Bankruptcy Prediction and Corporate Governance

Revisiting the Z-score in the post-Global Financial Crisis period

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Abstract

The purpose of this paper is to examine whether Altman's Z-Score bankruptcy prediction model is still valid and accurate in the post-Global Financial Crisis period and whether it can be improved by including corporate governance-related indicators. To examine this question, the paper employs multiple discriminant analysis to construct two separate models based on a sample of 30 bankrupt and 30 non-bankrupt US-listed firms. Our empirical results show improved predictive ability with the inclusion of corporate governance variables. We confirm that Altman’s 1968 model remains valid, but a re-estimation to the specific period produces a greater predictive ability. The paper contributes to the literature by constructing a bankruptcy prediction model that includes both financial ratios and corporate governance indicators and is relevant for a wide range of stakeholders including policymakers, financial market participants and individual firms.

Keywords: Bankruptcy Prediction, Corporate Governance, Discriminant Analysis, Z-score, Financial Ratios

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Abbreviations

Abbreviation	Meaning
ANOVA	Analysis of Variance
AUC	Area Under Curve
BvD	Bureau van Dijk
CCA	Canonical Correlation Analysis
Cov-lite	Covenant-light
DEF	Definitive Proxy Statement
EBIT	Earnings Before Interest and Taxes
EDGAR	Electronic Data Gathering, Analysis, and Retrieval system
EPA	US Environmental Protection Agency
FASB	Financial Accounting Standards Board
GAAP	Generally Accepted Accounting Principles
IASB	International Accounting Standards Board
IFRS	International Financial Reporting Standards
MDA	Multiple Discriminant Analysis
MVE	Market Value of Equity
NAICS	North American Industry Classification System
NASDAQ	National Association of Securities Dealers Automated Quotations
NYSE	New York Stock Exchange
OLS	Ordinary Least Squares
RE	Retained Earnings
REIT	Real Estate Investment Trust
ROA	Return on Assets
ROC	Receiver Operator Characteristic
SEC	Securities and Exchange Commission
SIC	Standard Industrial Classification
SME	Small and medium-sized enterprises
SOX	Sarbanes-Oxley Act
SPSS	Statistical Product and Service Solutions
TA	Total Assets
VW	Volkswagen
WC	Working Capital
$\boldsymbol{\Lambda}$	Wilk’s lambda

Part I

Introduction and Problem Delineation

1 Introduction

The importance of proper corporate governance has been widely documented in academic literature and has become more pronounced over the past few decades. Perhaps the most infamous case of corporate governance failure is the collapse of the Lehman Brothers, an influential US investment bank. One of the most seminal events in financial history, the Global Financial Crisis of 2007-08, is partly attributed to the implosion of the Lehman Brothers, a 30 to 1 leveraged company, which caused a subsequent collapse of the US housing market and the entire banking system. Leading up to the crisis, Lehman Brothers had long been known for pursuing an aggressive growth strategy based on engaging in high-risk business areas such as the trading of complex derivative instruments, subprime structuring and commercial real estate markets. This raises the question: "*why did the board and executive management of Lehman Brothers fail to effectively oversee the firm and alter its course before it was too late?*". A possible explanation can be traced back to the agency problem which existed and the lack of appropriate board oversight.

The Lehman Brothers case is a quintessential example of how poor corporate governance can have damaging consequences and ultimately lead to the bankruptcy of firms with otherwise long and successful operational histories. Lehman Brothers is not an isolated case. The Global Financial Crisis of 2007-08 created an exogenous shock to the economy that lead to the demise of other influential corporations, which exposed rent-seeking and other value-destroying practices by boards and executive management. As the former Chair of the Federal Reserve, Alan Greenspan, said in a congress hearing: "*I made the mistake in presuming that the self-interests of organizations, specifically banks and others, were such that they were best capable of protecting their own shareholders and the equity of the firm*" (OECD, 2009).

The Global Financial Crisis and the consequences that followed can to a large extent be attributed to "*failures and weaknesses in corporate governance arrangements which did not serve their purpose to safeguard against excessive risk taking in a number of financial services companies*" (Kirkpatrick, 2009). As history repeatedly has shown, poor corporate governance mechanisms, or the lack thereof, can have severe effects on companies, ultimately resulting in bankruptcy. The importance of appropriate governance should not be overlooked and leads to the question: "*Could the collapse of Lehman Brothers and the like have been foreseen, if more attention had been paid to corporate governance practices?*".

Historically, bankruptcy prediction literature has asserted the importance of financial ratios in predicting defaulting companies. Edward Altman (1968) was among the first to popularise and commercialise bankruptcy prediction with his Z-score model: a simple and intuitive classification model based on five financial ratios. Since then, bankruptcy prediction research has developed significantly, utilising new statistical methodologies, examining specific countries and industries and introducing new variables. Prediction accuracy of previous models has varied greatly with the studied industry, country and variables used. In general, previous bankruptcy models have been accurate, especially in predicting short-term default risk with one-year default classification accuracy well above 90 percent (e.g. Beaver, 1966; Altman, 1968; Blum, 1974).

Recently, a new stream of literature has emerged examining the role of corporate governance in predicting bankruptcy. Specifically, these studies (e.g. Daily & Dalton, 1994; Parker et al, 2002; Chan et al., 2016) investigate whether the combination of select corporate governance variables such as board size, CEO compensation and director independence, produces a superior bankruptcy prediction model measured by accuracy rates. Despite interesting results, especially for long-term default risk, studies including governance variables are still underrepresented in bankruptcy prediction literature. This has been ascribed to the cumbersome process of collecting accurate governance data. However, newer regulations, such as the 2002 Sarbanes-Oxley Act ("SOX"), have increased transparency and disclosure requirements and spurred attention within this particular research area. Based on this, there is a need for incorporating corporate governance variables to the bankruptcy prediction model, as also pointed out by Chan et al. (2016).

The importance of bankruptcy prediction has been rigorously discussed in previous literature. The discipline has become an important tool for myriad stakeholders and market participants. For the individual firm it can be used to examine underlying business health and respond with preventive actions. Investors can identify potential investment opportunities (both long and short positions), credit rating agencies can assign an appropriate credit risk and policymakers can use the tool when drafting new laws.

Generally, bankruptcy prediction becomes increasingly important during periods of ongoing financial crisis. Since, the Global Financial Crisis, the US stock market has witnessed the longest bull market since World War II (Li, 2019). The US S&P 500 Index has risen more than 460 percent in this period and has partly been sustained through "… *an explosive combination of monetary and fiscal policy*…" (Li, 2019). The low interest-rate environment has led to the issuance of more (and riskier) debt which has driven corporate valuations to an all-time high (Dallas, 2019). This economic environment leaves many companies vulnerable, should a recession emerge, and highlights the relevance of further research within bankruptcy prediction.

This paper should be viewed as an attempt to capture relevant corporate governance variables and introduce them to a well-defined and recognised bankruptcy prediction model, Altman's Z-score, to increase prediction accuracy. As a result of the ongoing development of corporate governance literature (recently, Laeven & Levin, 2008; Edmans, 2014; Burkat et al., 2017), and following the ratification of the SOX, it has become theoretically and economically meaningful to introduce corporate governance measurements to traditional models. Particularly, the included corporate governance parameters relate to three overall categories; (i) *shareholders*; (ii) *board of directors* and (iii) *executive management*; and based on empirical and theoretical findings are deemed to have a predictive ability. The paper is motivated by the requirement for further research within bankruptcy prediction in the light of high-profile bankruptcies linked to poor corporate governance, the considerable importance bankruptcies have to many stakeholders and the lack of empirical research thereof.

This paper seeks to contribute to the bankruptcy prediction literature by constructing a model that captures the importance of corporate governance indicators whilst confirming that several key financial indicators are still valid in accurately predicting bankruptcies in the post-Global Financial Crisis period.

1.1 Research question

The study of bankruptcy prediction has generated a substantial amount of literature over the past 35 years. New models have been developed, new industries and countries studied, and various financial variables added. Most papers and corresponding models draw direct parallels to the original model introduced by Altman in 1968. However, little research has examined the impact corporate governance measures have on bankruptcy prediction, especially in the period following the Global Financial Crisis.

In line with the numerous bankruptcies and scandals driven by corporate misconduct and the fruitful development of literature on corporate governance, as illustrated in the preceding section, we find that there is both theoretical and empirical grounds to explore this area in more detail and present the following research question:

> ***Is Altman's 1968 Z-score still valid and accurate in predicting bankruptcies of US-listed companies in the post-Global Financial Crisis period, and is there room for improving the accuracy rate using corporate governance indicators?***

Our paper aims to examine the accuracy of bankruptcy prediction models for US companies in the post-Global Financial Crisis period, defined as the time span stretching from 2012 to 2018. To explore the research question, we set up three models:

- **Model I:** Altman's original model using the estimated coefficients from the 1968 study
- **Model II:** Altman's original model with re-estimated coefficients based on a sample with a broader industry focus than solely manufacturing firms
- **Model III:** An extension of Altman's original model, re-estimated and including corporate governance indicators, based on the same period as in Model II

Model I does not involve any form of statistical computation or re-estimation. It is simply applied to the data set, which reflects a more recent time-period. Model II is a re-estimated Z-score model, which addresses the stream of literature suggesting that the Z-score model should be revised for bankruptcy prediction involving all types of firms in different time periods. Model III is a re-estimated Z-score model, which tests whether corporate governance indicators have discriminating power in classifying bankruptcies. By comparing the prediction accuracy of the three models, we can conclude which of them is superior in predicting bankruptcies in the US and determine whether corporate governance indicators improve the predictive ability. The coefficients underlying Model I were estimated in a different time period and were based on manufacturing firms. Hence, the re-estimated model (Model II) becomes important in comparing prediction accuracies with Model III on a like-for-like basis.

We examine the particular period to isolate any impacts exogenous economic events, such as the Global Financial Crisis, may have on bankruptcies. Due to data limitations on certain corporate governance measures and potential discrepancies in accounting standards across countries, this paper focusses on US-listed firms. We critically review both bankruptcy prediction and corporate governance literature to select the variables to input into our model and develop hypotheses underpinned by theory and past empirical findings.

The remainder of this paper is organised as follows:

Sections 2 and 3 – introduce the fields of bankruptcy prediction and corporate governance and the interplay and associations between the two.

Sections 4, 5 and 6 – provide empirical and theoretical literature reviews of bankruptcy prediction, with particular focus on Altman's Z-score model from 1968 and defines the paper's hypotheses in parallel.

Section 7 – provides an outline of the methodology and research framework applied in our analysis.

Section 8 – discusses the sample and data collection process and provides a description of the variables and data set.

Section 9 – presents the results of our empirical analysis and the associated validation tests.

Section 10 – discusses the main results of our analysis in relation to the research question and our hypotheses and provides a comparative evaluation vis-à-vis prior studies.

Section 11 – is the closing section and contains a summary of the paper.

Part II

Bankruptcy Prediction and Corporate Governance

This section broadly defines bankruptcy prediction as a tool and sheds light on the models that exist today. Moreover, it defines corporate governance and illustrates and exemplifies the importance of sound governance practices relating to overall firm health.

2 Bankruptcy Prediction

2.1 Introduction and relevance of bankruptcy prediction

Research on bankruptcy prediction has become a focal area in financial academia over the past 35 years. During this period, the global economy has gone through several business cycles and witnessed financial crises such as the 1996 Asian Financial Crisis, the late 1990's Dot-com bubble and most recently the Global Financial Crisis of 2007-08. These events led to a series of bankruptcies, which resulted in unemployment, decreased economic output, and write-downs of asset values. An overview of corporate bankruptcies in the United States is depicted in Figure 1. From Figure 1 it is clear that the number of bankruptcies peaked immediately after the Global Financial Crisis and has recently stabilised at around 20,000 business bankruptcies per annum.

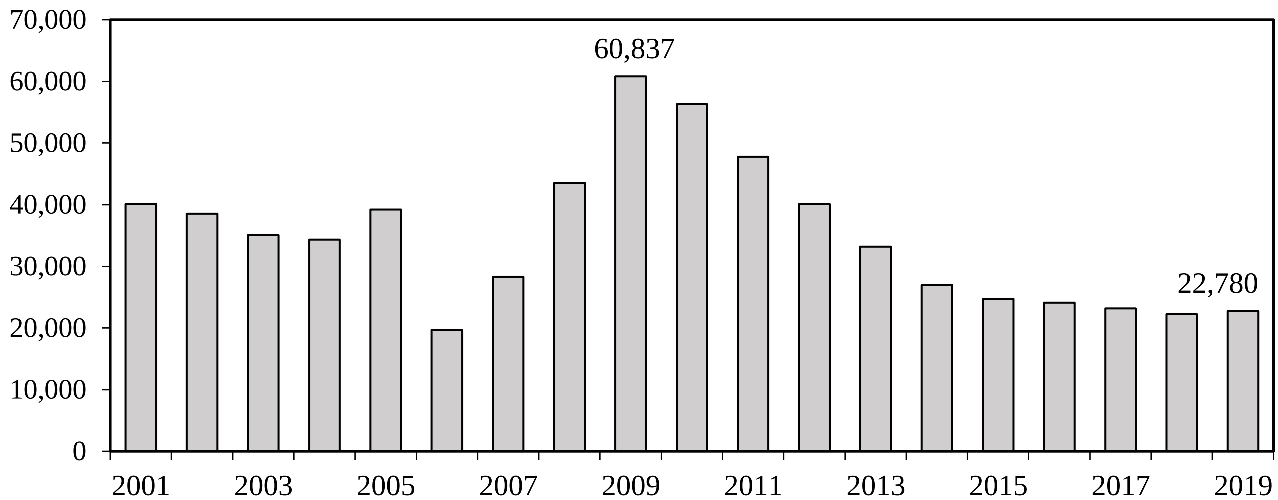

Figure 1. Annual US Number of Business Bankruptcy Cases; 2001-2019. Number of all business bankruptcies in the United States. The vertical axis indicates the number of bankruptcies, while the calendar year is expressed on the horizontal axis. Source: US Bankruptcy Courts.

There are several reasons for why bankruptcy prediction has become an important topic in corporate finance literature and for policymakers, market participants and society.

Bankruptcies have a large impact on a plethora of different stakeholders

Bankruptcies have a large impact on many stakeholders in society and the associated economic and social costs are significant. *Individuals* lose their jobs and source of income. Additionally, the social stigma attached to unemployment may have serious consequences on personal well-being. *Shareholders* have subordinated claims to company assets and will unlikely recover their investment, which results in asset write-offs. *Debtholders* can claim assets in the company according to their level of seniority but will, in most cases, not be able to recover the entire face value of the issued debt. *Governments* have to provide benefits for the unemployed, re-train them if the industry is declining, and try to stimulate business activities in other areas to compensate for the lost output. Other *industries, businesses and countries* are also impacted by bankruptcies as economies have become more interlinked and globalised. Hence, due to the large global consequences that result from bankruptcies, it becomes important to identify defaulting firms well in advance so preventive measures can be implemented.

Bankruptcy prediction as a tool for the Basel Accord

The Basel Accords are a set of regulatory measures designed to ensure that financial institutions have enough liquidity to meet their financing obligations and absorb unexpected losses. The Basel Committee has established a series of international standards for bank regulation, most notably on capital adequacy, which are commonly known as Basel I, Basel II and, most recently, Basel III (Bank for International Settlements, 2020). The latest accord, Basel III, was ratified in November 2010 and sets out measures on counterparty risk assessment. Basel III is a direct response to the Global Financial Crisis where highly levered companies with bad governance practices went bankrupt.

The Basel Accords require financial institutions to measure counterparty risk exposures associated with derivative transactions in order to determine an adequate capital buffer. As a result, advances in bankruptcy prediction would aid the financial sector as enhanced prediction accuracy would allow them to set optimal capital buffer levels (Bank for International Settlements, 2020).

Rising corporate debt levels

Corporate debt is at record levels having risen from USD 3.3tn before the Global Financial Crisis to USD 6.5tn in 2019 (Plender, 2020). As yields have decreased, lenders have accepted riskier debt terms. This type of debt is known as covenant-light loans ("Cov-lite") and is characterised by fewer restrictions on the borrower and fewer protections for the lender.

Due to the high debt levels in the US there is a risk that when the economic environment changes and monetary conditions tighten, many loans will start breaching their convents leading to default. For a lender it is therefore important to assess the financial health of a company before purchasing a tranche of their debt. Again, an accurate bankruptcy prediction model can assist in this assessment. As evidenced by Figure 2, the net debt issuance in the US has increased significantly over the past decade.

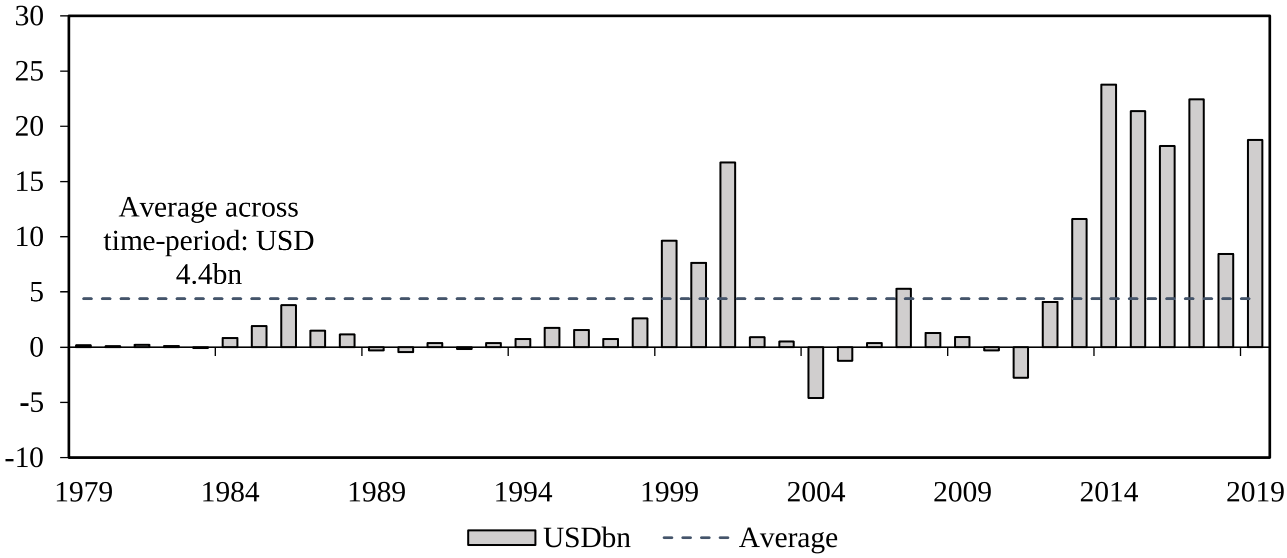

Figure 2. Annual Net Debt Issuance of US Corporations; 1979-2019. Annual Net Issues of International Debt Securities for Issuers in US Non-Financial Corporations (Corporate Issuers) in All Maturities, in Billions of US Dollars. The vertical axis indicates issuance volume in USDbn, while the calendar year is expressed on the horizontal axis. Source: Federal Reserve Bank of St. Louis (FRED).

Likelihood of a US recession is increasing due to overheating

Finally, the US equity markets have experienced the longest bull-market since World War II with the S&P 500 having risen more than 450 percent since the Global Financial Crisis (Li, 2019), as illustrated by Figure 3. This poses the question of how long this can be sustained before the economy overheats and eventually ends up in a recession.

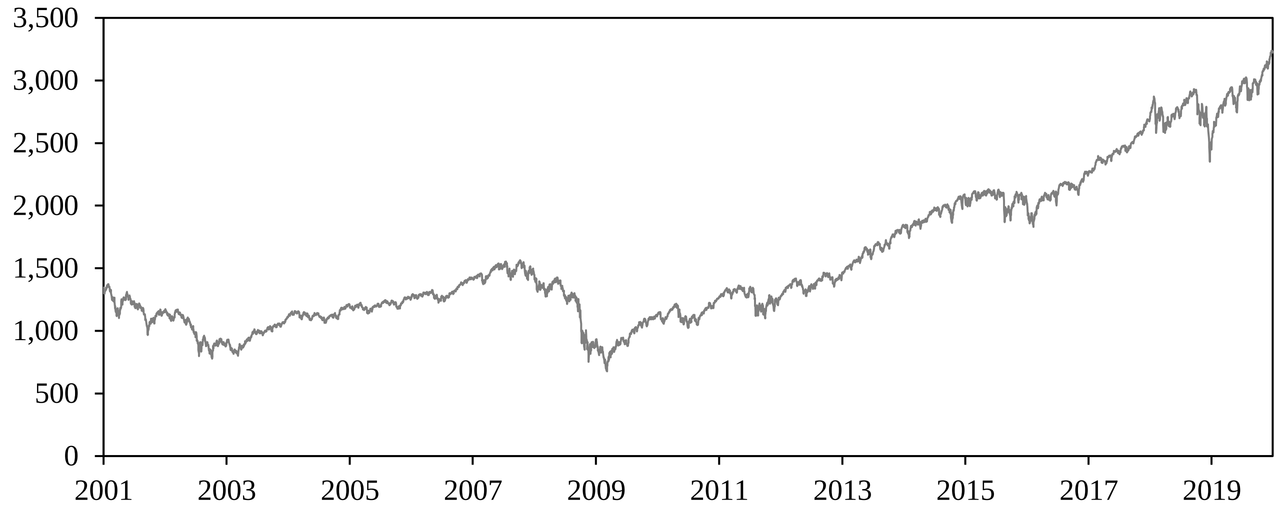

Figure 3. Historical Development of the S&P 500 Index; 2001-2019. The vertical axis shows the index price denominated in USD and the horizonal axis displays calendar years. Source: S&P Capital IQ.

