side, a low Type II error rate of 7.5% indicates that the Z''-score model is successful at capturing early indicators of financially distressed airlines filed for bankruptcy. Based on these observations, it can be concluded that Altman Z''-score has a high-performance rate when it comes to identifying early warnings of financial distress and capturing actual bankruptcies. However, in the context of this study and the aviation industry, it can be argued that Altman Z''-score is more relevant as a tool for risk and early financial distress signal assessment based on financial ratio analysis rather than a precise model for bankruptcy prediction and classification.

As presented in Table 9, the results of the chi-square test indicate a statistically significant relationship between the geographical region and predictive accuracy of the Z''-score model (x2=10.760, df=2, p=0.005). These findings indicate the performance of the model varies across the geographical regions. The variation on predictive accuracy might be explained by differences in accounting practices, market structures and regulatory environments. In contrast, the findings of the chi-square test reveal that there is no statistically significant relationship between airline market type and the predictive accuracy of the Altman Z''-score (p=0.594). These findings indicate the model performs with the similar level of accuracy across both developed and emerging markets.

5.2 Implications for airlines

This study provides practical insights for stakeholders, including investors, financial analysts and creditors in the aviation industry. By monitoring liquidity, profitability, and other Altman Z''-score financial ratios, managers can detect early warnings of financial distress. With this knowledge, there is an opportunity to strategically assess the state of a company and address the roots of financial distress.

As a result of this study, it can be concluded that Z''-score is an efficient tool for identifying bankruptcies. However, it is important to note that while the model is 92.5% precise when it comes to correctly classifying bankrupt airlines, as financially distressed, it has limited ability to correctly identify non-bankrupt airlines, which is supported by the low specificity rate of 34.9%. Therefore, this study suggests that it is not recommended to solely rely on Z''-score model in financial analysis and decision-making in the aviation sector, as the model tends to overestimate the probability of financial distress.

This indicates that it is important for involved stakeholders to understand the specifics of Altman Z''-score model, as low Z''-scores do not necessarily indicate that an airline is in severe financial distress and is at risk of bankruptcy. One of the ratios included in the model is working capital/total assets. Overall, airlines tend to have negative or close to zero working capital, as current liabilities can be higher than current assets due to the specific business model of airlines, with plane tickets being sold in advance. Therefore, negative working capital reduces the overall Z''-score, then in fact it is not necessarily a sign of financial distress when it comes to aviation industry.

To conclude the points discussed above, the findings of this study suggest that the model is highly reliable when it comes to identifying bankruptcies in the aviation industry. However, as the model has a high type I error rate of 65.1% indicates that the model struggles to differentiate non-bankrupt airlines from bankrupt ones. This means that the model should be incorporated as a part of a broader financial analysis framework alongside with industry-specific and qualitative assessments.

5.3 Limitations

While this study aims to provide objective results, it is important to acknowledge that there are certain limitations for this study, which means that the findings of this study should be interpreted with caution. To start with, a sample size of twenty non-bankrupt and twenty bankrupt companies might provide limited results, as a larger sample size might have provided more generalizable results. In addition, while data extraction was conducted with high precision, it still needs to be mentioned that since the financial data of the sample companies was extracted manually from their annual reports, there is a room for human error.

Furthermore, during the empirical part of this research, it was discovered that the availability of annuals reports and financial data of airlines that are already bankrupt is limited. Strict selection criteria were applied for the bankrupt companies to improve the validity and robustness of the study’s results. Finally, by selecting Z’’-score model for analysis, one needs to acknowledge that the model cannot capture qualitative factors that can also impact financial state of an airline.

5.4 Suggestions for future research

In this section a few potential ideas for future research will be discussed, most of which are based on the limitations discussed in the previous sub-chapter. Firstly, a larger sample of companies could be analysed as the next step. A sample size of hundred companies could increase the robustness and generalisability of the results. More bankrupt airlines from APAC geographical regions could be also included into the data sample to assess how it affects the predictive accuracy of Altman Z’’-score in this region. However, data availability might be limited for bankrupt airlines, as many companies do not publish their annual financial reports one year prior to bankruptcy declaration.