The points raised in this section underline the need and urgency for further research on bankruptcy prediction, as corporate bankruptcies have a material impact on many stakeholders and are relevant given the cyclical nature of the economy.

2.2 Definition of bankruptcy

In business, the terms '*bankruptcy*' and '*failure*' have been applied relatively loosely to mean several different things. In academic literature and bankruptcy prediction studies, four related terms have commonly been used: default, failure, insolvency, and bankruptcy. Whilst these terms have often been used interchangeably, they have distinct formal meanings. To ensure homogeneity in the state of bankruptcy amongst the sample being considered, it is important to choose one definition. As such, we ensure the predictive power of the selected variables is not distorted by sample heterogeneity.

The term '*default*' can refer to either a technical or legal default and, in both cases, revolves around the relationship between a company's borrower (debtor) and lenders (creditors). A technical default occurs when the borrower violates a provision in the loan agreement, which triggers the lender to seek legal action. As an example, this occurs if a particular covenant, such as the debt service coverage ratio, was broken. A legal default occurs when a company fails to honour a scheduled interest or principal payment as stipulated by the loan agreement, and also fails to rectify the matter within the grace period (if any). Another term used, '*insolvency*', refers to the inability of a firm to meet its combined short and long-term liabilities (i.e. total liabilities exceed total assets), such that its equity value (net worth) is negative.

Legal definition

The legal definition refers to a situation where a company issues a formal declaration of bankruptcy in a federal district court in addition to a Chapter 7 (liquidation) or Chapter 11 (reorganisation) filing (Altman & Hotchkiss, 2006).

The utilisation of the legal definition carries a number of benefits. Firstly, the time of failure can objectively be measured and observed as the official filing date for bankruptcy. Secondly, the legal definition also provides an objective criterion for categorising firms in bankrupt and non-bankrupt buckets. On the other hand, one of the drawbacks of using the legal definition is its tie to the applicable bankruptcy law, which differs from one jurisdiction to another. As such, comparability and the ability to draw generalisations across geographies may be misleading. Furthermore, the time of legal failure (i.e. formal filing date) may not necessarily be reflective of the actual or 'true' bankruptcy occurrence, as such filing may often be viewed as a final alternative. This is because bankruptcy is a dynamic process (Volkov et al., 2017), developing over time, which implies there may be a 'lag' between the true event and the actual bankruptcy date (Pompe & Bilderbeek, 2016). Finally, some papers argue that legal bankruptcy is too narrow a definition, since distressed companies may be faced with a range of alternative 'out-of-court' exit options versus a bankruptcy filing, including via a merger and acquisition (M&A) or voluntary liquidation (Schary, 1991).

2.3 Introduction to the main bankruptcy prediction models

The following section presents an overview of the main bankruptcy prediction models.

Overview of Models

Several bankruptcy prediction models exist today. These models can broadly be divided into five different categories (Nyambuu & Bernard, 2015); (i) *ccounting-based models*, (ii) *credit spread models*, (iii) *firm value models*, (iv) *rating agency models* and (v) *other models*. An overview of the different categories is provided in Table 1.

Classification	Examples	Description
(i) Accounting-based Models	*Univariate, Beaver (1967)* *Risk Index, Tamari (1966)* *MDA, Altman (1968)* *Conditional probability, Ohlson (1980)*	Uses different financial ratios as regressors in the econometric models. The models typically compare two data groups; a bankrupt and corresponding non-bankrupt one. The models generate an index score e.g. Z-score or O-score, which can be used as a proxy for the likelihood of default.
(ii) Credit Spread Models	*Hull and White (2000)*	Examines the spread between the interest rates on debt close to default and that of similar maturity risk-free debt. The spread will indicate how much investors need to be compensated for taking on the debt and will thus indirectly indicate the probability of default i.e. the larger the spread the larger probability of default. A point of critique has been that other factors than the probability of default has an impact on the credit spread.
(iii) Firm Value Models / Structural Models	*Merton (1974)* *Black and Scholes (1973)*	Assumes that the probability of default is captured in the firm's capital structure and translated to the stock price. The model constructs synthetic derivatives for the firm's debt structure which can be priced by applying the Black and Scholes (1973) option model pricing formula. Criticism of this model is centred around the reliance on financial statements (which are prone to a certain degree of manipulation) and that fluctuations in shares price can arise from a broad pallet of endogenous and exogenous factors.
(iv) Rating Agency Models	*Fitch* *Moody's* *Standard and Poor's*	Produces a credit rating translated into a letter ranging alphabetically from AAA (Best credit rating) to D (default). The underlying methodology is a black box to the public but combines historical financial data with more subjective analyst analyses.

(v) Other	*KMV Model*	Proprietary model developed by Kealhofer, McQuown, and Vasicek and purchased by Moody's Analytics in 2002. It combines several default-risk modelling methodologies such as the structural models and the statistical models. The model outputs a Distance-to-Default (DD) measure which is the number of standard deviations between the mean of the distribution of the assets value and its default point; the asset value at which the firm defaults. The final product is the Expected Default Frequency (EDF), a function of DD, which encompasses valuation, capital structure and the general market environment.

Table 1. Overview of Bankruptcy Prediction Models. The table provides an overview of the most popular groups of bankruptcy prediction model that exist today.

Several of the above-mentioned models and methodologies require expensive subscriptions and are not publicly available. We therefore wish to contribute to the development of a model that is made available to the wider public and which is simple and easy to apply and interpret. Hence, this paper will focus on examining accounting-based bankruptcy prediction models with an emphasis on extending and improving Altman's popular 1968 Z-score model. Altman's Z-score and other accounting-based bankruptcy prediction models will be described in more detail in the literature review.

2.4 Sub-conclusion

Bankruptcy prediction has become increasingly important in today's economy. History has shown the serious consequences bankruptcies carry to individuals, corporations and to the economy as a whole. The global economy has experienced a prolonged period of expansion, and high levels of debt combined with high valuations. In order to employ corrective and preventive measures to corporations it is important to be able to accurately predict the likelihood of bankruptcy. Several prediction models exist today however the majority require costly subscriptions. Hence, we seek to contribute to develop a model that is easy to use and free of charge for all stakeholders in society.

3 Corporate Governance

3.1 Definition of corporate governance

Corporate governance is widely defined as "*the system by which companies are directed and controlled*" and sets out the rules, procedures and best practices on how to balance conflicting stakeholder interests (Cadbury, 1992). The traditional issue within corporate governance arises when there is a misalignment of interest between owners and self-serving managers, stemming from the separation of ownership and control (Berle & Means, 1932) combined with the assumption that both parties are utility maximising (Jensen & Meckling, 1976). In other words, due to the separation of ownership, managers have incentives to deviate from what is best for the company and pursue opportunistic behaviour, which ultimately destroys value for the owner. This adversarial relationship has been recognised as the '*principal-agent problem'* (Jensen & Meckling, 1976). In financial literature, emphasis is placed on the relations between a company's executive management (agents) and the shareholders (principals). Corporate governance focusses on the allocation of rights and responsibilities to different stakeholder in an organisation such as the board, managers, shareholders whilst cementing the rules and procedures for decision making (European Central Bank, 2004).

3.2 The importance of prudent corporate governance

Bankruptcies in the early 2000s highlighted the importance of corporate governance

Corporate governance has become a focal point for many organisations as a direct consequence of scandals and corporate failures attributable to poor corporate governance practices. In the early 2000s, the high-profile cases involving Enron, WorldCom, and Arthur Anderson, sparked interest within corporate governance, as their collapses were considered to be partly attributed to the failed duties of executive management and board of directors. For example, all three cases trace back to accounting fraud in which management was aware of the issues but failed to address them at the expense of their shareholders, employees and society at large.

Following these high-profile bankruptcies, policymakers began to scrutinise corporate governance practises, which resulted in a tightening of regulations. A famous example is the 2002 Sarbanes-Oxley Act[1] ("SOX"), quoted as a "*mirror imagine of Enron: the companies perceived corporate governance failings are matched virtually point for point in the principal provision*" (Deakin &

[1] US Federal Law intended to improve corporate governance by legislative measures from the Cadbury and OECD reports

Konzelmann, 2003). The SOX, a US federal law, stipulates governance requirements for all US public boards, management teams and public accounting firms with the main purpose of protecting investors *"by improving the accuracy and reliability of corporate disclosures made pursuant to the securities laws"* (US Congress, 2002). After the introduction of the SOX, companies are required to disclose more information regarding compensation practises, board compositions and committees (Chan et al., 2016). As a result, both transparency and the quality of corporate governance indicators has increased significantly (Chan et al., 2016).

Poor corporate governance partly to blame for the Global Financial Crisis of 2007-08

The Global Financial Crisis of 2007-08 triggered another wave of bankruptcies even greater in magnitude than those witnessed in the early 2000s and with it, another spike of interest in corporate governance practices. The most prominent of all cases was the collapse of Lehman Brothers, a US investment bank, which has infamously been recognised as the largest corporate bankruptcy in history. Alongside Lehman Brothers, several other large financial institutions such as Northern Trust, AIG, and Washington Mutual also defaulted. Again, poor corporate governance played a central role and was widely to blame as management and governance policies "*did not serve their purpose to safeguard against excessive risk taking in a number of financial services companies"* (Kirkpatrick, 2009). Weak governance, in the form of broken incentive structures, led to the manipulation of company financials, inordinate risk-taking and other malpractice, which all contributed to the crisis. Grove and Victoravich (2012) conducted extensive research on governance practices during the crisis and concluded that the recurring issues leading to default include unchallenged CEOs, weak and non-independent boards, negligible management control, focus on short-term incentive schemes and a weak code of ethics.

Limited corporate governance legislation currently exists

Business and governments have conjunctively tried to address some of the governance problems brought to light during past times of crisis. This has primarily been done via the SOX as well as other guiding principles and corporate governance codes issued by institutional investors, businesses, and stock exchanges. Today, the most prominent guidelines on corporate governance are the G20/OECD '*Principles of Corporate Governance'*. These were originally published in 1999 and have since become an internationally acknowledged benchmark for a multitude of stakeholders globally. Most recently they were revised and updated in 2015 by the OECD Council and G20 Leaders' summit

(OECD, 2020). However, it is worth noting that these principles are not legally binding, and attention should therefore be paid to individual company practices.

An example of poor corporate governance

Poor corporate governance can have serious consequences for companies and may in the most extreme case lead to bankruptcy. It can also deteriorate company profitability and fundamentals, hence making them less robust and more prone to financial distress. Many corporate scandals have emerged since the Global Financial Crisis, including the Volkswagen 'Diesel Gate' scandal in 2015 (the "VW Diesel Gate Scandal"), British Petroleum's Deepwater Horizon oil spill and the collapse of Valeant Pharmaceuticals due to its overly aggressive acquisition spree. Again, these scandals arose from poor corporate governance practices. We briefly describe the VW Diesel Gate Scandal below to exemplify and concretise the impact poor governance can have on company performance.

The Volkswagen Diesel Gate Scandal

In September 2015, the US Environmental Protection Agency ("EPA") discovered that cars produced by Volkswagen ("VW") and sold in the US had a software installed, which could rig testing results on diesel engines thereby producing an inaccurately low result (Hotten, 2015). As a result, VW was forced to recall millions of cars worldwide, which resulted in a loss of EUR 2.5bn, its first quarterly loss in 15 years of operations. After VW admitted to cheating in the tests, the company lost almost a quarter of its market value as shown in Figure 4.

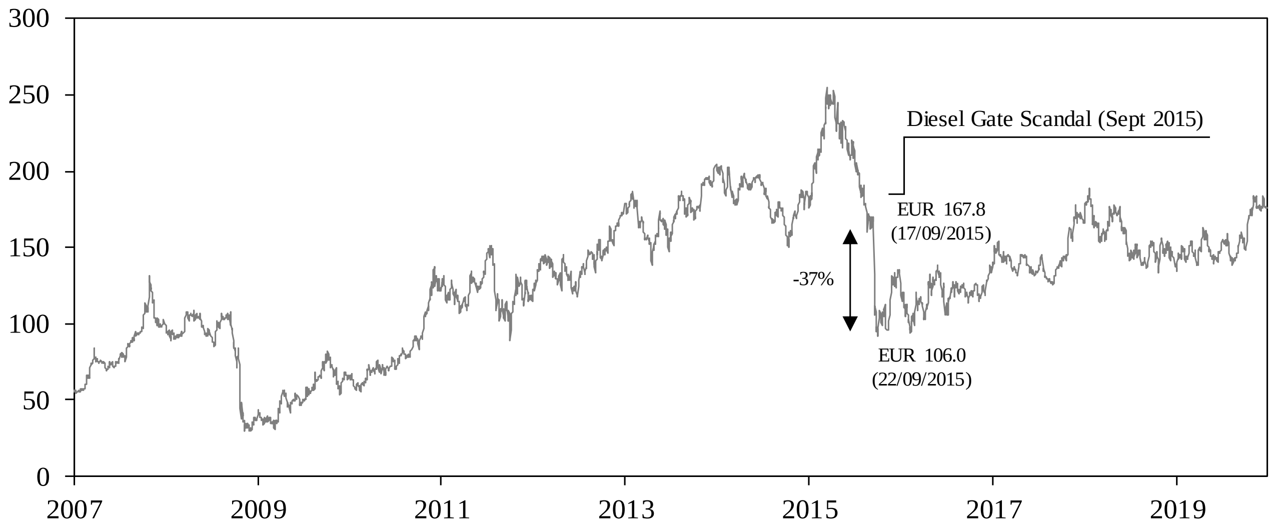

Figure 4. Volkswagen Stock Price Development; 2007-2019. The vertical axis shows the price per share denominated in EUR and the horizonal axis displays calendar years. The date of the VW Diesel Gate Scandal and relevant data points are called out in the figure. Source: S&P Capital IQ.

Following the VW Diesel Gate Scandal, shareholders began to question management and their dutifulness in their respective roles. The CEO at the time, Martin Winterkorn, resigned because of the scandal and wide outcry from blockholder investors. In 2019, an internal memo was leaked that suggested that management was aware of the cheating devices, but knowingly withheld market-moving information from shareholders (Burger, 2019). The VW case is a clear example of poor governance structures, which resulted in large costs for the owners and damaged the overall reputation and financial health of the German automotive giant.

3.3 Sub-conclusion

The section illustrates that poor performance and potential failure of companies in many instances can be partly or fully attributed to poor corporate governance practices and self-serving managers whose interests are not aligned with the shareholders. After the introduction of SOX in 2002 the availability and accuracy of data on corporate governance has improved significantly. Companies are now required to fill out standardised schedules on various metrics, which enables researchers to compare companies on a like-for-like basis. In this regard, we argue that examining corporate governance indicators in bankruptcy prediction is meaningful as the data is available for all listed companies and is comparable.

Part III

Literature Review and Hypothesis Development

This section conducts an empirical and theoretical literature review of bankruptcy prediction and corporate governance. The review is used to identify the variables used in the models and develop the hypotheses, which will explore the research question.

4 Empirical Literature Review

4.1 Multiple discriminant analysis

The first multivariate study was conducted by Altman in 1968, employing the multiple discriminant analysis model ("MDA"), and has since become one of the most important papers within bankruptcy prediction. Altman created a '*Z-score*', which allows practitioners to determine the likelihood of default based on five model parameters, namely:

- Working Capital to Total Assets
- Retained Earnings to Total Assets
- Earnings Before Interest and Taxes (EBIT) to Total Assets
- Market Value of Equity to Book Value of Debt
- Sales to Total Assets

These variables were selected from an initial group of 22 financial ratios based on popularity in prior literature and relevancy to the study (Altman, 1968). The ratios cover key financial health indicators such as liquidity, solvency, profitability, leverage and activity ratios.

Altman's Z-score considers a sample of 66 US manufacturing companies studied in the period 1956-1965. The sample is divided into two groups: 33 bankrupt firms and 33 non-bankrupt firms. The MDA model then determines a linear combination of the variables, which best discriminates between the two groups and outputs a single multivariate discriminant score, also known as the Z-score. A low (high) Z-score indicates poor (good) financial health. Altman derived the following discriminant equation:

(I) $Z = 1.2X_1 + 1.4X_2 + 3.3X_3 + 0.6X_4 + 0.999X_5$

Where:

X_1 = Working Capital to Total Assets

X_2 = Retained Earnings to Total Assets

X_3 = Earnings Before Interest and Tax (EBIT) to Total Assets

X_4 = Market Value of Equity to Book Value of Debt

X_5 = Sales to Total Assets

Z = Overall Index

Altman (1968) determined a cut-off point of 2.675, i.e. an optimum Z-score value that discriminates best between bankrupt and non-bankrupt firms. This critical value enables practitioners to predict bankruptcy without statistical software. Additionally, companies that have a Z-score greater than 2.99 are classified as 'non-bankrupt', while firms with a Z-score less than 1.81 are labelled 'bankrupt'. The area between the two cut-off values is known as the 'zone of ignorance' or 'grey area'. Altman's 1968 Z-score predicted accurately[2] in 95 percent of the initial sample in year one prior to bankruptcy. This figure dropped significantly in year two to 72 percent and in year three to 48 percent.

Following its publication, Altman's 1968 Z-score model gained a lot of interest and has since been the foundation of numerous studies within bankruptcy prediction. Researchers have tested the prediction ability of other variables than originally included in the model and tailored the model to certain industries or specific countries. In 1977, Altman et al. (1977) revised the original Z-score model and substituted Market Value of Equity (X_4) with Book Value of Equity. The rationale for this was to be able to examine both publicly traded and privately held companies. The loadings of the variables remained mostly unchanged with the only major difference being X_1 falling slightly (Altman et al., 1977). This model variation became known as the Zeta Analysis and the observed prediction accuracy was widely in line with the original model with a 90 percent classification success one year prior to bankruptcy. The MDA model is still generally recognised as the standard method for predicting bankruptcies despite the emergence of other prediction models (Balcaen & Ooghe, 2006).

[2] Prediction accuracy is defined as the sum of all correct predictions divided by the number of total classifications

Advantages and disadvantages of the discriminant model

The MDA model has several advantages compared to other prediction models. The MDA model is multivariate and thus allows the researcher to consider an entire range of variables that may have predictive power in bankruptcy prediction. This was both an improvement to Beaver's 1966 univariate bankruptcy prediction model, which only tested one variable at a time and the more subjective Risk Index Model (Tamari, 1966). Further, the MDA model allows for continuous scoring, as opposed to categorical scoring. Nevertheless, the MDA model has some disadvantages. The model is linear which means that for values of good and bad financial health is divided by a static cut-off point. Secondly, the Z-score is an ordinal measure. It is simply a relative ranking amongst firms belonging to the two groups. Thirdly, the coefficients of each variable cannot be interpreted as one would interpret the coefficients of a normal OLS regression. Lastly, the model is not resistant to severe multicollinearity.

Empirical review of the discriminant model

This paper conducts a comprehensive literature review of the discriminant model to examine different model nuances that exist and show how the model has developed over time. Appendix 1 lists 110 academic articles and PhD dissertations that employ some variation of the discriminant analysis method. The list has been constructed and reviewed based on article relevance measured by the number of citations. Although the list is comprehensive, we acknowledge it is not exhaustive.

Generally, it is evident that research follows three paths; (i) *altering the model to a specific industry*, (ii) *adjusting the model to a specific country* and/or (iii) *including new or different variables than the five Altman originally proposed*. The latter is typically closely tied to path (i), as industry specific variables allow the researcher to follow an industry approach. The following sub-sections address each literature stream and provide an insight on where the model is at its present state and identify potential gaps in literature that require further research.

<u>Discriminant analysis applied to different industries</u>

Altman's original model focussed on predicting bankruptcy for manufacturing firms. Several researchers have since tried to adapt the model and variables to fit a certain industry, in order to achieve a greater prediction accuracy. Examples include studies on financial institutions (e.g. Pettway & Sinkey, 1980; Rose & Kolari, 1985; Looney et al., 1989) and the airline industry (e.g. Scaggs &

Crawford, 1986). Each of these studies acknowledge that their respective industries have unique characteristics and can thus not be correctly categorised by applying Altman's original variables. For instance, bankruptcy prediction studies on banks include variables measuring capital adequacy (Capital and Reserves to Total Assets), liquidity (Net Borrowing to Cash) and loan metrics (percent growth in total loans from previous year) (Rose & Kolari, 1985). Rose and Kolari (1985) include several banking specific metrics to their discriminate model and classify 76 percent of the bankrupt companies correctly and 69 percent of the non-bankrupt firms correctly. We note that these classification results are in the lower spectrum of the one-year prediction accuracy range. Other industry specific studies have more success and achieve bankruptcy prediction accuracies in the 90-percentage range (El Hennawy & Morris, 1983; Scaggs & Crawford, 1986).

Despite several studies following an industry specific approach, the vast majority of the studies have chosen an industry agnostic approach (e.g. Blum, 1974; Moyer, 1977; Tinoco & Wilson, 2013; Bauer & Agarwal 2014). These studies employ variables that are not specifically tailored to an industry but give a more holistic view of the company financials and health. In general, these studies tend to exclude the companies mentioned above (banks, insurers and airlines) due to the aforementioned uniqueness of their business models. Prediction accuracies of models following the agnostic approach vary greatly with country, time-period and sample chosen, but generally result in a high one-year prediction accuracy. Most of the studies observed in this paper achieve accuracy rates greater than 80 percent in the first year prior to bankruptcy. Some studies such as Deakin (1972), Izan (1984) and Levitan and Knoblett (1985) even reach accuracies in the mid 90 percentage using the industry-agnostic approach. Hence, if the aforementioned '*outlier*' industries are excluded for the sample, the agonistic approach performs just as well, if not even better, than the industry specific model and can be applied to a much broader stakeholder group. Table 2 summaries the industries examined in the 110 studies observed in this paper.

Industry	**Frequency**	**Frequency (%)**
General / Agnostic	58	52.7%
Manufacturing	14	12.7%
Banking	10	9.1%
Construction	6	5.5%
SME	4	3.6%
Hospitality	4	3.6%

Retail	3	2.7%
Railroads	1	0.9%
Airlines	1	0.9%
Hospitals	1	0.9%
Other	8	7.3%
Total	**110**	**100.0%**

Table 2. Overview of Industries Studied; 1968 – 2019. The table provides an overview of the industries that have been studied in discriminate analysis in prior studies. The 'Other' category refers to studies that cover 'niche' industries e.g. Small private government contracts and brokerage companies. Source: Own analysis based on literature review in Appendix 1.

Discriminant analysis applied to different countries

The second dominant approach has been to alter the bankruptcy prediction model to a specific country. Some authors (Altman & Levallee, 1980; Taffler, 1982; Agarwal & Taffler, 2008) re-estimate the prediction model coefficients to country specific data whilst other simply apply Altman's weightings to companies in a new country (Kanapickiene & Marcinkevicius, 2014). The latter reports lower prediction accuracy (in the 70-percentage range) than the models which re-estimate the coefficients to the specific country (accuracy greater than 80 percent).

The rationale for this discrepancy is twofold. Firstly, reporting standards vary from country to country. Globally, financial reporting is overseen by the International Accounting Standards Board ("IASB") through the IFRS. These guidelines have been recognised as the global standard (IFRS, 2020). The US however follows the GAAP which is governed by the US Financial Accounting Standards Board ("FASB"). Despite efforts to mitigate any major discrepancies between the two standards, several significant differences between the IFRS and the US GAAP still exist. For instance, on the treatment of inventory, development costs and write-down of assets. All these factors have an impact on financial ratios and should be considered when using an estimation model based on US figures to predict bankruptcy in a non-US country and vice versa. Secondly, different definitions of bankruptcy exist across the globe. The US discriminant models primarily use Chapter 11 of the US Bankruptcy code to categorise a company as bankrupt. This definition is not necessary constant across other countries, as pointed out by Balcaen and Ooghe (2006). They find that the legal definition of bankruptcy depends on the country in which the prediction model has been constructed and the corresponding specific bankruptcy legislation (Balcaen & Ooghe, 2006). Hence, we note that caution has to be taken when applying bankruptcy prediction models across borders and that the best prediction results occur when the estimation model is tailored to that country and legislation and thus avoid the pitfalls mentioned above.

Table 3 describes the countries that have been studied in our literature review. The United States is the most popular country comprising almost half of the studies followed by the United Kingdom, which accounts for approximately 20 percent. A potential reason for the popularity of these countries could be that they both have large stock market exchanges and that the reporting quality and transparency is very high. The remaining studies primarily cover different countries in Europe and Asia.

Country	**Frequency**	**Frequency (%)**
United States	50	45.5%
United Kingdom	20	18.2%
Finland	4	3.6%
Australia	3	2.7%
South Korea	3	2.7%
Lithuania	3	2.7%
Canada	2	1.8%
Japan	2	1.8%
Greece	2	1.8%
Turkey	2	1.8%
Czech Republic	2	1.8%
Slovakia	2	1.8%
Italy	1	0.9%
Indonesia	1	0.9%
Taiwan	1	0.9%
Norway	1	0.9%
Pakistan	1	0.9%
China	1	0.9%
Croatia	1	0.9%
Malaysia	1	0.9%
India	1	0.9%
Argentina	1	0.9%
Vietnam	1	0.9%
Other	4	3.6%
Total	**110**	**100.0%**

Table 3. Overview of Counties Studied; 1968 – 2019. The table provides an overview of the countries that have been studied in discriminate analysis in prior studies. The ‘Other’ category refers to studies examining more than one country. Source: Own analysis based on literature review in Appendix 1.

Overview of variables used in bankruptcy prediction

The third literature stream within bankruptcy prediction introduces new variables to the model in order to probe if they classify bankruptcy better. Table 4 includes variables that have been used in more than five of the studied 110 papers. Hence, niche variables specific to a certain industry are not depicted. Altman's original variables (marked in bold) are still widely used, which suggests that they continue to have a good bankruptcy predicting ability. Other popular variables include the Current Ratio, Return on Assets ("ROA"), Quick Ratio and Debt to Equity. In general, we observe that other variables included for predicting bankruptcy generally cover the same categories as Altman's 1968 model i.e. Activity, Liquidity, Solvency and Profitability.

Variable	**Frequency in previous studies**
EBIT / Total Assets	**32**
Working Capital / Total Assets	**29**
Sales / Total Assets (Asset turnover)	**28**
Retained Earnings / Total Assets	**26**
Current Ratio	26
Net Income / Total Assets (ROA)	25
Quick Ratio	17
Total Debt / Total Assets	14
Market Value of Equity / Book Value of Debt	**14**
Current Liabilities / Total Assets	13
Current Assets / Total Assets	11
Net Income / Sales	10
Net Income / Net Worth	9
Net Worth / Total Debt	8
Total Liabilities / Net Worth	7
Long Term Debt + Current Liabilities / Total Assets	7
Cash Flow / Total Debt	7
Working Capital / Sales	6
Quick Assets / Total Assets	6
Cash / Total Assets	6
Operating Income / Total Revenue	5
Net Cash Flow / Total Assets	5
Inventory / Sales	5
Sales / Current Assets	5
EBIT / Interest Expense	5
Shareholders' Equity / Total Assets	5

Table 4. Overview of Variables Studied; 1968 – 2019. The table provides an overview of the variables that have been used in discriminate analysis in prior studies. The table only contains variables that have been used in five or more academic papers. Source: Own analysis based on literature review in Appendix 1.

The previous sections indicate that several versions of Altman's original model exist today. Altman's original variables have been widely used in previously research suggesting that they still possess discriminating power if re-estimated to the specific time period. Hence, we hypothesise:

> **Hypothesis 1 (H_1):** Altman's original model has different coefficients and a lower prediction accuracy than the re-estimated Altman model.

4.2 Corporate governance and bankruptcy prediction

As shown in the preceding sections the majority of bankruptcy prediction models have focussed on accounting and market variables as discriminating factors for bankruptcy. Since the 1990s, a new research stream within bankruptcy prediction has emerged, which examines the classification ability of different corporate governance indicators. Several studies (Fich & Slezak, 2008; Parker et al., 2002; Chen, 2016) find that governance characteristics significantly affect the probability of bankruptcy and can therefore be used as a classification tool between the two groups. Chen (2008) compares the traditional financial ratio bankruptcy prediction model with one that contains additional corporate governance variables in Taiwan and finds a 2.9 percentage point improvement in model accuracy by including said indicators. Other studies, such as Daily and Danton (1994), find no major difference in accuracy when including corporate governance variables. However, the model still predicts bankruptcy with more than 90 percent accuracy. Lastly, Simpson and Gleason (1999) find that only specific corporate governance indicators, such as characteristics of the CEO and the board, have a significant effect on bankruptcy prediction.

Interest in research on bankruptcy prediction including corporate governance variables is expected to continue to grow due to (i) lack of research within the field, despite, high accuracy rates, (ii) improved availability, transparency and accuracy of corporate governance indicators driven by the SOX and (iii) other reforms such as the SEC's requirement on independent directors for companies listed on the NYSE and NASDAQ. On this basis we hypothesise:

Hypothesis 2 (H_2): Including corporate governance indicators in the bankruptcy prediction model decreases the number of Type I and Type II errors relative to the re-estimated Altman model.

4.3 Other accounting-based bankruptcy prediction models

The *Univariate model*, constructed by William Beaver (1966), was the first accounting-based bankruptcy prediction model dating back to the mid-1960s. The model examines the ability of a single financial indicator to predict the likelihood of bankruptcy and is based on a sample of 79 firms that went bankrupt in the period 1953 to 1964. The model was able to classify companies going into bankruptcy with 78 percent accuracy five years prior to the bankruptcy filing (Beaver, 1966). Advantages of the univariate model include statistical simplicity and intuitiveness, while the main drawbacks are the inability to test more than one variable at a time and its linearity assumptions. The univariate model has since been developed further (Pinches et al., 1975; Chen & Shimerda, 1981), but has never gained the same popularity in research when compared to other bankruptcy prediction models.

In response to the publication of the univariate model, Meir Tamari (1966) developed the *Risk Index model* in 1966 to address the issue of only including one variable. The model allocates a score to the company based on the performance of six financial ratios, weighted according to their importance. The greater the score, the less prone the company is to bankruptcy. Tamari (1966) tested the index on 28 distressed Israeli companies in the period from 1956 to 1960 and found that the group had a lower score than the industry average and that the ratios weakened as years to bankruptcy declined. The Risk Index model is simple, intuitive and easy to use. However, when tested on a larger sample of 130 firms the model only classified 52 percent correctly, thereby raising concerns regarding the robustness of the model. Additionally, the weighted contributions of the six variables are considered subjective. Other researchers such as Moses and Liao (1987) have since attempted to popularise the Risk Index model by removing the point allocation subjectivity but the model never seemed to gain a significant foothold in practice and was eventually replaced by Altman's MDA model.

Following a long period during which the MDA model was the undisputed bankruptcy prediction technique within corporate finance, researchers began to test bankruptcy prediction abilities of other statistical models known as the *Conditional Probability models*. In 1980, James Ohlson (1980) introduced a *Logit model* (O-Score) to test the explanatory power of financial ratios in predicting company bankruptcy. The O-score was constructed on a sample of 105 US bankruptcies in the period 1970 to 1976. The model generates a multivariate probability of failure score where if default is given by zero (one) then a corresponding low (high) score indicates a greater risk of failing. Advantages of the logit model include the independence from distribution assumptions, the direct probability output (no conversion to a probability of default score needed like e.g. the MDA model) and that each variable can be interpreted on an individual basis (Balcaen & Ooghe, 2006). Drawbacks to the model include a high sensitivity to multicollinearity and a time-consuming pre-modelling stage, as the logit model is sensitive to outliers, missing values and non-normal distributed samples. The logit model has become a popular bankruptcy prediction model and challenged the traditional MDA model.

Table 5 summarises the advantages and disadvantages of the accounting-based prediction models introduced in this section.

Model	**Advantages**	**Disadvantages**	**Original model**
Univariate	▪ Simple and intuitive	▪ Linearity ▪ Only includes one predictor variable	Beaver (1966)
Risk Index	▪ Simple and intuitive and easy to apply ▪ Includes more than one predictor variable ▪ Ratios are weighted according to importance	▪ Highly subjective (point allocation) ▪ Classification ability not robust	Tamari (1966)
MDA	▪ Includes more than one predictor variable (multivariate analysis) ▪ Continuous scoring system	▪ Linearity and cut-off value ▪ Ordinal measurement (ranking compared to other firms) ▪ Not resistant to severe multicollinearity	Altman (1968)
Conditional Probability	▪ Includes more than one predictor variable (multivariate analysis)	▪ Ordinal measurement (ranking compared to other firms ▪ Extremely sensitive to: (i) multicollinearity, (ii) non-normality of	Ohlson (1980)

▪ Continuous scoring system ▪ No linearity ▪ Output is a probability of default measure	independent variables, (iii) outliers and (iv) missing values

Table 5. Advantages and Disadvantages of Accounting-Based Bankruptcy Prediction Models. The table provides an overview of the pros and cons of the most popular accounting-based bankruptcy prediction models. Source: Own analysis based on literature review

4.4 Sub-conclusion

This section has given an introduction and an empirical overview of the MDA model. We find that the MDA model is still relevant and among the most popular bankruptcy prediction models. Further, the section has covered an extensive literature review of the MDA model and finds that a variety of studies have been conducted on different industries, countries and the introduction of new variables. We note that Altman’s five original variables are still widely used in research and it can therefore be hypothesized that the prediction power is still valid. Secondly, an overview of bankruptcy prediction models has been presented. The majority of previous research suggests corporate governance indicators have a positive impact on predicting bankruptcy. Lastly, to get a holistic overview and understanding of the MDA model, other accounting-based bankruptcy prediction models were briefly introduced, and their advantages and disadvantages presented.

5 Theoretical Literature Review

5.1 Agency problems and the role of corporate governance

Corporate governance issues arise when two conditions are present: (i) *an agency problem* (e.g. a conflict of interest) involving several stakeholders of an organisation; and (ii) *transaction costs*; such that the agency problem cannot be dealt with through a contract. Agency problems arise due to a misalignment of incentives combined with information asymmetry, which makes it difficult for the shareholders (principal) to monitor management (agent) (Jensen & Meckling, 1976). The shareholder can insert a board of directors, which can monitor the management on their behalf. However, this introduces yet another agency layer of which the effect has been discussed in literature at a board of directors and management level. Figure 5 illustrates the different levels of internal stakeholders in a corporation and their respective duties.

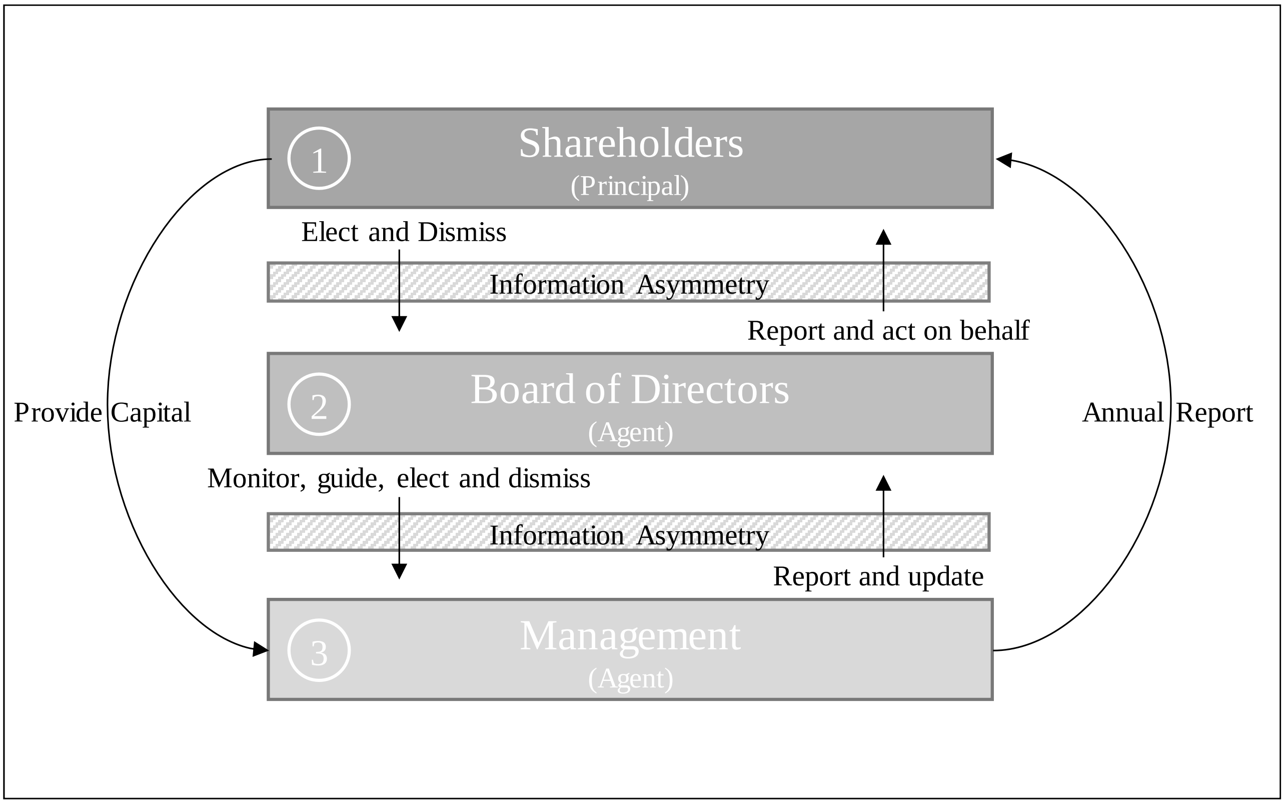

Figure 5. Levels of Stakeholders in a Corporation. The figure illustrates the three organisational layers of a corporation and the corresponding roles and duties key people have. Source: Own construction based on stakeholder theory (Jensen & Meckling, 1976).

The following sub-sections review corporate governance theory and construct bankruptcy hypotheses based on the three above-mentioned stakeholder levels. The section commences by addressing issues concerning the ‘*principal’* dimension (shareholders) and then moves on to the ‘*agent’* dimension (board of directors and management).

5.2 Shareholders

Blockholders and governance

According to Edmans 2014, the existence of agency problems can be attributed to the fact that managers have inadequate stakes in their firms. In other words, they do not have enough ‘*skin in the game*’ to sufficiently align their incentives.

The theory supports the notion that ‘*blockholders*’, defined as shareholders with over 5 percent equity stake, reduce the principal-agent problem for a firm. This can be explained by the fact that the sizeable stakes give them an incentive to bear the cost of monitoring managers. Moreover, these large shareholders possess the ability to exert governance through two mechanisms: (i) *voice* (direct intervention); and (ii) *exit* (indirect intervention). Direct intervention is defined as any action that an investor can undertake to enhance firm value but that is costly to the investor, such as suggesting strategic change via a public shareholder proposal or voting against a director. Indirect intervention implies a blockholder ‘*exiting*’ a firm by selling off their shares, thereby putting downward pressure on the stock and punishing the manager ex-post (Edmans, 2014). In the case of equity being highly dispersed, shareholders have been found to be too small and numerous to exercise control due to the associated cost, and therefore lack of incentive, in monitoring management.

Conversely, blockholders may also serve to exacerbate agency problems in a variety of ways. For example, a threat posed by blockholder intervention may erode managerial incentives, and their presence may lower trading liquidity. In addition, the theory of ‘*rent-seeking*’ can be extended to blockholders, who may take advantage of their influence to extract personal benefits as opposed to maximising firm value. Finally, there may be conflicts of interest arising between shareholders if a blockholder holds competing interests in a firm’s competitor or another firm related by the supply-chain.

> **Hypothesis (H_{2a}):** Bankrupt firms will have a lower number of blockholders compared to non-bankrupt firms.

5.3 Board of directors

A board of directors acts as a fiduciary on behalf of a company's shareholders, setting appropriate corporate policies to ensure prudent governance and curbing managerial discretion. In general, a board has three separate roles: (i) *monitoring*, (ii) *advising*; and (iii) *mediating among shareholders*, which all entail different allocations of authority.

Board ownership

Prior literature regarding board ownership and its influence on firm value and performance has been mixed. In extension of the prior hypothesis, Vishny (1997) presents the argument that blockholders, also in the form of board directors, provide effective oversight and monitoring due to their direct influence on decision-making via board votes. On the other hand, other papers hold an opposing view. For example, a paper by Morck et al. (1988) contends that greater board ownership leads to worse firm performance, as explained by theory of '*entrenchment*'. Entrenchment theory puts forward the idea that managers with large shareholdings place more emphasis on increasing market share and "*technological leadership*" as opposed to increasing profits. The negative impact of board ownership on firm value is further supported by Dwivedi and Jain (2005) and Séverin (2001), who examined this relationship within Indian and French contexts, respectively.

> **Hypothesis (H_{2b}):** Bankrupt firms will have a lower percentage of board ownership compared to non-bankrupt firms.

Board size

Existing conceptual literature regarding board size relies on a number of corporate governance theories: agency theory, resource dependency theory, and stewardship theory. Under the *agency theory*, there is reasonable supposition that added board members lead to an increased capacity to fulfil the monitoring and controlling functions. Similarly, *resource dependency theory* suggests that a greater number of board members contributes to broadening and diversifying the level of expertise and knowledge, which a firm can draw upon. Hence, from these two theories, the increased monitoring and controlling capabilities couples with a greater availability of resources is thought to lead to increased firm performance, indicating a positive relationship with board size. Conversely, *stewardship theory*, a normative alternative to agency theory, states that managers provide greater stewardship of the firms they manage when left on their own. In other words, "*the executive manager*, *under this theory, far from being an opportunistic shirker, essentially wants to do a good job, to be a good steward of the corporate assets*", implying "*there is no inherent, general problem of executive motivation*" (Donaldson & Davis, 1991).

In addition, Lipton and Lorsch (1992) argue the benefits brought about according to agency and resource dependency theory are outweighed by costs related to a slower decision-making process and greater reluctance to challenge established views and opinions. Their paper states that "*[...] the norms of behaviour in most boardrooms are dysfunctional*", since the views and policies of the management team are seldomly challenged or opposed. This relationship is believed to be exacerbated with board size.

Empirical literature regarding appropriate board size has generally concluded, with exception, that smaller boards are more productive, work more effectively, and reduce the likelihood of corporate fraud being committed. For example, Yermack (1996) finds that companies with a smaller board of directors generally achieve higher market valuation and exhibit more attractive financial ratios. We formulate our next hypothesis:

Hypothesis (H_{2c}): Bankrupt firms will have larger boards compared to non-bankrupt firms.