In addition, as differences in the Z’’-score predictive accuracy across different geographical regions, with APAC predictive rate of 28.1%, further research could be conducted to investigate deeper the root causes and drivers of such variations. The potential factors affecting the performance of the model can be accounting standards, regulatory policies and other cultural practices.

Furthermore, considering the increasing role of sustainable finance, it would be a good idea to incorporate Environmental, Social and Governmental (ESG) factors into the research. Traditional bankruptcy prediction models, such as Altman Z’’-score fully rely on the accounting data, while ESG metrics can capture non-accounting factors that can also affect stability of a company, for example changes in environmental regulations.

In terms of the aviation industry, the bankruptcy prediction model could be further developed by applying different weight coefficient to correspond with the specifics of the aviation business model, which is known for high leverage, negative working capital and high fixed costs. These factors contribute to lower financial ratios and thus lower overall Z''-score.

6 Conclusions

Aviation industry is highly exposed to external economic shocks, such as pandemics, geopolitical tensions and rising fuel prices. These factors make aviation companies exposed to small operating margins and potential financial distress, as these shocks can drastically affect the financial stability of airlines. The aviation industry became significantly exposed to financial losses and bankruptcy after the industry was deregulated in 1978. Before this event, no major airline had declared bankruptcy, however, after that, the competition had significantly increased, fuel and labour costs have increased (Kroeze et al., 2018). Due to this, having reliable tools to predict financial distress some years prior to the actual failure can be crucial for airlines.

The main objective of this thesis was to identify whether Altman Z''-score can be utilized as a reliable tool for bankruptcy prediction in the aviation industry. To achieve this objective, financial data of twenty bankrupt and thirty non-bankrupt airlines was collected. The companies were selected from the list of the airlines found in the Orbis database using the filters described in the results section.

For more objective results, non-bankrupt companies were all analysed during years 2018 and 2019 to capture financial conditions under stable pre-pandemics and other global crisis market circumstances, ensuring a more consistent comparison between the bankrupt and non-bankrupt airlines. When it comes to bankrupt companies, financial data was analysed one and two years prior to the year of bankruptcy filing. In total, 100 observations from 50 unique airlines were identified. The financial data needed for calculation of the Z''-scores was collected from the Orbis database and publicly available annual reports of the sample companies.

Another objective of this study was to assess whether there is any statistically significant difference in the model's predictive performance across market types and geographical regions. For this reason, the sample airlines were divided into groups based on their market type (emerging and developed) as well as business region (EMEA, AMER and APAC) when analysing the results.

As a result of this study, it can be concluded that Z''-score can serve as a useful tool for identifying bankrupt firms in the aviation industry, as based on the conducted study, its classified accuracy rate is 62.7 %. Using the sample data from 2005-2025 of 20 bankrupt and 30 non-bankrupt airlines, 83 observations out of 100 are defined as classified observations. 17 observations that were categorized to grey zone are excluded from the classified observations in binary metrics, as these observations do not provide definitive predictions on financial bankruptcy. 15 observations from non-bankrupt companies were accurately classified as financially stable, meaning that their Z''-scores are categorized in safe zone, while 37 observations from bankrupt airlines are correctly identified as bankrupt companies, meaning that their Z''-scores are placed under distress zone. When including all classified and non-classified observations (100), the predictive accuracy rate of the model decreases to 52%.

Furthermore, a low error type II rate of 7.5% and high sensitivity rate of 92.5% demonstrate that the model can correctly classify the majority of bankrupt airlines as financially distressed when analysing the financial data of t-1 and t-2 prior to bankruptcy filing.

However, as discussed in the previous section, the Altman Z''-score model cannot be considered as a fully reliable standalone model for evaluating financial stability when applied to a sample data of companies in the aviation sector. A high Type I error rate of 65.1% and a low specificity rate of 34.9% indicate that a tendency of the model to incorrectly classify financially healthy companies as distressed. For this reason, the model might be more appropriately used as a part of a broader framework for identifying early warning signals and for analysing which financial ratios contribute negatively to overall financial performance. Based on the findings described above, H1 is only partially supported. The Altman Z''-score model is provenly good at capturing financially distressed airlines but tends to falsely label financially stable non-bankrupt airlines as distressed as well.