Board independence

According to Clarke (2007), an independent director can be defined as: "*one who has no need or inclination to stay in the good graces of management, and who will be able to speak out, inside and outside the boardroom, in the face of management's misdeeds in order to protect the interests of shareholders*". It can also be argued that the "*threat-rigidity thesis*" may be prevalent and affect decision-making at the board level. Specifically, assuming the existence of a dominant CEO reluctant to pursue alternative strategies to reverse financial decline, it can be conceptualised that a board with outside directors may be more successful in effectuating change. This notion is supported by prior studies which have shown that boards with strong outsider representation generally take a more active approach in making strategic decisions (Johnson et al., 1993).

There have been many different approaches to defining the status of '*independence*' of a board director. The traditional definition has been an individual who is not directly employed by the corporation. Despite its simplicity, this definition has been criticised for its lack of stringency. For example, if said individual has significant stock holdings in the firm or a personal relationship with the corporation or its CEO, this would likely jeopardise their '*true*' independence from the firm. To address this issue, certain studies have relied on a stricter definition inspired by the Securities and Exchange Commission's regulation 14A, Item 6b. This regulation stipulates the conditions under which a director's affiliation with a firm must be disclosed in proxy statement. In essence, any material relationships between the board members and the CEO and wider corporation must be disclosed (SEC, 1934). We regard this approach as being the most robust and therefore use it for our analysis. On this basis we formulate our next hypothesis:

> **Hypothesis (H_{2d}):** Bankrupt firms will have a lower ratio of independent board directors compared to non-bankrupt firms.

Board (gender) diversity

Over the past decade, the topic of board diversity, and the impact of female directors specifically, on firm performance has gained significant research interest. According to Robinson and Dechant (1997), having a diverse board composition can bring a number of benefits. Firstly, greater diversity is argued to enhance a firm's understanding of consumer preferences, as added diversity is more representative of the customer spectrum and employee base. Moreover, the paper states that greater diversity produces higher quality problem-solving and increases creativity and innovation (Robinson & Dechant, 1997). Finally, the paper argues that whilst board heterogeneity may at first create frictions between directors in terms of cooperating as a cohesive unit, it ultimately generates superior solutions to business challenges.

Both theoretical and empirical literature regarding female directors is inconclusive. On one hand, according to Adams (2008), a gender-diverse board composition leads to an enhanced monitoring function and effective oversight, which can lead to preventive measures being introduced earlier, reducing the risk of firm bankruptcy. Other studies claim that a higher proportion of female directors may not enhance monitoring due to the added risk of marginalisation and higher occurrence of conflicting opinions, which creates delays in decision-making (Mosakowski, 2000; Murnighan, 1998). Therefore, we hypothesize:

> **Hypothesis (H_{2e}):** Bankrupt firms will have a lower ratio of female board directors compared to non-bankrupt firms.

Duality (simultaneous CEO and Chairman)

In theoretical literature, the overarching conclusion regarding optimal CEO-board structures is that an individual serving as CEO should not simultaneously hold the role of board chairman (Dalton & Kesner, 1987; Zahra & Pearce II, 1989; Malette & Hatman, 1992). However, the empirical evidence is not nearly as substantive, and even conflicting at times, on the matter. For example, a study by Rechner and Dalton (1991) concluded that firms with duality outperformed other firms.

Moreover, Anderson and Anthony (1986) make the argument that a joint structure creates a single point of command, which yields "*no ambiguity about responsibility*". However, a single point of command is not necessarily ideal under certain situations, particularly when a firm is approaching bankruptcy. A study by D'Aveni (1992) showed that firm bankruptcy was more likely under the reign of a '*dominant*' CEO. Resistance to changing opinion or altering strategy is known as the "*threat-rigidity thesis*" (Staw et al., 1981). Given the fact that firm bankruptcy is generally not caused by a singular event, but rather the result of a "*protracted process of decline*" and deteriorating performance (Hambrick & D'Aveni, 1988), this would imply that management would have some room to implement changes to turn around the business. Hence, it can be theorised that the coupling of an assertive CEO, reluctant to changes in strategy and processes, simultaneously serving as chairman of the board, is unlikely to take advantage of the limited opportunity to make the changes necessary to alter course. Accordingly, we formulate our next hypothesis:

> **Hypothesis (H_{2f}):** Bankrupt firms will have a higher incidence of CEO duality compared to non-bankrupt firms.

5.4 Management

CEO tenure

Existing literature on CEO tenure generally shows that firm performance follows a negative parabola or inverted U-shaped curve, with performance initially increasing before reaching a plateau, after which performance subsequently declines (see Appendix 2). The reason for this trend can be explained by the fact that a CEO tends to gain significant knowledge during the initial phase of their tenure and is more willing to take risks. As time passes, the CEO gradually amasses more expertise and knowledge thereby enhancing the company's performance (Wu et al., 2005). However, at a certain point, the CEO becomes more complacent, risk-averse, and reluctant to adapt to changes in the business environment, which ultimately leads to deteriorating performance (Miller, 1991; March, 1993).

Another interesting theory was proposed by Miller and Shamsie (2001): CEO tenure can both positively and negatively affect firm performance depending on the stage of the CEO's '*life cycle*'. The term '*life cycle'* is intended to capture the idea that over the course of an individual's working life, there are certain periods in which said individual is more or less productive. In other words, individual productivity is not constant over their working life. This has implications for CEO tenure as an input parameter and its analytical interpretation. Notwithstanding, the majority of empirical studies have concluded that CEOs with longer tenure are associated with lower returns (Luo et al., 2014). On this basis, we formulate our next hypothesis:

> **Hypothesis (H_{2g}):** Bankrupt firms will have higher CEO tenure compared to non-bankrupt firms.

CEO change/turnover

If the board determines the incumbent CEO is not delivering satisfactory results and achieving the full potential of the business, they may choose to dismiss and replace the individual. According to Cheng et al. (2014) the decision to replace a CEO reflects the board's effort to reclaim control and power over a firm due to the "*destabilization of governance equilibrium"*. Other studies have theorised that high turnover within a management team or other key job functions can serve as an early indicator for business failure (Evans et al., 2014). Due to the nature of certain CEO compensation being strongly performance-based (i.e. variable), a CEO may be tempted to '*jump ship*' if they do not believe they will be able to turn company around or reach performance targets. Having said this, other papers argue that CEO dismissals are generally associated with positive stock-market reactions, suggesting the decision is value-creating (Furtado & Rozeff, 1987; McCahery, 2003; Mansi, 2009).

There are two academic theories, which can be used to explain this phenomenon: (i) *scapegoat theory*; and (ii) *improved management theory*. Scapegoat theory (Hölmstrom, 1979) assumes all managers are equally qualified and proficient, and that poor firm performance is therefore a function of bad luck and not managerial quality. Hence, in the case of poor performance, the board will dismiss the

CEO, thereby using them as a '*scapegoat*'. Improved management theory (Huson et al., 2004) states that boards choose to replace incumbent CEOs if their realised performance does not meet the board's expectations, and the costs of replacement are outweighed by the benefit of bringing on a new CEO.

The results from empirical literature regarding CEO turnover and bankruptcy risk are divided. Finkelstein et al. (2009) argue that dominant CEOs face a lower risk of being replaced relative to less dominant CEOs. When considering this finding in relation to the '*threat-rigidity'* theory outlined earlier, one can theorise that lower turnover can suggest the existence of a dominant CEO, which may increase the likelihood of bankruptcy. However, this is in contrast to the findings of Mokarami & Motefares (2013), which found that firms with higher CEO turnover frequency are more likely to file for bankruptcy. A more recent study conducted by Darrat et al. (2016) found that bankruptcy risk is lower if a CEO change takes place within the prior three years. On this basis, we hypothesize that:

> **Hypothesis (H_{2h}):** Bankrupt firms will have a higher incidence of CEO turnover compared to non-bankrupt firms.

Performance-based compensation

The traditional way to motivate senior management teams to make decisions in the best interest of the shareholders (i.e. achieve profit-maximisation) is via incentive compensation risk. Incentive compensation risk involves tying executives' personal wealth to firm performance. This can be done through a variety of compensation items, such as the proportion of variable (performance-based) salary tied to certain milestones or financial metrics, pay-outs from long-term incentive plans, stock options, performance share units, etc. Hence, through a well-structured compensation scheme, including a large proportion of variable pay (options and stocks), the agency problem can be mitigated.

Empirical studies have yielded interesting results regarding incentive compensation and firm performance. A study by Sun et al. (2013) found that firm efficiency is positively correlated with total executive compensation. In addition, according the same study, revenue efficiency is positively associated with cash compensation, whilst cost efficiency is associated with variable compensation. It has also been shown that CEOs with a high sensitivity to stock price performance generally pursue riskier investment policies, have a higher appetite for leverage, invest more resources into R&D

activities, and possess a higher degree of operational focus (Coles et al., 2006). On this basis, we formulate our next hypothesis:

> **Hypothesis (H_{2i}):** Bankrupt firms will have a lower degree of performance-based CEO compensation compared to non-bankrupt firms.

CEO ownership

The role of CEO is viewed as being the single-most important position within a firm, as this individual is in charge of making high-level strategic decisions to determine its overall direction. Hence, following from the principal-agent problem, it would seem self-evident that an alignment of this individual's interest with shareholders would result in superior performance.

The empirical literature has presented interesting results. Griffith (1999), studied the influence that the level of CEO ownership of a firm's common stock has on the value of the firm. Notably, the paper found that firm value was a non-monotonic function of CEO ownership, rising between 0 to 15 percent, declining thereafter until 50 percent, rising again above 50 percent to 100 percent. These results are further reinforced by a recent study from Papadopoulos (2019), who noted that increases in profit margins and profitability momentum were associated with increased CEO ownership in dollar terms. We formulate our final hypothesis:

> **Hypothesis (H_{2j}):** Bankrupt firms will have a lower percentage of CEO ownership compared to non-bankrupt firms.

6 Hypothesis Summary

Table 6 provides an overview of the hypotheses developed in the preceding sections.

Hypothesis	**Description**
H_1	Altman's original model has different coefficients and a lower prediction accuracy than the re-estimated Altman model
H_2	Including corporate governance indicators in the bankruptcy prediction model decreases the number of Type I and Type II errors relative to the re-estimated Altman model
H_{2a}	Bankrupt firms will have a lower number of blockholders compared to non-bankrupt firms
H_{2b}	Bankrupt firms will have a lower percentage of board ownership compared to non-bankrupt firms
H_{2c}	Bankrupt firms will have larger boards compared to non-bankrupt firms
H_{2d}	Bankrupt firms will have a lower ratio of independent board directors compared to non-bankrupt firms
H_{2e}	Bankrupt firms will have a lower ratio of female board directors compared to non-bankrupt firms
H_{2f}	Bankrupt firms will have a higher incidence of CEO duality compared to non-bankrupt firms
H_{2g}	Bankrupt firms will have higher CEO tenure compared to non-bankrupt firms
H_{2h}	Bankrupt firms will have a higher incidence of CEO turnover compared to non-bankrupt firms
H_{2i}	Bankrupt firms will have a lower degree of performance-based CEO compensation compared to non-bankrupt firms
H_{2j}	Bankrupt firms will have a lower percentage of CEO ownership compared to non-bankrupt firms

Table 6. Hypothesis Summary. The table provides an overview of the hypothesis developed from the literature review which will be tested empirically.

Part IV

Methodology and Data

This section presents the data and methodology used in the study. Firstly, we outline the development of our methodology based on the '*research onion*' framework (Saunders & Thornhill, 2007). Secondly, we introduce the multiple discriminant analysis model and the corresponding statistical robustness and validation tests. Finally, we present the sample of bankrupt and non-bankrupt firms, the data collection process and the chosen variables. Throughout the section we underline the considerations and choices made in selecting the methodology.

7 Methodology

7.1 Research philosophy, approach and strategy

Along with other bankruptcy prediction studies, we use a scientific method to probe our research question and follow the positivism epistemological perspective. In other words, our approach is based on a scientific method with the purpose of making legitimate knowledge claims. Our research process integrates a string of knowledge sources, including authoritarian, empirical and logical knowledge, within a single study. Specifically, authoritarian knowledge is gained via our literature review of corporate governance theories, logical knowledge is generated via our data analysis, and empirical knowledge is gained via the conclusions found in our study.

Furthermore, our paper employs a deductive research approach, developing a range of hypotheses formulated on the basis of findings from prior studies and relevant literature. Hereafter, the paper seeks to test these hypotheses via a statistical technique, multiple discriminant analysis, and examine the outcome. Specifically, we investigate the predictive ability of three bankruptcy prediction models. Bankruptcy prediction modelling is quantitative by nature as estimation models are typically constructed based on numerical data points. The collection of data involves the use of secondary data techniques.

7.2 Multiple discriminant analysis

Our paper employs multiple discriminant analysis. This method was originally developed by Ronald Fisher (1936) and has subsequently been adopted within a wide range of fields from neurology to bankruptcy prediction (Altman, 1968). Its objective is to construct discriminant functions for objects assigned to two groups by finding linear combinations of the variables, which maximise the differences between the populations being studied.

There are several parallels between discriminant analysis and multiple regression analysis. Both methods have two uses: prediction and description. The principal difference between the two methods is due to the nature of the dependant variable. Regression analysis deals with a continuous (quantitative) dependent variable, where the independent variables are used to determine a linear function, which will estimate the values of the dependent variable. On the other hand, discriminant analysis must have a discrete (qualitative) dependent variable. In effect, discriminant analysis creates a function from the independent variables, which discriminates between the conditions of the dependent variable. The factor loadings, also known as '*discriminant coefficients*', assigned to the independent variables are adjusted for interrelationships among the variables. Often, the dependent variable represents two or more categories or groups.

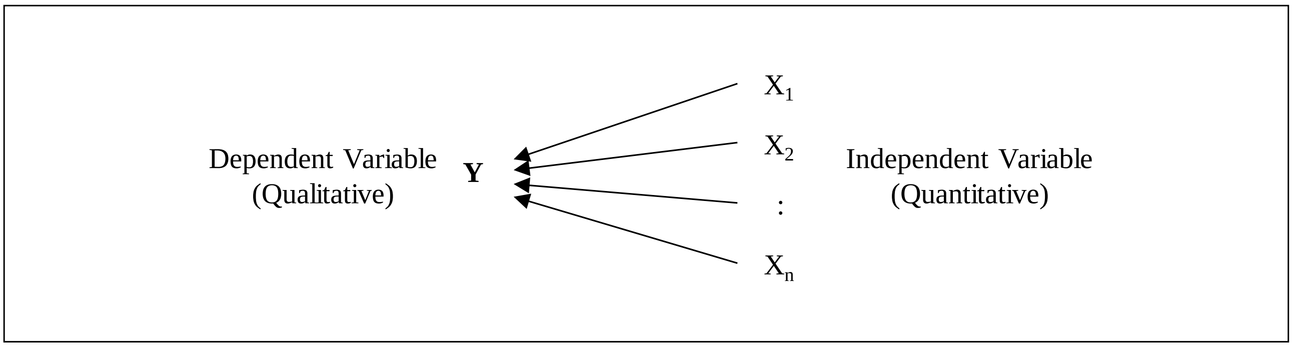

Figure 6. Illustration of the MDA Model. The figure describes the mechanisms of the MDA model and depicts how quantitative independent variables have an impact on the qualitative dependent variable.

For example, let us consider a set of n variables, X_1, X_2 ,..., X_n, via which we wish to discriminate between two groups of firms. We let:

$$Z = b_0 + b_1 \cdot X_1 + b_2 \cdot X_2 + \cdots + b_n \cdot X_n,$$

Where:

Z : the latent variable formed by a linear combination of the independent variables

X_n : the n independent variables

b_0 : the intercept

$b_1, b_2, \ldots, b_n$: the discriminant coefficients

MDA assumptions

A number of assumptions underlie the MDA model:

1. The variables X_1, X_2, X_3, are independent of each other
2. Groups are mutually exclusive and the group sizes are not materially different
3. The number of independent variables is not more than two less than the sample size
4. The variance-covariance structure of the independent variables are similar within each group of the dependent variable
5. Errors (residuals) are randomly distributed
6. For purposes of significance testing, the independent variables are assumed to follow a multivariate normal distribution

The discriminant analysis results in an overall index for each observation based on the weightings of the independent variables. In bankruptcy prediction this index is known as the Z-score and can be computed for each observation (firm). The higher the score, the healthier the firm is, and the less prone it is to go bankrupt. The opposite holds true.

7.3 Model validation techniques

Type I and Type II errors

Type I and Type II errors can be observed to determine the prediction accuracy of the discriminant model. Table 7 shows the possible outcomes of the model prediction estimates.

Actual Membership	**Predicted Membership**	
	Bankrupt	*Non-Bankrupt*
Bankrupt	Hit	Miss (Error I)
Non-Bankrupt	Miss (Error II)	Hit

Table 7. Illustration of Type I and Type II Errors. The table illustrates the different errors bankruptcy prediction models generate in a two by two matrix. Source: Huberty and Olejnik (2006).

A *Type I error* refers to a misclassification where a bankrupt company is misclassified as a non-bankrupt company (false positive). Alternatively, a *Type II error* occurs when a non-bankrupt firm is classified as a bankrupt firm (false negative).

The sum of the diagonal values (‘*Hits*’) equals the number of correct predictions the model has made. The prediction accuracy of the discriminate model is therefore defined as:

$$\text{Prediction Accuracy} = \frac{\text{Sum of correct predictions (Hits)}}{\text{Total number of classified companies}}$$

This percentage has a similar interpretation as the Pearson correlation coefficient (R^2) in a regression analysis and reflects the accuracy of the model in predicting bankruptcy (Altman, 1968).

Secondary sample

A common method of carrying out an external analysis and validation of the prediction model is to divide the sample into two groups (i) an *estimation sample*, in which the prediction model is constructed on and (ii) a *secondary (holdout) sample*. The prediction model is then applied to the secondary sample and the prediction accuracy examined (Huberty & Olejnik, 2006). This approach is an acknowledged validation method but requires a large sample, which is not always easy to obtain, especially in bankruptcy prediction.

7.4 Measurements of model fit

Wilks’ lambda

One test which can be used to determine the contribution of variables is the Wilks’ lambda (Λ) test (Wilks, 1932). It determines how much of the variance is explained by the independent variables and is given by the following equation:

$$\Lambda = \frac{|E^*|}{|T^*|}$$

Where:

Λ : Wilks’ lambda

E^* : Determinant of the of the adjusted error matrix

T^*: Adjusted total matrix

If the independent variables only explain a fraction of the variance, it can be argued that there is no effect of the grouping variable (the ratios) and the groups (bankrupt and non-bankrupt) have no different mean value (Klecka, 1980). The closer the test gets to zero, the more the variable helps to discriminate between the two groups and hence the better the model is. The Wilks' lambda test is computed together with a Chi-squared statistic which determines the significance of the Wilks' lambda test. A rejection of the null hypothesis concludes that the discriminant function classifies group membership well.

Eigenvalue analysis

The purpose of the eigenvalue analysis is to determine whether two sets of variables are related. The larger the eigenvalue, the greater the variance explained by the function in the dependent variable. When the model only contains two grouping variables, the canonical correlation coefficients provide a better indication of the model fit (Huberty & Olejnik, 2006). The squared canonical correlation coefficient is known as the '*effect size*' and expresses the magnitude or strength of the relationship between the discriminate scores and the grouping variables (Cohen, 1988). The effect size can be compared to the R-squared value in a regression analysis.

Receiver Operator Characteristic

Receiver Operator Characteristic ("ROC") is a widely recognised diagnostic accuracy test used for validating classification models and examining their predictive ability (Shatnawi et al., 2010). Empirically, it is typically used to compare the predictive ability between two models (Agarwal & Taffler, 2008). The test illustrates the predictive ability of the binary classifier (bankrupt and non-bankrupt) as the discrimination cut-off value is varied. The graph's y-axis states the true positive rate, a situation where the model has correctly classified a company as non-bankrupt. The x-axis depicts the false positive rate, a situation where a company has been incorrectly classified as non-bankrupt. The diagonal 45-degree dashed line on the graph indicates the results if the model took a random guess between the two binary variables, i.e. a 50:50 chance of getting the correct classification.

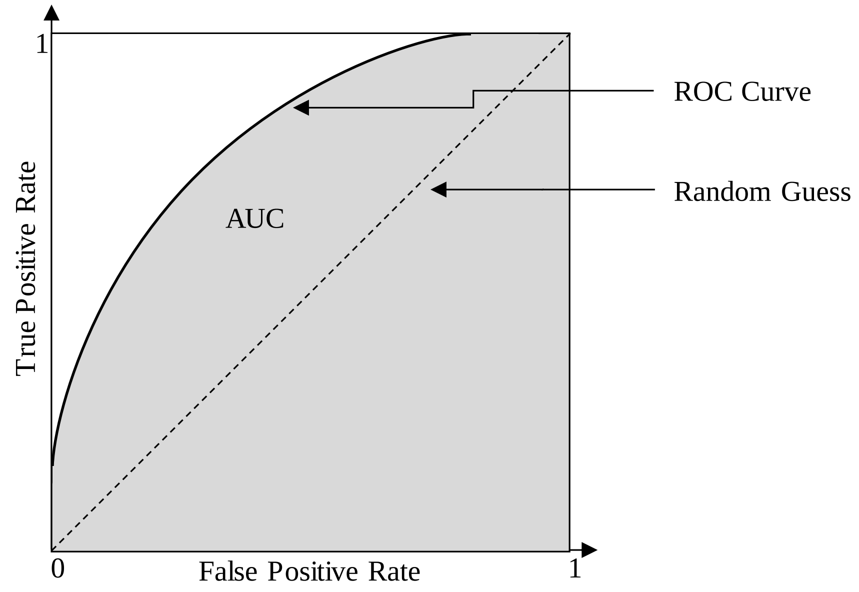

Figure 7. Illustration of the ROC Curve. The vertical axis indicates the number of correct predictions and the number of the false predictions are shown on the horizontal axis. The further the curve is to the top left the greater is the prediction accuracy. The dashed line represents a random guess i.e. a 50 percent probability of getting the prediction right. Source: Own illustration based on Hosmer and Lemeshow (2000).

The grey area under the ROC curve, Area Under Curve ("AUC"), ranges from zero to one and provides a measure of the model's ability to discriminate between the two binary classifiers. The closer the ROC curve is to the top left corner, the greater the AUC will be and the better the model is in predicting bankruptcy. Hosmer and Lemeshow (2000) have developed a general rule for the values of ROC and the corresponding predicting ability:

- If AUC = 0.5 — *No* classification ability (random guess)
- If 0.7 ≤ AUC < 0.8 — *Acceptable* classification ability
- If 0.8 ≤ AUC < 0.9 — *Excellent* classification ability
- If AUC ≥ 0.9 — *Outstanding* classification ability

7.5 Sources of model bias

The discriminant bankruptcy perdition model is prone to two overall types of biases (i) *sampling bias* and (ii) *search bias*. These biases may have an impact on the prediction accuracy and should therefore be examined.

Sampling bias

Sampling bias stems from sampling errors when creating the original data set, which is used for the construction of the prediction model. The nature of bankruptcy is such that the number of occurrences makes up a significant minority relative to the total population comprising all companies.

We consider the following equations:

- Proportion of bankrupt firms in sample: $s_1 = \frac{n_1}{N}$
- Proportion of non-bankrupt firms in sample: $s_2 = \frac{n_2}{N}$
- Proportion of bankrupt firms in population: $p_1 = \frac{b}{P}$
- Proportion of non-bankrupt firms in population: $p_2 = \frac{h}{P}$

As such, the number of non-bankrupt firms (h) is far greater than that of bankrupt firms (b). However, this relationship is generally not reflected in past bankruptcy prediction studies, and the choice of firms is therefore not representative of the population. It is important to note this mismatch creates imbalances in the data samples from a statistical point of view. The vast majority of prior bankruptcy prediction models have relied on '*matched-pairs sample design*' to construct '50:50' samples (Skogsvik & Skogsvik, 2013). The '*matching technique'* is an approach in which every bankrupt firm is 'matched' to a non-bankrupt firm, which shares similar characteristics in terms of industry, size, etc.

A sample may be considered unbalanced in two ways:

i. if s_1 and s_2 are not equal (i.e. the amount of bankrupt and non-bankrupt firms is not equal)
ii. if the proportions s_1 and s_2 differ from their relative proportions in the population p_1 and p_2

Again, the nature of corporate bankruptcies is such that both criteria cannot be met simultaneously. For example, in order for condition (i) to be true, this would imply an underrepresentation of non-bankrupt firms, which violates condition (ii). Vice versa, if the relative proportions of bankrupt and non-bankrupt firms in the sample are to equal those in the population, this would violate condition (i).

We note that as our data was collected via the matching method, it may suffer from non-random sampling biases, which is common among these types of studies. Specifically, the sample is prone to selection bias (Platt, 2002), which occurs as a result of observations with incomplete information or particular industries being discarded from the sample.

Search bias

Search bias arises when the model parameters are chosen. Initially, a group of variables is presented, which later is condensed into a smaller number of variables, which feed into the discriminant model. This process can contain some bias, as a subset of variables may be effective in the estimation sample but there is no guarantee that this holds true for the population. Bias arising from extensive search is inherent in any empirical research (Frank et al., 1965).

Acknowledging this, it is therefore important that a second sample is introduced from which data has not been used to construct the prediction model. We denote this the secondary sample. If the secondary sample data predicts bankruptcy correctly while employing the parameters of the estimation model, it can be concluded that the model possesses discriminating power and that a significant search bias is not apparent. In other words, the estimation model can be used to discriminate between observations other than those used to estimate the model and can be applied to the total population.

8 Discussion of Sample, Data Collection and Variables

The following section presents and describes the data set used in conducting the empirical analysis in Section 9. Firstly, the underlying sources from which the data set was constructed are outlined. Secondly, the data treatment process and variables' expected effects are described and discussed.

8.1 Time period (2012-2018)

The paper studies bankruptcies occurring in the post-Global Financial Crisis period. We define this as the period between 2012 and 2018. We limit our study to this specific period due to three reasons. Firstly, we wish to isolate the effect of governance and firm health. Therefore, we need to control for the overall industry and macroeconomic environment, which may affect the likelihood of bankruptcy independently, as pointed out by Chen et al. (2016). The study is therefore limited to the post-Global Financial Crisis period to avoid any potential distortions to the financial data and thereby our model estimates. Secondly, after the collapse of several big corporates in the early 2000s and following the Global Financial Crisis, more legal requirements on reporting, especially on corporate governance metrics, were introduced. Therefore, the quality, uniformity and availability of corporate governance data is of a higher calibre than before the Global Financial Crisis. Lastly, as is evident from our empirical literature review, there is a lack of research examining bankruptcy prediction and corporate governance during this time period.

8.2 Data sources

We use four databases to gather our secondary data and construct and validate our unique data set. To sample data on corporate governance indicators we employ EDGAR, a public database operated by the US Securities and Exchange Commission (SEC). To collect financial data, we use a combination of three subscription-based services: Bloomberg, Compustat and Orbis BvD. In addition to the primary databases we use Factiva for bankruptcy validation of and FRED for empirical background on bankruptcies in the US. All databases used are introduced in more detail below.

EDGAR

The Electronic Data Gathering, Analysis, and Retrieval (EDGAR) database is a public database hosted by the US financial regulator the SEC. All publicly traded companies are required by law to file registration statements, periodic reports (e.g. 10-K (Annual Report), 10-Q (Quarterly Report)) and other forms electronically. EDGAR processes about 3,000 filings per day and accommodates 40,000 new filers per year on average (SEC, 2020).

The EDGAR database is used to collect data on corporate governance indicators. Following the ratification of the 2002 SOX, companies are now required by law to disclose different governance metrics in their 10-K filings. Screening 10-K statements individually is a time-consuming but necessary task, given the limited availability of data on bankrupt companies in commercial databases. For example, a popular database on executive pay, Capital IQ's ExecComp Analytics, deletes data on companies that have filed for bankruptcy and director data from Orbis is similarly removed for bankrupt companies. We note that collecting data directly from EDGAR enhances the reliability of the data, as it is taken directly from the primary source.

10-K

Part III of the 10-K comprises specific information on corporate governance indicators. Item 10 contains information on the background and qualification of management and the board of directors. Item 11 covers executive compensation including a detailed breakdown of the payment components. Item 12 illustrates the beneficial owners (i.e. holders of more than 5 percent of common equity) as well as management ownership. Lastly, Item 13 includes data on director independence and discloses potential relationships amongst different company stakeholders.

Section 302 of the SOX, '*Corporate Responsibility for Financial Reports*', requires that both the CEO and CFO of listed companies certify that their financial disclosures are fairly presented and reflect the true operational and financial condition of the company. Also, the 10-K is audited. The 10-K is therefore viewed as a very accurate source of data.

DEF 14A

Certain times, Part III is omitted from the 10-K and presented in a different document known as DEF 14A. DEF 14A is a definitive proxy statement and is required by law ahead of meetings involving shareholder voting. It acts as the investors' main source of information in understanding a specific company's corporate governance practises and describes the board of directors, management, compensation practices and discloses blockholder ownership.

Bloomberg

The Bloomberg terminal is a financial database that contains information on all listed companies worldwide. Bloomberg has been widely used for the collection of secondary financial data in bankruptcy prediction studies (Almamy et al., 2016). We extract financial data for our entire sample from Bloomberg to ensure that figures are consistent across the different companies.

Compustat

Compustat is a comprehensive financial database owned by S&P Global Market Intelligence which contains fundamental financial and price data for more than 24,000 active and inactive publicly traded companies. Compustat is used to identify and construct the bankrupt sample.

Orbis (BvD)

Orbis Bureau van Dijk is a financial database owned by Moody's Analytics comprising financial information for more than 100 million companies worldwide. Orbis' Boolean search tool is particularly useful in constructing different groups of companies based on different search criteria such as size, location, industry etc. Orbis is used to define and identify the non-bankrupt group based on the characteristics of the bankrupt sample as per the '*matching technique*' described in Section 8.

Other

Our paper also employs two additional databases, FRED (the Federal Reserve Economic Data), and Factiva. Factiva, an international news database hosted by Dow Jones, is employed to validate our bankrupt sample. FRED, which is managed by the Research department of the Federal Reserve Bank of St. Louis, is used for providing empirical background on the bankruptcies in the United States.

8.3 Data sampling

The following sub-sections will explain the stepwise process and considerations behind constructing our sample. Firstly, we gather a list of bankrupt firms. Then the group is matched with non-bankrupt firms that share similar characteristics in terms of location, industry and size. Particular emphasis is placed on the selection process, as the underlying data will be used for estimating the coefficients of the discriminant model.

Bankrupt sample

The bankrupt sample was initially envisaged to be constructed using the Orbis BvD database and the corresponding Boolean search tool, which facilitates a search adhering to multiple criteria. However, after review of the extracted data, the bankruptcy identification criterion was deemed to be of poor quality and inconsistent across years due to two critical sampling limitations. Firstly, the search tool was unable to recognise that companies with a bankruptcy status in the database, which are naturally not publicly listed anymore, may have been listed before filing for bankruptcy. Introducing this criterion limited the sample to companies recently filing for bankruptcy and therefore not the entire study period (2012-2018). Secondly, Orbis did not provide a complete picture of all bankruptcies, as they were removed from the database on a rolling basis. Hence, potentially relevant bankruptcies would not have been retrieved.

To avoid these limitations, we use Standard and Poor’s Compustat to compile a list of bankrupt companies. Compustat does not have the same detailed Boolean Search tool as Orbis, but its bankruptcy identification of listed companies is more accurate and has been used in previous empirical corporate finance papers (Corbae & D'Erasmo, 2017).

Search criteria

Our sample is extracted by applying the following search criteria.

<u>Criteria 1: US publicly listed companies</u>

The criteria of including only publicly listed companies was chosen to ensure established corporate governance structures. This is due to companies listed on security exchanges, such as the New York Stock Exchange and NASDAQ, being subject to particular listing guidelines and standards, including disclosing corporate governance practices.

<u>Criteria 2: Chapter 11 bankruptcy</u>

Like other databases, Compustat deletes companies that have gone bankrupt but retains a historical log that describes the date and reason for deletion. For a deleted firm to be counted in the sample it must have the deletion code 02 (i.e. Chapter 11 bankruptcy). We only include companies that have filed for bankruptcy under Chapter 11 of the US Bankruptcy Code, in line with common practise in previous bankruptcy prediction literature (Betker, 1995; Brockmann et al., 2004; Balcaen & Ooghe, 2006). As discussed in Section 2, by selecting only firms which have filed for bankruptcy under Chapter 11, homogeneity in the bankruptcy status is achieved, and the predictive power of the variables is unaffected by sample heterogeneity. We do not consider other reasons for deletion such as 01 (Mergers and Acquisitions), 03 (Liquidation associated with Chapter 7) or 04 (reverse acquisition).

Criteria 3: Selected industry exclusion

Finally, we exclude Finance and Insurance as well as Real Estate Rental and Leasing companies from the sample due to their unique characteristics. For instance, for financial services firms, high leverage is a 'normal' part of their business operations, which does not necessarily indicate financial distress as is often the case for non-financial companies. Industry groups are defined according to the North American Industry Classification System or NAICS classification (See Appendix 3). The NAICS is used extensively in the United States, Mexico and Canada and has superseded the Standard Industry Classification (SIC) and is therefore deemed relevant for classification purposes.

Resulting gross sample of bankrupt firms

After applying these criteria, we generate a gross sample of 864 firms that went bankrupt in the period 2012 to 2018. Following our gross data sample screening criteria, we amend the data based on a number of considerations. Firstly, duplicate firms (three firms) were discarded from the sample. Secondly, due to the nature of our research question, we introduce a size criterion as the financial ratios of small firms have been found to be less robust and therefore not as appropriate for statistical modelling (Balcaen & Ooghe, 2006). Hence, firms with assets below USD 50m in the last available reporting year are discarded. This reduces the sample to 159 firms. Next, we randomly select 60 firms. The number of observations is in line with previous studies and follows Altman's (1968) methodology. We cross-reference and verify the accuracy of each of the 60 observations with Factiva to ensure that bankruptcy has occurred in said year and find no discrepancies.

Datapoint collection

Financial data for our sample of 60 firms are collected from Bloomberg through their company tickers. Unlike Compustat, Bloomberg does not delete historical data on bankrupt firms and is therefore deemed a superior financial database for this research purpose (Almamy et al., 2016).

Corporate governance variables are sampled from the EDGAR (SEC) database by going through individual company 10-K or DEF 14A fillings. In order to ensure that our data set is complete and comprehensive, we exclude companies where all data points for the estimation year (one prior to bankruptcy) have been unable to retrieve. Our final bankrupt sample contains 51 companies that have filed for Chapter 11 bankruptcy in the period 2012 to 2018.

Non-bankrupt sample

The non-bankrupt sample is constructed using the '*matching technique*' described in Section 8. This method has been widely used in previous research such as Altman (1968), and more recently Almamy et al. (2016) and Chan et al. (2016). As the name suggests, the sample is composed by selecting companies that match the initial bankrupt sample on three parameters namely: (i) *geographic location*, (ii) *industry*; and (iii) *asset size*. By controlling for these factors, we limit any exogenous impacts to our model. Additionally, the sample is drawn from the same time period as the bankrupt sample, from 2012 to 2018. We set the maximum asset size to USD 5,000m, as this is the largest observation in the non-bankrupt data set. In order to construct the non-bankrupt sample group, we use Orbis' Boolean search function to apply the criteria described above. The sample selection process is shown in Appendix 4.

<u>Resulting gross sample of non-bankrupt firms</u>

The search yields a sample of 2,563 firms. We follow the approach set out for the bankrupt sample and collect the financials of these firms from Bloomberg using individual company tickers. In order to pick financially sound firms, we screen for operating income (EBIT) and remove companies with three years of consecutive negative EBIT, as they do not display the characteristics of a financially healthy firm. Additionally, we remove companies with fewer total asset than ten million USD to match the bankrupt sample thus ultimately reducing the sample to 731 firms. Next, we use the same techniques as employed in previous studies and select the 51 non-bankrupt firms to match the bankrupt sample by industry. Finally, the financial data from the non-bankrupt sample is aligned to the bankrupt sample based on the year of bankruptcy. For example, if six companies from the bankrupt sample go bankrupt in 2014 then we match the financial data of six of the non-bankrupt sample to this time frame. In this way we ensure that time effects are considered.

Like the bankrupt sample corporate governance data is sampled from EDGAR (SEC) by looking at individual company 10-K and DEF 14A filings. This is done to ensure consistency of the data across the two groups.

Estimation sample and secondary (hold-out) sample

The total sample of 102 companies is divided into two groups: (i) the *estimation sample* and (ii) the *secondary sample*. The estimation sample comprises 30 bankrupt companies and 30 non-bankrupt companies and is used to construct the prediction model. The sample size fulfils the empirical modelling of Altman (1968).

The secondary (or hold-out) sample contains the remaining 21 bankrupt companies and 21 non-bankrupt companies and will be used to validate the prediction model. As they have not been part of the estimation sample, they are not prone to any upwards prediction bias.

The estimation sample of 60 US firms (30 bankrupt and 30 non-bankrupt) and our secondary sample of 42 US firms (21 bankrupt and 21 non-bankrupt) form the basis for the empirical analysis.

8.4 Variable selection

Our paper considers the financial ratios Altman (1986) originally used for the development of his 1968 discriminate model and a group of corporate governance indicators selected based on their empirical and theoretical relevance. This sub-section will firstly present the financial ratios chosen and thereafter describe the rationale for including various corporate governance metrics.

Financial ratios

Variables in bankruptcy prediction are typically selected based on: (i) *popularity in literature*; (ii) *relevance to the particular study*; and (iii) *significance in predicting bankruptcy in previous studies* (Altman, 1968; Blum, 1974; Taffler, 1982; Almamy et al., 2016). As noted by Taffler (1982), a thorough review of past literature does not provide a solid theoretical justification for using certain financial ratios as opposed to other. We include all five of Altman's original ratios in order to re-estimate the model coefficients in the post-Global Financial Crisis period. Our literature review provides strong evidence suggesting that these variables are still commonly used and popular within bankruptcy prediction studies. The variables and their source are described in Table 8.

Variable	Description	Database
X_1: Working Capital / Total Assets	Measure of company liquidity	Bloomberg Terminal
X_2: Retained Earnings / Total Assets	Measure of cumulative profitability	Bloomberg Terminal
X_3: EBIT / Total Assets	Measure of the true productivity of assets	Bloomberg Terminal
X_4: Market Value of Equity / Book Value of Debt	Measure of insolvency	Bloomberg Terminal
X_5: Sales / Total Assets	Measure of capital turnover	Bloomberg Terminal

Table 8. Overview of Financial Variables. The table presents the financial ratios which are tested in the paper Additionally it adds a description of the main focus of the variable and which database it is retrieved from. Source: Bloomberg.

The ratios have been manually constructed by extracting the financial data from Bloomberg and have not directly been extracted as a ratio, due to unavailability. In the pre-modelling stage, each variable's discriminating ability is tested to determine the individual contribution to the overall classification accuracy of the model.

Working Capital to Total Assets (X_1)

This ratio measures the firm's overall liquidity. We follow Altman's (1968) specification of Working Capital, defined as a firm's Current Assets less Current Liabilities. When a company is experiencing sustained losses, the current assets will shrink and hence give liquidity issues as it cannot meet its current liabilities.

Retained Earnings to Total Assets (X_2)

This ratio measures cumulative profitability of the assets since firm inception. As such, there is a small discrimination against younger firms. We note, all other things being equal, younger firms are also more prone to default than older, mature companies (Damodaran, 2010).

EBIT to Total Assets (X_3)

The ratio reflects the true productivity of the company's assets as it removes any distorting effect of tax and leverage. EBIT or operating income is a core measure of operational performance, which when examined in relation to its asset base provides a good relative measure for classifying bankrupt and non-bankrupt companies.

Market Value of Equity to Book Value of Debt (X_4)

Altman (1968) defines equity as "*the combined market value of all shares of stock (including common and preferred)*" and debt as *"current plus long-term debt"*. This measure is a proxy for company solvency as it reflects how much a company's assets can decline before being exceeded by liabilities and going into default. For example, if a company has an equity market value of USD 200m and debt of USD 100m (i.e. 2:1 ratio), then assets can drop by USD 100m (66 percent) before it becomes insolvent and unable to meet its obligations. The measurement adds a market-based dimension to the model, which is a more accurate indicator than Net Worth to Total Debt (book value) (Altman, 1968).

Sales to Total Assets (X_5)

The final ratio of the re-estimated Altman model, Sales to Total Assets, measures capital turnover and shows how effective a company's assets are in generating sales and revenue.

Corporate governance indicators

In addition to financial ratios, this paper considers several corporate governance indicators' ability to predict bankruptcy. Whereas there is a large literature stream on corporate governance theories underpinning different measurements as outlined in Section 5, the same supporting theories are not existent for financial ratios to the same extent. Hence, for the selection of governance indicators, we look at: (i) the *theoretical rationale*; (ii) *popularity in previous literature*; and (iii) *significance in prediction bankruptcy in previous studies*. Since bankruptcy prediction models including corporate governance indicators are a relatively novel topic, the emphasis will be placed on selection mechanism (i), whilst (ii) and (iii) will supplement the findings with empirical evidence. The variables and their corresponding database are described in Table 9.

Variable	Measurement	Database
X_6: Number of Blockholders	Number of blockholders	10-K Section III, Item 12
X_7: Female Directors (%)	Number of female directors / Total number of directors	10-K Section III, Item 10
X_8: Independent Directors (%)	Number of independent directors / Total number of directors	10-K Section III, Item 13
X_9: Variable Compensation (%)	Variable compensation / Total compensation	10-K Section III, Item 11
X_{10}: CEO Tenure	Continuous CEO tenure in years	10-K Section III, Item 10
X_{11}: Director Ownership (%)	Director shares / Total shares outstanding	10-K Section III, Item 12
X_{12}: Board Size	Number of board members	10-K Section III, Item 10
X_{13}: CEO Duality	Dummy variable (1 if CEO duality is present)	10-K Section III, Item 10
X_{14}: CEO Change	Total changes in CEO over past 5 years	10-K Section III, Item 10
X_{15}: CEO Ownership (%)	CEO shares / Total shares outstanding	10-K Section III, Item 12

Table 9. Overview of Corporate Governance Indicators. The table presents the corporate governance variables which are tested in the paper. Additionally, it describes the main focus of the variable and which database it is retrieved from. Source: EDGAR

Similar to the financial ratios, the difference in means between each variable will be tested to determine the variable's classification power. For the sake of clarity, we define the following selected variables from Table 9.