In this study, an F1 score was calculated to assess a balanced model performance. The F1 score of this study is 70.5%, showing a medium performance between the model's strong ability to identify bankrupt airlines and its low precision when it comes to the distress predictions that are actually correct. A high F1 test score does not indicate a strong overall performance of the model, as it combines a high recall rate (92.5%) and a low precision rate (56.9%).

In addition, the study demonstrates that the Z''-score model has a different predictive accuracy across different business regions. The findings show that a significantly lower accuracy rate is observed in the APAC business region (28.1%) compared to the EMEA and AMER regions (63.9% and 62.5% respectively).

However, no statistical significance is found in the predictive power of the Z''-score model between developed and emerging markets. This indicates that the model performs with the similar accuracy both market types. To conclude the factors outlines above, H2 hypothesis is only partially supported. The results suggest that geographical region is a relevant factor in explaining differences in the predictive accuracy of the Altman Z''-score in the aviation sector, whereas market development status does not appear to have a statistically significant role in the predictive accuracy.

From a theoretical point of view, the results of this study are in line with the previous research conducted on Altman Z-score bankruptcy prediction model, for example the study completed by Shi et al. (2024). In their study, Shi et al. (2024) concluded that European airlines tend to demonstrate lower Z''-score values compared to companies in other business sectors, with the majority of sample airlines displaying low working capital and negative or close to zero EBIT. In addition, the results of this study also support the early research by Altman (1984), where he discussed that bankruptcy prediction models based on accounting ratios can accurately identify the financial distress.

The findings of this study are also in line with the research conducted by Kroeze et al. (2018), where the authors compared Z’’-score predictive power with an alternate model. As a result of their study, the overall predictive rate of the Z’’-score model was 57.5%, which is in the same range as the overall accuracy rate of the model observed in this study.

The findings of this study indicate that financial indicators have a significant role in explaining financial distress. For example, out of 40 bankrupt airlines observations, 33 of them had negative working capital, indicating that current obligations exceeded current assets. For most of the bankrupt companies these patterns were visible already two years prior to the year of bankruptcy declaration, and even more noticeable one year prior to bankruptcy, indicating the increasing financial distress of the airlines.

The same pattern is noticed in the sample of non-bankrupt airlines. Out of 60 total non-bankrupt observations, 33 displayed negative working capital. The coefficient with the highest weight included in the Z’’-score model is X1, which calculated as 6.56*working capital divided by total assets. This also explains the overall tendency of lower Z’’-scores in the aviation industry, since majority of the observations displayed negative working capitals, which combined with the highest coefficient weight negatively affects the overall Z’’-score. These findings correspond with the academic literature and previous research conducted in the aviation sector bankruptcy prediction, where it was discussed that aviation industry is characterized by low working capital, high leverage and fluctuating EBIT (Shi et al., 2024).

However, it is worth mentioning that to obtain a broader picture on financial state of an airline, it is important to consider other external factors that can affect financial state of an airline but are not incorporated into Altman Z’’-score model. While Altman Z’’-score can capture key financial indicators such as liquidity, operating profitability and leverage, there are other factors or causes that can contribute to financial distress of an airline. For example, such qualitative factors as external shocks, including fuel price increase, pandemics, international sanctions, can substantially affect the financial performance of an airline. In addition, as an idea for the future research, ESG factors could be incorporated in the study to obtain more comprehensive results. While the Z''-score is an accounting-based model, ESG variables might also influence the risk of bankruptcy through their impact on operating performance and other financial ratios.

Furthermore, the study could be expanded by integrating some modern bankruptcy prediction mechanisms, such as machine learning in order to gain insights into how these models perform in comparison to traditional Altman Z''-score model. As discussed in the theoretical part of this study, machine learning techniques can provide some valuable insights for the involved stakeholders, as they do not solely rely on the financial data and ratios and can achieve higher predictive accuracy.

In addition, the study could be further developed by conducting a comparison study between the Z''-score and Airscore predictive power when applied a data sample of global airlines, as it would provide valuable insights on how Airscore model (1991), developed specifically for the aviation sector, performs compared to general bankruptcy prediction Z''-score model.