Number of Blockholders (X_6)

A blockholder is defined as a shareholder with beneficial ownership greater than 5 percent of a company's voting share class. This definition is in line with Edmans (2014) and constitutes the threshold that triggers a disclosure requirement of ownership in relation to the SEC's Schedule 13D, also known as the beneficial ownership report (SEC, 2002).

Independent Directors (X_8)

For the purpose of our analysis, an '*independent director*' is defined as: "*a person other than an officer or employee of the company or its subsidiaries or any other individual having a relationship, which, in the opinion of the company's board of directors, would interfere with the exercise of independent judgment in carrying out the responsibilities of a director*" (SEC, 2004).

Variable Compensation (X_9)

We define variable compensation to encompass all forms of compensation excluding the base salary, such as discretionary cash bonuses, and equity-based compensation such as the grant of stock options, and warrants.

8.5 Descriptive statistics

The following sub-section describes the data set used for constructing the bankruptcy prediction model. During the collecting process, the data has been cleaned for any outliers to ensure the results are not distorted, in line with the approach proposed by Easterby-Smith et al. (2015). Table 10 displays the summary statistics for the estimation sample. We observe the data on three parameters: (i) *location*; (ii) *spread*; and (iii) *symmetry*. Firstly, we present the two most common measurements of location, the mean and median values. The mean shows the average value of the data set whereas the median is the middle value of the data set once the data has been arranged in rank order. For the majority of the variables these are similar which suggests that the data set does not comprise any large outliers. Secondly, we examine how much spread there is around the mean by looking at the standard deviation. Lastly, we look at the symmetry of the data. Again, for most variables the mean and median are similar which indicates symmetry. From the summary statistics table, we observe that there are differences in parameter values between the bankrupt and non-bankrupt group. This provides preliminary evidence suggesting the variables have discriminating ability. The difference in means is formally tested in Section 9 where a parametric test is conducted.

Variable	Group	Mean	S.E.	Median	Std. Dev.	Min.	Max.
Working Capital to Total Assets	Bankrupt	0.062	0.085	0.102	0.467	-1.420	0.966
	Non-Bankrupt	0.296	0.035	0.289	0.190	-0.015	0.674
Retained Earnings to Total Assets	Bankrupt	-1.435	0.290	-1.223	1.587	-6.674	0.577
	Non-Bankrupt	0.518	0.055	0.493	0.303	-0.251	1.387
EBIT to Total Assets	Bankrupt	-0.368	0.131	-0.161	0.719	-3.726	0.243
	Non-Bankrupt	0.160	0.016	0.145	0.088	0.053	0.451
Market Value of Equity to Book Value of Debt	Bankrupt	1.496	0.754	0.227	4.128	0.000	22.307
	Non-Bankrupt	8.521	1.728	4.925	9.466	0.728	33.292
Sales to Total Assets	Bankrupt	1.385	0.220	1.197	1.205	0.014	5.908
	Non-Bankrupt	1.371	0.183	1.078	1.001	0.254	4.550
Blockholders	Bankrupt	2.500	0.302	2.000	1.656	0.000	8.000
	Non-Bankrupt	4.033	0.169	4.000	0.928	2.000	6.000
CEO Ownership (%)	Bankrupt	0.036	0.017	0.014	0.091	0.000	0.506
	Non-Bankrupt	0.023	0.006	0.009	0.034	0.001	0.135
Director Ownership (%)	Bankrupt	0.126	0.026	0.068	0.142	0.001	0.648
	Non-Bankrupt	0.074	0.016	0.044	0.088	0.004	0.334
Board Size	Bankrupt	8.267	0.555	7.500	3.039	4.000	16.000
	Non-Bankrupt	9.033	0.269	9.000	1.474	7.000	12.000
Female Directors (%)	Bankrupt	0.083	0.021	0.031	0.112	0.000	0.500
	Non-Bankrupt	0.142	0.019	0.146	0.104	0.000	0.300
Independent Directors (%)	Bankrupt	0.602	0.033	0.633	0.178	0.250	0.909
	Non-Bankrupt	0.831	0.014	0.857	0.079	0.571	0.917
CEO Duality	Bankrupt	0.300	0.085	0.000	0.466	0.000	1.000
	Non-Bankrupt	0.367	0.089	0.000	0.490	0.000	1.000
CEO Variable Compensation (%)	Bankrupt	0.483	0.048	0.461	0.263	0.002	0.948
	Non-Bankrupt	0.755	0.036	0.836	0.195	0.136	0.983
CEO Changes	Bankrupt	1.033	0.148	1.000	0.809	0.000	3.000
	Non-Bankrupt	0.133	0.063	0.000	0.346	0.000	1.000
CEO Tenure	Bankrupt	4.267	0.732	3.000	4.008	0.000	16.000
	Non-Bankrupt	11.400	1.630	10.000	8.927	2.000	36.000

Table 10. Group Descriptive Statistics; One year prior to bankruptcy for the estimation sample. The table summarises the group statistics for the bankrupt and non-bankrupt group for estimation sample. Key statistical indicators are displayed including means, standard errors, median, standard deviation and min and max values. Source: SPSS Statistics.

Year of bankruptcy

Figure 8 illustrates how the observations of bankruptcies in the data sample are distributed across the studied period. We note there is a general decreasing trend in the number of bankruptcies across time, with the highest occurrence (ten) in 2012, and the lowest (four) in 2018.

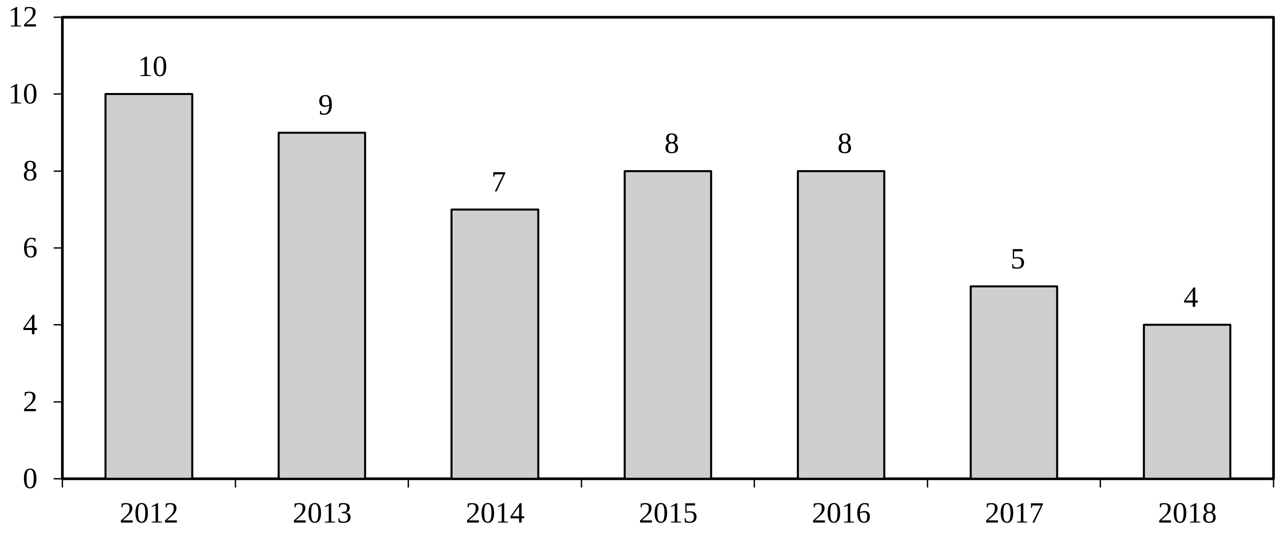

Figure 8. Year of Bankruptcy from Sample; 2012-2018. Number of bankruptcies per year for both the estimation and holdout sample. The vertical axis indicates the frequency of observations, while the calendar year is expressed on the horizontal axis. Source: Own Analysis.

Industry focus

Finally, we present our estimation sample divided into the NAICS industry groups (Table 11). Following our selection process, we confirm that no financial, insurance or real estate related firms are included in the list. Following matching principle, the bankrupt and non-bankrupt firms are considered to be well balanced between the remaining industries. The minor industry discrepancies between the two groups arise from data limitations but are considered negligible, as industries with very distinct characteristics have been excluded in the sampling process.

NAICS Industry Group	*Bankrupt*		*Non-Bankrupt*	
	Count	**(%)**	**Count**	**(%)**
Manufacturing	4	13.3%	5	16.7%
Retail Trade	6	20.0%	6	20.0%
Educational Services	2	6.7%	1	3.3%
Professional, Scientific, and Technical Services	11	36.6%	9	30.0%
Utilities	3	10.0%	3	10.0%
Construction	1	3.3%	1	3.3%
Transportation and Warehousing	1	3.3%	3	10.0%
Information	1	3.3%	1	3.3%
Mining	1	3.3%	1	3.3%
Total	30	100%	30	100%

Table 11. NAICS Industry Group Split; estimation sample. The table shows the distribution of companies from the estimation sample across the different NAICS Industry Groups. Count and percent of group sample are presented. Source: Own Analysis

8.6 Reflections on choice of methodology

The paper follows the methodology Altman developed for his original study in 1968, which has become the most extensively used approach within bankruptcy prediction modelling. In bankruptcy prediction modelling, the construction of the estimation sample is important, as it determines the coefficients of the discriminant model. We constructed the non-bankrupt sample through the matching technique; a method used widely in previous studies. The selection of variables was based on relevant theory, popularity in previous literature and empirical prediction accuracy, also fulfilling the empirical modelling techniques.

We note that, while our approach may lead to sampling errors as data is manually retrieved from individual 10-K statements, we argue that the suggested approach mitigates other potential bias arising from the collection of secondary data, as it is taken directly from the primary source. Lastly, to secure the validation of estimation model we divided the data set into two groups: an estimation sample used to construct the model, and a secondary sample used to test prediction accuracy.

Part V

Empirical Analysis and Results

9 Empirical Analysis and Results

This section presents our empirical analysis and results for the three models. Firstly, we present the empirical findings for the application of Altman's Z-score Model (Model I) on our sample. Secondly, we present the analysis, results and validation tests for the two variations of the Z-score model (Model II and Model III). The empirical analysis for Model II and Model III is structured as follows:

- Pre-modelling
- Model development
- Assessment of model fit and discriminating ability
- Model validation

9.1 Altman's 1968 model (Model I)

We begin by testing Altman's 1968 model originally designed for US manufacturing companies. We recall the model is given as:

(I) $Z = 1.2X_1 + 1.4X_2 + 3.3X_3 + 0.6X_4 + 0.999X_5$

Where:

X_1 = Working Capital to Total Assets

X_2 = Retained Earnings to Total Assets

X_3 = Earnings Before Interest and Tax (EBIT) to Total Assets

X_4 = Market Value of Equity to Book Value of Debt

X_5 = Sales to Total Assets

Z = Overall Index

The cut-off value (or critical value) is 2.675. Hence, firms with Z-scores above (below) 2.675 are classified as non-bankrupt (Bankrupt).

Model validation

Applying this model on our data set we obtain the following results:

Actual Membership	Predicted Membership		Total
	Bankrupt	*Non-Bankrupt*	
Bankrupt	26	4	30
Non-Bankrupt	2	28	30
Total	28	32	60

Table 12. Prediction Accuracy of Model I; one year prior to bankruptcy for the estimation sample.
Source: SPSS Statistics

Error Type	Errors	Percent Correct	Percent Error	n
Type I	4	86.7%	13.3%	30
Type II	2	93.3%	6.7%	30
Total	6	90.0%	10.0%	60

Table 13. Type I and Type II Errors for Model I; one year prior to bankruptcy for the estimation sample.
Source: SPSS Statistics

We note the model correctly classifies 54 out of 60 firms, corresponding to a prediction accuracy of 90 percent. Of the six misclassified firms, four are Type I (false positive) errors and two are Type II (false negative) errors.

<u>Secondary sample of bankrupt and non-bankrupt firms</u>

We run Altman's original model on the secondary sample and achieve the following results:

Year Prior to Bankruptcy	Number of Observations (n)	Hits	Misses	Accuracy
1	42	33	9	78.6%
2	42	32	10	76.2%
3	40	28	12	70.0%

Table 14. Prediction Accuracy of Model I; one to three years prior to bankruptcy for secondary sample. Hits refer to the amount of correct classifications and misses to refer incorrect classifications (Type I and Type II classifications). Number of observations lower in year 3 due to missing data points. Source: SPSS Statistics

We observe that the prediction accuracy is the highest at one year prior to bankruptcy, as in the estimation sample test, correctly classifying 33 out of 42 firms (79 percent), after which the accuracy falls in the following two years.

9.2 Re-estimated Altman model (Model II)

Pre-modelling

Assessing the contribution of individual predictors

Following the methodology of Altman (1968) the discriminating ability of the different variables is tested on an individual basis to determine whether or not they should be included in the model. This is done by performing a one-way ANOVA for the independent variables using the grouping variables (bankrupt or non-bankrupt) as the factor. The one-way ANOVA compares the means of the two classification groups, to determine if there is a significant difference between the two. Testing the equality of group means ensures that only variables with significant classification power are included in the discriminant model. The one-way ANOVA test for Altman's original variables one year prior to bankruptcy is shown in Table 15. The estimation sample includes 30 bankrupt and 30 non-bankrupt companies in the period 2012 to 2018.

Variable	**Mean**		**Wilks' Lambda**	**F Ratio**
	Bankrupt	*Non-Bankrupt*		
	n = 30	n = 30		
X_1: WC / TA	0.062	0.296	0.887	12.706***
X_2: RE / TA	-1.435	0.518	0.900	11.052***
X_3: EBIT / TA	-0.368	0.160	0.804	24.334***
X_4: MVE / BV of Debt	1.496	8.521	0.838	19.295***
X_5: Sales / TA	1.385	1.371	0.997	0.0346

* Significant at a 0.05 level; ** Significant at a 0.01 Level; *** Significant at a 0.001 level

Table 15. One-way ANOVA test for Model II; bankrupt and non-bankrupt estimation sample. Source: SPSS Statistics

Table 15 shows a high significance between the two groups when testing variables X_1, X_2, X_3 and X_4, whereas variable X_5 does not display a significant difference in means. The significance findings of the variables are in line with Altman 1968's original study. Here, variable X_5 was also found to be insignificant. Table 15 illustrates that firms that have gone bankrupt are generally associated with a low Working Capital to Total Assets ratio (X_1), a negative Retained Earnings to Total Assets ratio (X_2), a negative EBIT to Total Assets ratio (X_3) and a low Market Value of Equity to Book Value of Debt (X_4) ratio. The non-bankrupt group is classified by having a higher Working Capital to Total Assets ratio (X_1), a positive Retained Earnings to Total Assets ratio (X_2), a positive EBIT to Total

Assets ratio (X_3) and a higher Market Value of Equity to Book Value of Debt (X_4) ratio. On a strictly univariate basis all ratios for the non-bankrupt group display higher values than those of the bankrupt group except for Sales to Total Assets (X_5), which is higher for the bankrupt group. Additionally, the Wilks' lambda, where smaller values indicate better discriminating ability of independent variables, confirms the observations above.

<u>Assessing collinearity of predictors</u>

Table 16 provides a pair-wise correlation matrix for the different variables.

Variable	**X_1**	**X_2**	**X_3**	**X_4**	**X_5**
X_1	**1.000**	-	-	-	-
X_2	0.754	**1.000**	-	-	-
X_3	-0.039	0.153	**1.000**	-	-
X_4	0.141	0.030	0.089	**1.000**	-
X_5	-0.096	0.028	0.208	-0.061	**1.000**

Table 16. Variable Correlation Matrix for Model II variables. Source: SPSS Statistics

The within-groups correlation matrix displays the correlation between the predictor variables. The correlations are all found to satisfy the independence assumption, with the one exception being Working Capital to Total Assets (X_1) and Retained Earnings to Total Assets (X_2) highlighted in grey. The latter correlation displays a relatively high correlation indicating potential collinearity between the two variables. The remaining variable correlations are either uncorrelated or have insignificant minor negative or positive correlations.

Additionally, we can check for homogeneity of the covariance matrix by looking at Box's M test. Since Box's M is significant (Appendix 6), suggesting unequal population covariances, we run a second analysis using separate-groups covariance matrixes to determine whether this changes the classification ability of the model. As seen in Appendix 8 the classification results and accuracy have not changed which indicates that we can proceed with the model. We note, in line with Huberty and Olejnik (2006), that the Box's M can be overly sensitive to even small departures of covariance equality and should therefore not solely be relied on.

Variable selection

All significant variables are added to the model i.e. X_1 to X_4. Additionally, we also include X_5 as per the Altman's 1968 study, despite its lack of significance. Altman (1968) also found this variable to be insignificant on a univariate basis but argued that in a multivariate context is adds significant discriminating power to the model. We find a similar result, which justifies the inclusion of the variable in the model. The structure matrix is presented in Appendix 5.

Discriminant analysis

Model development

The discriminant analysis is conducted based on the estimation sample of 30 bankrupt and 30 non-bankrupt firms for the five independent variables and the one categorical variable. Using the statistical software, SPSS, we obtain the following canonical discriminant function coefficients:

Variable	**Coefficient**
X_1: WC / TA	0.719
X_2: RE /TA	0.009
X_3: EBIT / TA	1.428
X_4: MVE / BV of Debt	0.078
X_5: Sales / TA	-0.145
k (constant)	-0.040

Table 17. Canonical Discriminant Function Coefficients for Model II. The table presents the unstandardized coefficients of Model II. Source: SPSS Statistics

From the values above we construct our re-estimated discriminant function, Model II:

$$\text{(II)} \quad Z = -0.040 + 0.719X_1 + 0.009X_2 + 1.428X_3 + 0.078X_4 + -0.145X_5$$

Where the variables X_1 to X_5 are identical to the notation in the previous model.

We observe, in line with our univariate one-way ANOVA test, that variables X_1 to X_4 have a positive loading to the discriminant function, while X_5 has a negative loading. In other words, if the value of variables X_1 to X_4 increases then the firm will achieve a higher Z-score and is less prone to bankruptcy. By the same logic, if variable X_5 increases then a lower Z-score will be computed which, all other things being equal, will result in a greater likelihood of bankruptcy. The weights of the function suggest that EBIT to Total Assets (X_3) has the greatest classification power followed by the working capital measurement (X_1).

Functions at group centroids

We compute the functions at group centroids to determine the cut-off point for classifying the firms into bankrupt and non-bankrupt. The group centroids represent the mean discriminant scores for each group. The optimal cut-off point is determined as the weighted average of the two centroid values. In our case, since the size of the groups are equal, the optimal cut-off point is exactly between the two values (i.e. average), -0.698 and 0.725, which is 0.014. Hence, the model will categorise the observation into the bankrupt (non-bankrupt) group if the Z-score is below (above) the cut-off point of 0.014.

Model fit

After the model has been constructed, we assess how well the model discriminates as a whole. This is done by observing Wilks' lambda, conducting an eigenvalue analysis and examining the ROC curve.

Wilks' lambda

Wilks' lambda tests how much variance is explained by the independent variables and determine the Model's overall discriminating ability. Model II has a Wilks' lambda of 0.659, indicating that 0.341 of the proportion of total variance in the discriminant scores is explained by differences among the groups. The value suggests that a significant proportion of the variance is explained by the independent variables. Additionally, we look at the associated Chi-squared test to measure the "goodness of fit" of the statistical model by analysing how the observed distribution of data matches with the expected distribution under the assumption of variable independence. As observed in Table 18, the Chi-squared test is highly significant. We, therefore, note that the independent variables depended on their classification and the model has a significant discriminating ability.

Model	Wilks' Lambda	Chi-Squared
Model II	0.659	40.594***

* Significant at a 0.05 level; ** Significant at a 0.01 Level; *** Significant at a 0.001 level

Table 18. Wilks' Lambda and Chi-Squared Test for Model II. Source: SPSS Statistics

Eigenvalue analysis

The analysis of the eigenvalues examines the efficacy of the discriminating function. The larger the eigenvalue, the greater the variance explained by the function in the dependent variable. The eigenvalue of 0.516 is considered reasonable. As our model only includes two groups (Bankrupt and non-bankrupt), the canonical correlation is a more useful measure to investigate. The squared canonical correlation coefficient is known as the 'effect size', which expresses the magnitude or strength of the relationship between variables. In this case, the effect size is 0.341, which is considered to be moderate for a bivariate canonical-correlation analysis ("CCA") (Cohen, 1988).

Model	Eigenvalue	% of Variance	Cumulative %	Canonical Correlation
Model II	0.516	100%	100.0	0.584

Table 19. Canonical Correlation Analysis for Model II. Source: SPSS Statistics

Receiver operating characteristic (ROC)

Figure 9 illustrates the prediction ability of Model II. The blue line is located close to the top left of the graph which suggests that the model is a good instrument for predicting bankruptcy. The area below the blue line, the AUC, is 0.936 as observed in Table 20. The asymptotic significance level suggests that the ROC curve is statistically significant. Additionally, the 95 percent confidence bounds fall between 0.865 and 1.000. In summary, Model II is deemed a good bankruptcy predictor, as its confidence level boundaries fall between the excellent and outstanding AUC classification criteria.

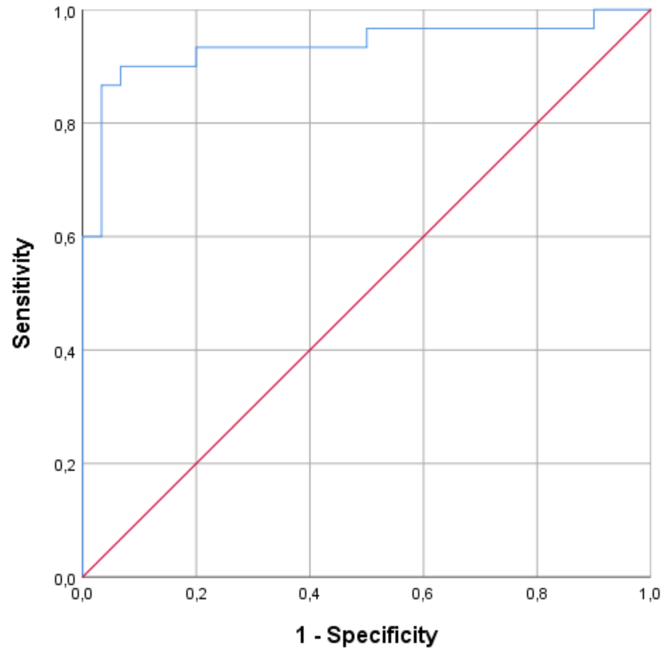

Figure 9. ROC Test for Model II. The vertical axis indicates the percentage true positives (sensitivity) and the percentage of false positives (1 – Specificity) shown on the horizontal axis. The red line is the diagonal reference line, at which the model prediction is equal to a random guess. Source: SPSS Statistics

Area	S.E.	Asymptotic Significance	Asymptotic Confidence Interval (95%)	
			Lower Bound	*Upper Bound*
0.936	0.036	0.000	0.865	1.000

Table 20. ROC Test Summary for Model II. Source: SPSS Statistics

Model validation

After having concluded that the model is statistically significant, we perform a series of tests to examine the validity and robustness of the model in predicting bankruptcies across different years and data sets.

<u>Test 1: Estimation sample one-year prediction accuracy</u>

Model II's prediction accuracy is tested using the initial sample of 30 bankrupt and 30 non-bankrupt companies. We test the one-year prediction accuracy using financial data from one year prior to the bankruptcy year. Since the estimation model has been derived from this data sample, we expect to achieve a high prediction rate.

Actual Membership	Predicted Membership		Total
	Bankrupt	*Non-Bankrupt*	
Bankrupt	27	3	30
Non-Bankrupt	2	28	30
Total	29	31	60

Table 21. Prediction Accuracy of Model II; one year prior to bankruptcy for the estimation sample.
Source: SPSS Statistics

Error Type	Errors	Percent Correct	Percent Error	n
Type I	3	90%	10%	30
Type II	2	93.3%	6.7%	30
Total	5	91.7%	8.3%	60

Table 22. Type I and Type II Errors for Model II; one year prior to bankruptcy for the estimation sample.
Source: SPSS Statistics

We note that Model II correctly classifies 55 out of 60 firms, corresponding to a prediction accuracy of 92 percent. Of the five misclassified firms, three are Type I (false positive) errors and two are Type II (false negative) errors.

Test 2: Results two years prior to bankruptcy

The accuracy of the model is then tested using data two years prior to the date of bankruptcy. This prediction accuracy is expected to be lower than using data one year prior to bankruptcy as the estimation model is based on the latter sample data.

Actual Membership	Predicted Membership		Total
	Bankrupt	*Non-Bankrupt*	
Bankrupt	23	6	29
Non-Bankrupt	2	28	30
Total	25	34	59

Table 23. Prediction Accuracy of Model II; two years prior to bankruptcy for the estimation sample.
Source: SPSS Statistics

Error Type	Errors	Percent Correct	Percent Error	n
Type I	6	79.9%	20.1%	29
Type II	2	93.3%	6.7%	30
Total	8	86.4%	13.6%	59

Table 24. Type I and Type II Errors for Model II; two years prior to bankruptcy for the estimation sample.
Source: SPSS Statistics

The two-year prior to bankruptcy results show that the model correctly classifies 51 out of 59 firms, corresponding to a prediction accuracy of 86 percent. We note that the sample decreases to 59 firms due to missing data points. As anticipated, the prediction accuracy has fallen relative to the results for one year prior to bankruptcy. We note that the decrease in accuracy is attributable to an increase in Type I errors (6, i.e. 21 percent), whilst Type II errors remain the same (2, i.e. 7 percent). Nevertheless, the model remains accurate in predicting bankruptcy two years prior to the event.

<u>Test 3: Secondary sample of bankrupt and non-bankrupt firms</u>

In order to test the stability of Model II's predicting power, we now introduce a secondary sample containing 42 new observations. The importance of a secondary sample prediction test cannot be over-emphasised, as it illustrates the robustness of the model. Applying Model II to the secondary sample we present the following results:

Year Prior to Bankruptcy	Number of observations (n)	Hits	Misses	Accuracy
1	42	35	7	83.3%
2	42	31	11	73.8%
3	40	31	9	77.5%

Table 25. Prediction Accuracy of Model II; one to three years prior to bankruptcy for secondary sample. Hits refer to the amount of correct classifications and misses to refer incorrect classifications (Type I and Type II errors).
Source: SPSS Statistics

We observe that the prediction accuracy is the highest at one year prior to bankruptcy, as in the in-sample test, correctly classifying 35 out of 42 firms. Interestingly, we also note that the model achieves a higher accuracy at 3 years prior to bankruptcy (78 percent) compared to two years before bankruptcy (74 percent). However, as noted by Altman, this reversal in accuracy can be explained by the fact that the predictive ability of the discriminant model deteriorates after the second year and that the changes thereafter have a negligible meaning (Altman, 1968).

Test 4: Long-range predictive accuracy

Our prior results have shown that bankruptcy can be predicted with meaningful accuracy two years prior to failure. However, we wish to determine whether this can be predicted even further out, such as in the third, fourth, and fifth year prior to bankruptcy. The reduced number of observations is due to some firms not being in existence for more than two years, or due to data not being available for prior years.

Year Prior to Bankruptcy	Number of observations (n)	Hits	Misses	Accuracy
1	60	55	5	91.7%
2	59	51	8	86.4%
3	55	39	16	70.9%
4	44	30	14	68.2%
5	39	24	15	61.5%

Table 26. Long-range Prediction Accuracy of Model II; one to five year prior to bankruptcy for estimation sample. Hits refer to the amount of correct classifications and misses to refer incorrect classifications (Type I and Type II classifications). Source: SPSS Statistics

In line with our expectations, we observe a clear trend of falling prediction accuracy as the years prior to bankruptcy increase. In addition, we note there is a significant drop in accuracy between years 2 and 3. The accuracy five years prior to bankruptcy is 62 percent which is considered low. We recall that a random guess would result in a 50 percent prediction accuracy.

9.3 Extended Altman model with corporate governance indicators (Model III)

Pre-modelling

Assessing the contribution of individual predictors

We follow the same methodology applied for the construction of Model II. Firstly, a one-way ANOVA test is conducted for the corporate governance indicators on our sample one year prior to bankruptcy to determine which variables should be included in the estimation model.

Variable	**Means**		**Wilks' Lambda**	**F Ratio**
	Bankrupt	*Non-Bankrupt*		
	n = 30	n = 30		
X_6: Number of Blockholders	2.500	4.033	0.887	8.901**
X_7: Female Directors (%)	0.083	0.142	0.900	13.541***
X_8: Independent Directors (%)	0.602	0.831	0.804	28.360***
X_9: Variable Compensation (%)	0.483	0.755	0.838	31.132***
X_{10}: CEO Tenure	4.267	11.400	0.997	11.650***
X_{11}: Director Ownership (%)	0.126	0.074	0.918	9.341**
X_{12}: Board Size	8.267	9.033	0.881	12.772***
X_{13}: CEO Duality	0.300	0.367	0.962	3.998
X_{14}: CEO Change	1.033	0.133	0.865	59.849***
X_{15}: CEO Ownership (%)	0.036	0.023	0.993	0.7280

* Significant at a 0.05 level; ** Significant at a 0.01 level; *** Significant at a 0.001 level

Table 27. One-way ANOVA test for Model III; bankrupt and non-bankrupt estimation sample. Source: SPSS Statistics

Table 27 indicates that there is a significant difference in means for all the included corporate governance indicators except for CEO Duality (X_{13}) and CEO Ownership (X_{15}). All significant variables' means are larger for the non-bankrupt group than the bankrupt group with the exception of Director Ownership (X_{11}) and CEO Change (X_{14}). Further, we observe that the majority of significant variables have good discriminating abilities as reflected in the Wilks' lambda values.

Assessing the collinearity of predictor variables

Table 28 provides a pair-wise correlation matrix for the different corporate governance variables.

Variable	**X_6**	**X_7**	**X_8**	**X_9**	**X_{10}**	**X_{11}**	**X_{12}**	**X_{13}**	**X_{14}**	**X_{15}**
X_6	**1.000**	-	-	-	-	-	-	-	-	-
X_7	0.068	**1.000**	-	-	-	-	-	-	-	-
X_8	0.152	0.198	**1.000**	-	-	-	-	-	-	-
X_9	-0.045	0.156	0.345	**1.000**	-	-	-	-	-	-
X_{10}	0.051	-0.044	0.028	-0.277	**1.000**	-	-	-	-	-
X_{11}	0.236	-0.052	-0.249	-0.359	0.256	**1.000**	-	-	-	-
X_{12}	-0.046	0.281	0.011	0.181	-0.104	-0.131	**1.000**	-	-	-
X_{13}	0.060	-0.009	-0.127	-0.190	0.441	0.215	-0.250	**1.000**	-	-
X_{14}	-0.169	0.100	-0.182	0.334	-0.734	-0.049	0.207	-0.263	**1.000**	-
X_{15}	0.124	-0.053	-0.164	-0.320	0.419	0.596	-0.125	0.289	-0.149	**1.000**

Table 28. Correlation Matrix for Model III's Corporate Governance Variables. Source: SPSS Statistics

Overall, we observe that the variables are not strongly correlated, with coefficients generally ranging between +/-0.25. The main exception is CEO Tenure (X_{10}) and CEO Change (X_{14}), which show a high negative degree of correlation (-0.734). Also, CEO Tenure (X_{10}) and CEO Duality (X_{13}), and Director Ownership (X_{11}) and CEO Ownership (X_{15}), show moderate positive correlations, albeit to a lesser extent. Further, we note that there is a moderate negative correlation between variables Variable Compensation (X_9) and Director Ownership (X_{11}). The exhaustive correlation matrix including the financial ratios is attached in Appendix 10.

Variable selection

All significant variables are added to the model, i.e. X_6 to $X_{12.}$ We do not include variables X_{13}, CEO Duality, and X_{15}, CEO Ownership, as the former does not meet the condition of being normally distributed, and both variables do not exhibit significant variation between the two groups. Furthermore, we exclude X_{14}, CEO Change, as this variable is highly correlated with CEO Tenure, and would otherwise create multicollinearity.

Discriminant analysis

Model development

A discriminant analysis is conducted based on the estimation sample of 30 bankrupt and 30 non-bankrupt firms for 12 independent variables and one categorical variable using SPSS. For the sake of comparability, we employ the same sample as for the re-estimation of the Altman model (Model II). We obtain the following canonical discriminant function coefficients:

Variable		**Coefficient**
X_1	Working Capital / Total Assets	0.795
X_2	Retained Earnings / Total Assets	-0.077
X_3	Earnings Before Interest and Tax (EBIT) / Total Assets	1.130
X_4	Market Value of Equity / Book Value of Debt	0.052
X_5	Sales / Total Assets	0.140
X_6	Blockholders	0.184
X_7	Female Directors	0.599
X_8	Independent Directors	0.949
X_9	Variable Compensation	2.389
X_{10}	CEO Tenure	0.054
X_{11}	Director Ownership	-1.940
X_{12}	Board Size	0.107
k (constant)		-4.426

Table 29. Canonical Discriminant Function Coefficients for Model III. The table presents the unstandardized coefficient of Model II. Source: SPSS Statistics

From the values above we construct our discriminant function, Model III:

$$\text{(III)} \quad Z = -4.426 + 0.795X_1 + -0.077X_2 + 1.130X_3 + 0.052X_4 + 0.140X_5 + 0.184X_6 + 0.599X_7 + 0.949X_8 + 2.238X_9 + 0.054X_{10} + -1.940X_{11} + 0.107X_{12}$$

We observe, in line with our univariate one-way ANOVA test, that all variables have a positive loading to the discriminant function, with the exception of Retained Earnings to Total Assets (X_2) (insignificantly negative) and Director Ownership (X_{11}). In other words, if these positively loaded variables increase, then the firm will achieve a higher Z-score and is thereby assumed to be less bankruptcy prone. Conversely, if Director Ownership (X_{11}) increases, this will imply a lower Z-score, which all other things being equal, will suggest a greater likelihood of bankruptcy. Evaluating the factor loadings we observe that Variable Compensation (X_9) has the greatest classification power followed by Director Ownership (X_{11}).

<u>Functions at group centroids</u>

We compute the functions at group centroids to determine the cut-off points for classifying the firms into bankrupt and non-bankrupt. As with the previous model, since the size of the groups are equal, the optimal cut-off point is exactly between the two values (i.e. average), -1.260 and 1.310, which is 0.025. Hence, the model will categorise the observation into the bankrupt (non-bankrupt) group if the Z-score is below (above) the cut-off point of 0.025.

Model fit

Like for Model II we examine the discriminating ability of the model investigating Wilks' lambda, conducting an eigenvalue analysis and examining the ROC curve.

<u>Wilks' lambda</u>

Model III has a Wilks' lambda of 0.373. which suggests that 0.627 of the variance is explained by the independent variables. Additionally, the Chi-squared test is highly significant which indicates that the model has a significant discriminating ability.

Model	**Wilks' Lambda**	**Chi-Squared**
Model III	0.373	92.790***

* Significant at a 0.05 level; ** Significant at a 0.01 Level; *** Significant at a 0.001 level

Table 30. Wilks' Lambda and Chi-squared Test for Model III. Source: SPSS Statistics

<u>Eigenvalue analysis</u>

We examine the eigenvalue to determine variance explained by the function in the dependent variable. The eigenvalue of 1.684 in conjunction with squared canonical correlation of 0.627 indicate a good model. We note that both these measurements are larger than for Model II.

Function	Eigenvalue	% of Variance	Cumulative %	Canonical Correlation
Model III	1.684	100%	100.0	0.792

Table 31. Canonical Correlation Analysis for Model III. Source: SPSS Statistics

Receiver operating characteristic (ROC)

Figure 10 illustrates the prediction ability of Model III. The blue line is located close to the top left of the graph which suggests that the model is a good instrument for predicting bankruptcy. The AUC is 0.994 as observed in Table 32. The asymptotic significance level suggests that the ROC curve is statistically significant. Additionally, the 95 percent confidence bounds fall between 0.982 and 1.000. In summary, Model III is deemed a good bankruptcy prediction model, as its confidence level boundaries confirm an outstanding AUC classification criteria.

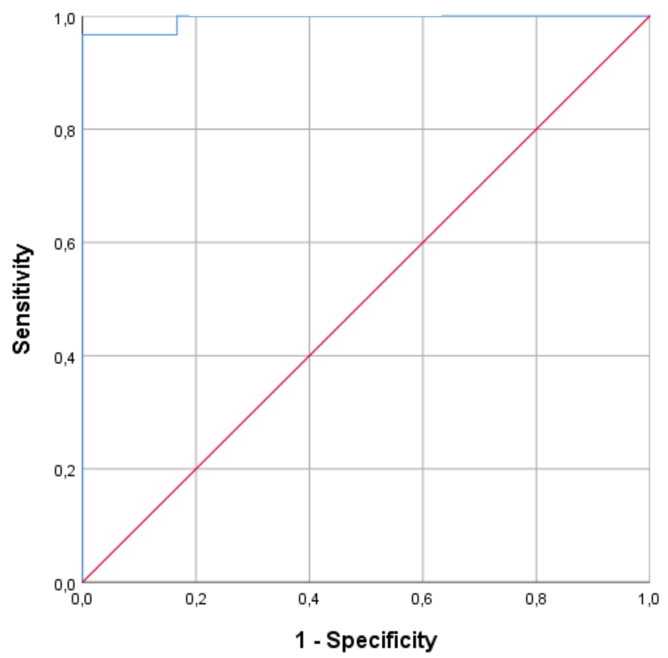

Figure 10. ROC Test for Model III. The vertical axis indicates the percentage true positives (sensitivity) and the percentage of false positives (1 – specificity) shown on the horizontal axis. The red line is the diagonal reference line, at which the model prediction is equal to a random guess. Source: SPSS Statistics

Area	S.E.	Asymptotic Significance	Asymptotic Confidence Interval (95%)	
			Lower Bound	*Upper Bound*
0.994	0.006	0.000	0.982	1.000

Table 32. ROC Test Summary for Model III. Source: SPSS Statistics

Model validation

After having concluded that the model is statistically significant, we perform a series of tests to examine the validity and robustness of the model as well as its predictive ability, as done for Model II.

Test 1: Initial (one year) sample prediction accuracy

Model III's prediction accuracy is tested using the initial sample of 60 firms (30 bankrupt and 30 non-bankrupt companies). We test the one-year prediction accuracy using financial data from one year prior to the bankruptcy year. Like for Model II, we expect to achieve a high prediction rate.

Actual Membership	**Predicted Membership**		**Total**
	Bankrupt	*Non-Bankrupt*	
Bankrupt	28	2	30
Non-Bankrupt	0	30	30
Total	28	32	60

Table 33. Prediction Accuracy of Model III; one year prior to bankruptcy for the estimation sample.
Source: SPSS Statistics

Error Type	**Errors**	**Percent Correct**	**Percent Error**	**n**
Type I	2	93.3%	6.7%	30
Type II	0	100%	0%	30
Total	2	96.7%	3.3%	60

Table 34. Type I and Type II Errors for Model III; one year prior to bankruptcy for the estimation sample.
Source: SPSS Statistics

From Table 34 above we observe that the extended model, including corporate governance variables, correctly discriminates (classifies) 58 out of 60 firms, corresponding to a prediction accuracy of 97 percent. We note this is higher than the re-estimated version of Altman's original model (Model II).

Test 2: Results two years prior to bankruptcy

The accuracy of the model is then tested using data two years prior to the date of bankruptcy. Again, the prediction accuracy is expected to be lower than using data one year prior to bankruptcy.

Actual Membership	Predicted Membership		Total
	Bankrupt	*Non-Bankrupt*	
Bankrupt	24	5	29
Non-Bankrupt	2	28	30
Total	26	33	59

Table 35. Prediction accuracy of Model III; two years prior to bankruptcy for the estimation sample. Source: SPSS Statistics

Error Type	Errors	Percent Correct	Percent Error	n
Type I	5	82.8%	17.2%	29
Type II	2	93.3%	6.7%	30
Total	7	88.1%	11.9%	59

Table 36. Summary of Model III Type I and Type II errors for the estimation sample; two years prior to bankruptcy. Source: SPSS Statistics

As anticipated, the prediction accuracy falls to 88 percent. Type II errors have increased from zero (0 percent) to two (7 percent), and Type I errors have similarly increased from two (7 percent) to five (17 percent). The model is therefore still very accurate in predicting bankruptcy two years prior to the bankruptcy event.

Test 3: Secondary sample of bankrupt and non-bankrupt firms

Again, in order to test the stability of our model's predicting power, we now introduce the secondary sample containing 42 new observations and achieve the following results.

Year Prior to Bankruptcy	Number of observations (n)	Hits	Misses	Accuracy
1	42	40	2	95.2%
2	42	35	7	83.3%
3	40	32	8	80.0%

Table 37. Prediction Accuracy of Model III for Secondary Sample; One to three year prior to bankruptcy. Hits refer to the amount of correct classifications and misses to refer incorrect classifications (Type I and Type II classifications). Source: SPSS Statistics

As in the initial sample, we observe that the prediction accuracy falls as the years prior to bankruptcy increase. At one year prior to bankruptcy, the model achieves an accuracy of 95 percent, which is very high, before dropping to 83 and 80 percent in years 2 and 3, respectively. We also note that the fall in accuracy is not equal between years, but more significant between years 1 and 2.

Test 4: Long-range predictive accuracy

Our prior results have shown that the extended model including corporate governance parameters can predict firm bankruptcy with significant accuracy two years prior to failure. Again, we wish to determine whether this can be predicted even further out, such as in the third, fourth, and fifth year prior to bankruptcy. We apply the same data sample as in the case of Model I and Model II and obtain the following results.

Year Prior to Bankruptcy	Number of observations (n)	Hits	Misses	Accuracy
1	60	58	2	96.7%
2	59	52	7	88.1%
3	55	46	9	83.6%
4	44	36	8	81.8%
5	39	29	10	74.4%

Table 38. Long-range Prediction Accuracy of Model III for estimation sample; one to five years prior to bankruptcy. Hits refer to the amount of correct classifications and misses to refer incorrect classifications (Type I and Type II errors). Source: SPSS Statistics

Again, there is a clear trend of falling accuracy as the years to bankruptcy increase. However, we note that even in years 4 and 5 prior to bankruptcy, the model achieves an accuracy of over 70 percent, which can be considered to be very high. As stated earlier, we note that as the number of observations falls, the accuracies produced become less robust and must be viewed with a higher degree of scepticism.

9.4 Summary of results

The previous sub-sections have systematically presented the analysis and considerations made while constructing Model II and Model III. Additionally, we have presented the key findings and validation tests associated with Model I, II and III, which provide empirical evidence to substantiate the research question and test the underlying hypothesis. Below we present a summary of the model accuracies for both the estimation sample and the secondary sample.