In conclusion, this study proves that Altman Z''-score model is still relevant and applicable for bankruptcy prediction. Despite having designed over fifty years ago, the model is still an effective tool for observing financial distress, as it can capture the major financial indicators of distress, which include the liquidity, profitability, retained earnings and leverage ratios. However, when applied in the aviation sector, the model tends to misclassify financially healthy as distressed, which is supported by the high number of false positives observed in the study's data. Therefore, it is important to keep that in mind before classifying an airline as financially distressed. In turn, the model can serve as a tool for identifying early distress signals instead of the precise classifier for bankruptcy prediction in the aviation industry.

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Appendices

Appendix 1. Bankrupt airlines selected for the study

Name of an airline	Continent	Year of bankruptcy
SkyEurope Holding AG	Europe	2008
Air Berlin	Europe	2017
MONARCH AIRLINES LIMITED	Europe	2017
OY AIR FINLAND LTD	Europe	2012
AVIANCA HOLDINGS S.A.	Central America	2020
AMERICA WEST HOLDINGS CORPORATION	North America	2005
FLYBE GROUP LIMITED	Europe	2020
TRANSASIA AIRWAYS CORPORATION	Asia	2016
AIR MEDITERRANEE	Europe	2016
SPIRIT AIRLINES, INC.	North America	2024
AIR POLAND SP. Z O.O.	Europe	2012
FRONTIER AIRLINES HOLDINGS, INC.	South America	2008
LATAM AIRLINES GROUP S.A.	South America	2024
DELTA AIR LINES, INC.	North America	2005
US AIRWAYS GROUP, INC.	North America	2013
Kingfisher Airlines Ltd	Asia	2012
GOL LINHAS AEREAS INTELIGENTES S.A.	South America	2024
1TIME HOLDINGS LIMITED	Africa	2012
AZUL S.A.	South America	2025
GRUPO AEROMEXICO S.A.B. DE C.V.	North America	2020

Appendix 2. Non-bankrupt airlines selected for the study

Name of an airline	**Country of HQ**	**Continent**
United Airlines Holdings, Inc.	United States	North America
Air France	France	Europe
Air Canada	Canada	North America
Jet2 Plc	United Kingdom	Europe
Air China Limited	China	Asia
Wizz Air Holdings Plc	Hungary	Europe
Japan Airlines Company Ltd	Japan	Asia
International Consolidated Airlines Group S.A.	Spain	Europe
Qantas Airways Limited	Australia	Oceania
Easyjet Plc	United Kingdom	Europe
Ryanair Holdings Plc	Ireland	Europe
American Airlines Group Inc.	United States	North America
Ana Holdings Inc.	Japan	Asia
Korean Air Lines Co., Ltd.	South Korea	Asia
Alaska Air Group, Inc.	United States	North America
Air New Zealand Limited	New Zealand	Oceania
China Airlines Ltd.	China	Asia
Fedex Corporation	United States	North America
China Southern Airlines Company Limited	China	Asia
Finnair Oyj	Finland	Europe
Alliance Aviation Services Limited	Australia	Oceania
Icelandair Group HF	Iceland	Europe
Air Astana	Kazakhstan	Asia
Vietjet Aviation Joint Stock Company	Vietnam	Asia

Tong Cong Ty Hang Khong Viet Nam - CTCP	Vietnam	Asia
Thai Airways International PCL	Thailand	Asia
Hainan Airlines Holding Co., Ltd.	China	Asia
Abu Dhabi Aviation PJSC	United Arab Emirates	Asia
Blue Dart Express Limited	India	Asia
Skywest Inc.	United States	North America

Appendix 3. Z''-score accuracy across business regions and markets

Business Region Table				
Region	Correct	Incorrect	Total	Accuracy
EMEA	23	13	36	63.9 %
AMER	20	12	32	62.5 %
APAC	9	23	32	28.1 %
Total	52	48	100	52.0 %

Business Region p = 0.005

Business Region Table		
Region	Correct	Incorrect
EMEA	18.7	17.3
AMER	16.6	15.4
APAC	16.6	15.4
Chi-Square Test		0.004608

Market Type Table:				
MarketType	Correct	Incorrect	Total	Accuracy
Developed	32	32	64	50.0 %
Emerging	20	16	36	55.6 %
Total	52	48	100	52.0 %

Market Type p = 0.594

Market Type Table:		
MarketType	Correct	Incorrect
Developed	33.3	30.7
Emerging	18.7	17.3
Chi-Square Test:		0.593507