	Estimation sample			**Secondary sample**		
Year	Model I	Model II	Model III	Model I	Model II	Model III
1	90.0%	91.7%	96.7%	78.6%	83.3%	95.2%
2	86.4%	86.4%	88.1%	76.2%	73.8%	83.3%
3	69.1%	70.9%	83.6%	70.0%	77.5%	80.0%
4	61.4%	68.2%	81.8%	n/a	n/a	n/a
5	56.4%	61.5%	74.4%	n/a	n/a	n/a

Table 39. Summary of Model Accuracy for Model I, II and III; one to five years prior to bankruptcy. The table presents model accuracies across the estimation sample and the secondary sample. Source: SPSS Statistics

Part VI

Discussion and Conclusion

This section discusses the main findings of the empirical analysis in order to answer the research question and underlying hypotheses. Further, we reflect on the limitations of the paper and suggest areas of further research. Finally, we conclude the paper.

10 Discussion and Evaluation of Results

10.1 Is Altman's Z-score still valid in the post-Global Financial Crisis period?

In order to address whether Altman's Z-score is still valid in the post-Global Financial Crisis period, we investigate the empirical findings of Model I and Model II in more detail. We focus on the secondary sample to avoid a potential upwards bias that may be embedded in the estimation sample and estimation differences stemming from different sample sizes (estimation sample of 60 firms vs. prediction sample of 42 firms). At a first glance, we find that the original Z-score (Model I) remains accurate in predicting bankruptcies, despite the different period and the inclusion of other industries, displaying a 79 percent one-year prediction accuracy for the secondary sample. Conversely, Model II shows 83 percent accuracy for the same period and sample. The prediction accuracy of Model I falls to 70 percent in year three, which is lower than Model II, which has an accuracy of 76 percent. Our findings are consistent with prior research, which find that Altman's original model (Model I) is still accurate in predicting corporate financial stress for both manufacturing and non-manufacturing firms across different periods (Li, 2012; Li & Rahgozar, 2012)

Contributions of the individual predictors are similar across both models

When comparing the two models (Model I and II), we observe they share similar characteristics regarding the loadings of the coefficients. Both models display a positive contribution of variables X_1 to X_4, but diverge in the weighting for X_5, Sales to Total Assets. The positive weightings are in line with findings in other re-estimated models (Li, 2012; Boďa & Úradníček, 2016; Singh & Singla, 2019) and make intuitive sense. For example, X_1, Working Capital to Total Assets, is a liquidity measure. The higher the ratio, the more liquidity the company has and the less prone it is to go bankrupt. Thus, a positive loading to the model is intuitively sound. Similarly, variable X_3 (EBIT to Total Assets), is a measure of asset productivity. The higher the ratio, the more EBIT the assets generate (i.e. higher asset productivity implies a lower likelihood of bankruptcy). Again, the positive weighting is intuitive. Contrarily, variable X_5 has a positive loading in Altman's original model (Model I), but a negative loading in our re-estimated model (Model II). It is worth noting that more recent studies, such as Almamy et al. (2016) and Boďa and Úradníček (2016), find a similar negative loading when re-estimating the model with a more recent data set. Additionally, like Altman (1968), Almamy et al. (2016) and Boďa and Úradníček (2016), we do not find a significant difference in means between the bankrupt and non-bankrupt group for X_5, Sales to Total Assets. This could be a possible explanation for the ambiguous direction of the variable across the two models.

Examining the coefficients further, we observe differences in the absolute values between the two groups. The coefficients express the importance (contribution) of the variables in classifying bankruptcy. For instance, a large coefficient implies that the corresponding variables carry high discriminating power between bankrupt and non-bankrupt groups. We observe that for both models X_3 (EBIT to Total Assets) is the greatest discriminating variable. Similarly, Variable X_1 (Working Capital to Total Assets) possesses a strong discriminating ability ranking second and third in Model I and II, respectively. The remaining variables, X_2, X_4 and X_5 do not share any immediate similarities across the models. One possible reason for this could be that Altman's original model (Model I) is constructed on a sample containing manufacturing firms only, whereas the re-estimated model (Model II) has a broader industry focus due to the rather scarce amount of bankrupt manufacturing firms in the post-Financial Crisis Period. The discrepancy in the ordinal contribution of the weightings is also widely supported by prior research. For example, Li (2012) found that variable X_1 carried the greatest discriminating ability followed by variable X_5. Almamy et al. (2016), find a similar pattern.

Instability of model coefficients evident over time

Finally, we note that the absolute scale of the coefficients of all five variables varies across the two models. This finding is similar to that of Grice and Ingram (2001)'s study, which concludes that the Z-score model is not stable across economic conditions and time periods. Given that Altman's original model (Model I) was constructed in the mid-1960s, where the business environment, accounting standards and economic cycle differ to the current time, it is not surprising that the observed values of the coefficients also differ. The financial ratios, from which the original model coefficients have been estimated, naturally reflect general macroeconomic trends and specific trends of that time, which most likely do not exist to today. Hence, we find evidence to support Grice and Ingram (2001)'s observation and note that the coefficients of Altman's Z-score model are not stable and therefore sensitive to periods and various business environments. This observation is aligned with other studies focussing on bankruptcy prediction in the 2000s such as Balcaen and Ooghe (2006) and Li (2012).

In summation, we find that Altman's original model (Model I) is still valid and possesses a solid discriminating ability in the post-Global Financial Crisis period, thus supporting **Hypothesis 1**. This is reflected through the high prediction accuracy over the one- and two-year period prior to bankruptcy. However, we note that the Z-scores coefficients are unstable and change with the time period and business cycles. We observe that our re-estimated model (Model II) outperforms Model I in prediction accuracy for the same sample and time period. We stress the importance of re-estimating the Z-score routinely to achieve the greatest prediction accuracy.

10.2 Do corporate governance indicators enhance Altman's model?

We determined that Altman's original model (Model I) still has predictive power in a post-financial crisis period, but that a re-estimation of the model (Model II) achieves higher results and is therefore warranted. On this basis, we examine and compare Model II and the re-estimated model including corporate governance indicators (Model III) to ascertain if these contribute to the prediction accuracy. We note that a comparison between the two models is justified as they are re-estimated based on the same underlying data. Thus, we avoid potential distortions stemming from the instability of Z-score coefficients discovered in the precedent sub-section.

Comparing bankruptcy prediction accuracies

Interestingly, Model III seems to have better bankruptcy predictability than Model II, as measured by a lower Wilks' lambda and a larger AUC in the ROC test compared to Model II. Both measurements support **Hypothesis 2** and suggest that adding corporate governance variables to the model increases the discriminating ability and thereby the prediction accuracy. This is further underscored in the one-year prediction accuracy which is superior for Model III (97 percent) compared to Model II (92 percent). The underlying mechanisms of the classification ability can be further investigated by comparing the distribution of actual Z-score for the sample.

Model III has greater discriminatory power

In comparing the two series of discriminant scores, it becomes clear that the Model III generates a more effective and accurate classification of firms, as evidenced by the distribution plots in Figures 11 and 12. Model II shows a greater concentration of Z-scores around the cut-off point, which results in a higher number of errors. Model III, on the other hand, has a wider distribution of Z-scores, which are not clustered around the cut-off point. The distribution of Z-scores can be compared across the two models by studying the centroids for the bankrupt and non-bankrupt groups. We find that Model II's centroids are relatively more concentrated (located closer to each other) with a spread of 1.42, while Model III displays a much wider gap between the centroids of 2.57. In other words, the figure suggests that corporate governance variables contribute to the discriminating ability of the bankruptcy prediction model.

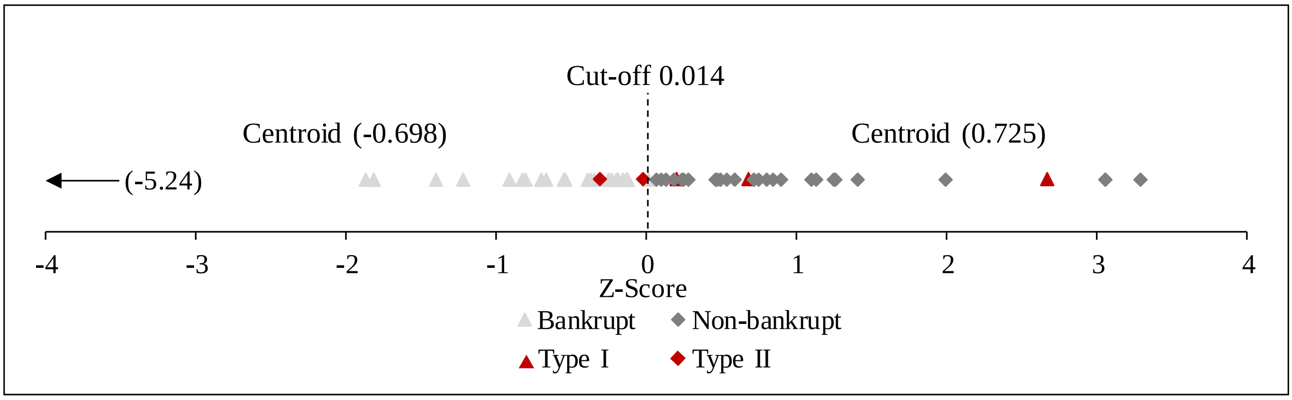

Figure 11. Discriminant Scores and Group Centroids for Model II; one year prior to bankruptcy. The figure shows the distribution of individual firm Z-scores for the estimation sample. The triangle indicates a bankrupt firm while the diamond is a non-bankrupt firm. The vertical axis expresses the Z-score. Source: Own Analysis based on SPSS Statistics

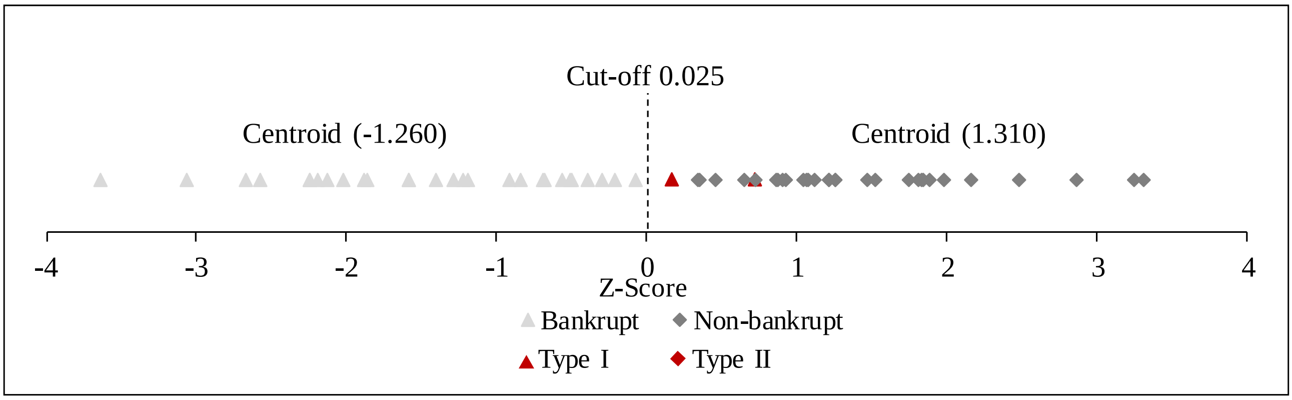

Figure 12. Discriminant Scores and Group Centroids for Model III; one year prior to bankruptcy. The figure shows the distribution of *individual* firm Z-scores for the estimation sample. The triangle indicates a bankrupt firm while the diamond is a non-bankrupt firm. The vertical axis expresses the Z-score. Source: Own Analysis based on SPSS Statistics

Secondly, we examine Type I and II errors depicted in red in Figures 11 and 12. The re-estimated model (Model II) classifies 92 percent correctly with only 10 percent Type I (false positives) and 7 percent Type II (false negatives) errors. Model III displays extremely high accuracy in classifying 97 percent of the sample correctly with merely 7 percent Type I errors and zero type II errors. The inclusion of corporate governance indicators in bankruptcy prediction models facilitate less Type I and Type II errors, enabling the model to outperform previous prediction models. The distribution of Z-scores reflected by the centroids and the examination of model errors provides support for **Hypothesis 2**. These findings are consistent with previous research (Chan et al., 2016; Chen, 2008; Simpson & Gleason, 1999) which also find the use of corporate governance indicators yield superior prediction accuracies.

Secondary sample supports Model III's superiority

To isolate any potential upwards bias stemming from using the estimation sample to test accuracy, we follow Altman (1968)'s methodology and introduce a secondary sample that has not been used for estimating the prediction model's parameters. We find that these prediction results are lower than for the estimation sample with 83 percent and 95 percent prediction accuracy for Model II and Model III respectively. We note that this accuracy is still very high. The decline in prediction accuracy is expected when probing a sample that is different from the estimation sample as the upwards bias is avoided. The fall in prediction accuracy when switching to a secondary sample is well-documented in bankruptcy literature (Li, 2012; Balcaen & Ooghe, 2006; Altman & Hotchkiss, 2006). The finding supports **Hypothesis 2** given that Model III has a persistently greater prediction accuracy than Model II across different samples and confirms the robustness of both Models.

The previous observations have generally been based on measurements expressed one year before bankruptcy in line with previous research (Altman, 1968; Balcaen & Ooghe, 2006). This gives a good indication of the short-term prediction accuracy of the models. At this point, it would appear that firm bankruptcy is effectively inevitable and that no form of interference, from a corporate governance standpoint, is able to ameliorate the financial conditions. Our empirical findings confirm this, showing similar high prediction accuracies one year prior to bankruptcy. Therefore, we investigate how both models perform as the years to bankruptcy increase. This is particularly interesting, as prediction accuracies in previous accounting-based models have shown a significant drop more than two years prior to bankruptcy (Balcaen & Ooghe, 2006).

Inclusion of corporate governance variables increases predictive ability

In line with the majority of previous studies (Altman, 1968; Balcaen & Ooghe, 2006; Li, 2012), we find that only focusing on financial ratios, Model II's, mean Z-scores for the Bankrupt group are negative in years one and two and well below the cut-off value of 0.014. Interestingly, we see that these values become positive in the following years and thereby surpass the cut-off value. This explains why the model accuracy falls for the Model II as years to bankruptcy increase and suggest that Type I errors should increase which is coherent with our empirical findings. Specifically, as years to bankruptcy increase Model II will incorrectly classify bankrupt companies as non-bankrupt. We note that the non-bankrupt group has a relatively stable positive mean Z-score throughout the studied period, which explains the lower frequency of Type II errors.

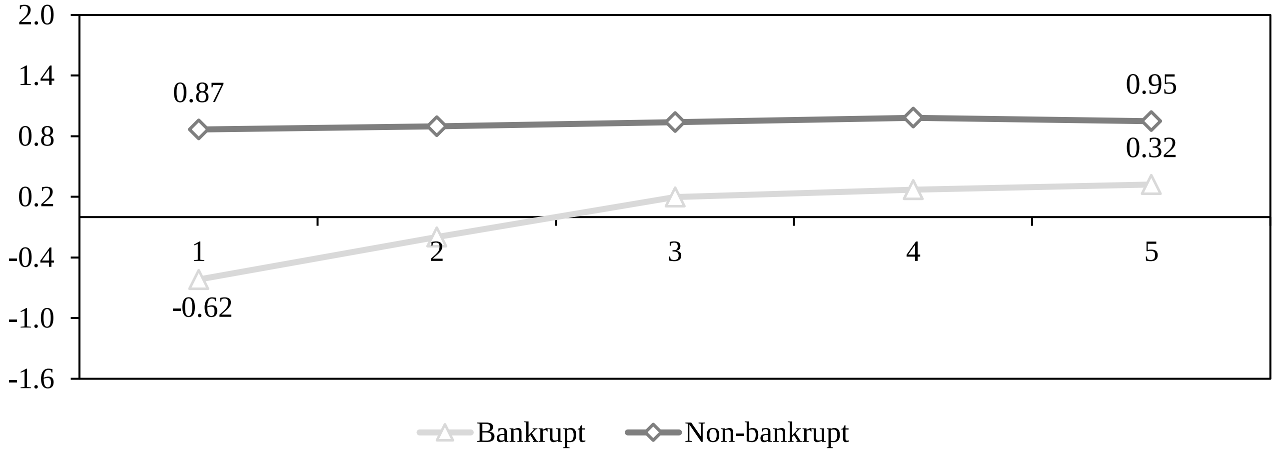

Figure 13. Development of Mean Z-score for Model II; one to five years prior to bankruptcy. Development of the mean Z-score for the estimation sample. The vertical axis indicates the Z-score, while the calendar year is expressed on the horizontal axis. Source: Own Analysis based on SPSS Statistics

Examining Model III, which includes corporate governance indicators, we observe a different pattern in the development of the mean Z-score. For the bankrupt group, the mean Z-score is negative and below the cut-off value (0.025) for the entire period. Similarity, the non-bankrupt exhibits stable, positive Z-score means. We observe that the mean Z-scores converge as years to bankruptcy increase. This is intuitive as it becomes increasingly difficult to predict something that is further out in the future.

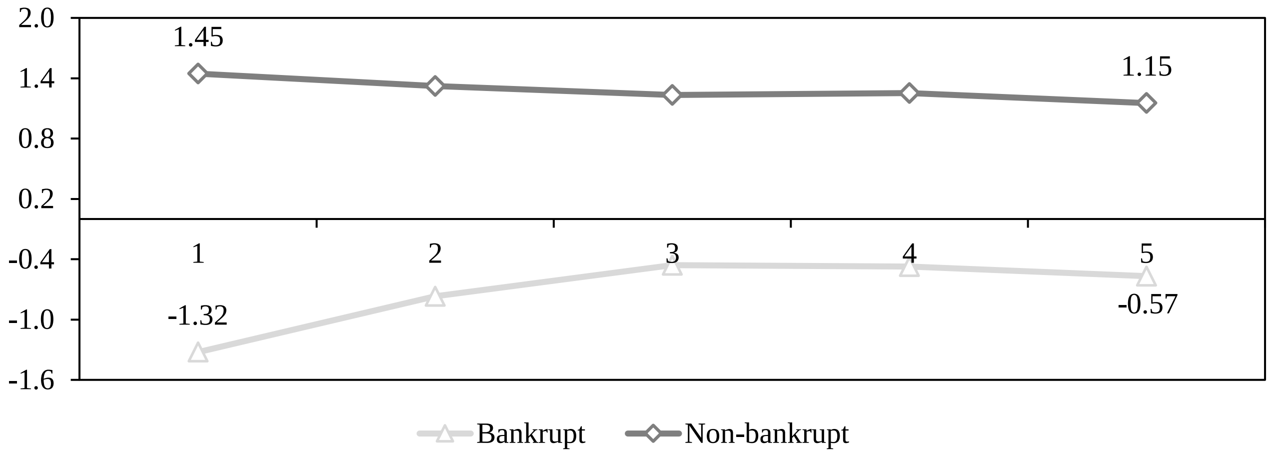

Figure 14. Development of Mean Z-score for Model III; one to five years prior to bankruptcy. Development of the mean Z-score for the estimation sample. The vertical axis indicates the Z-score, while the calendar year is expressed on the horizontal axis. Source: Own Analysis based on SPSS Statistics

Comparing the two models, we find that Model III has a greater discriminative ability based on the greater divergence between the Z-scores over time, producing fewer classification errors and thus higher precision accuracy. The latter is especially prevalent over the longer run.

Model III has greater long-term prediction accuracy

Further, linked to Z-scores trends, we compare the actual long-term prediction accuracy of the models. From Figure 15, a key observation is that Model III has a superior long-term predictive accuracy relative to Model II, which confirms the points raised previously. The accuracy of Model II falls significantly after year 2, which was also the case in Altman's original findings. Similarly, the accuracy of Model III also tapers off as years increase, but at a more modest pace. Model III's prediction accuracy appears to stabilise after year three. These results tie well with previous studies where a similar trend is observed (Chen, 2008; Chan et al., 2015). Arguably, the most interesting result to emerge from the data is that the accuracy of the corporate governance model was more robust (i.e. did not fall as much) compared to the re-estimated version of Altman model with the increase of lead time, as illustrated in Figure 15.

One possible explanation for this may be that governance mechanisms arguably have a longer-lasting impact on the financial health of a firm and are not as volatile and backward-looking as financial indicators. This is empirically supported by Gharghori et al. (2006) who argue that the original variables selected by Altman, which primarily rely on financial statements, are backward-looking and may therefore not be able to predict a firm's future wellbeing. Similarly, Gutzeit and Yozzo (2011) find that the 'backwardness' limits the prediction accuracy of Altman's model as only one variable, Market Value of Equity to Book Value of Debt (X_4), is 'forward-looking'. Backwardness has been a central critique point of accounting-based models and research has shown that including more 'forward-looking' metrics can enhance prediction ability significantly (Li, 2012). As noted, financial metrics can be manipulated by varying accounting and calculation principles to conceal true financial health, which is not the case with corporate governance indicators. Additionally, the long-term prediction ability of corporate governance indicators is theoretically sound. The forwardness can be traced back to governance theories, which suggest that if proper structures and incentives are in place, interests between shareholders and management will be aligned (Jensen & Meckling, 1976). This will demote the manipulation of financial data and moral hazard and will ultimately lead to less risk of bankruptcy. However, these changes do not happen overnight and have to be embedded into the firm mentality. Therefore, we argue that corporate governance helps with longer-term prediction, which can be observed in the stability of the prediction accuracy of Model III when compared to Model II in years three to five.

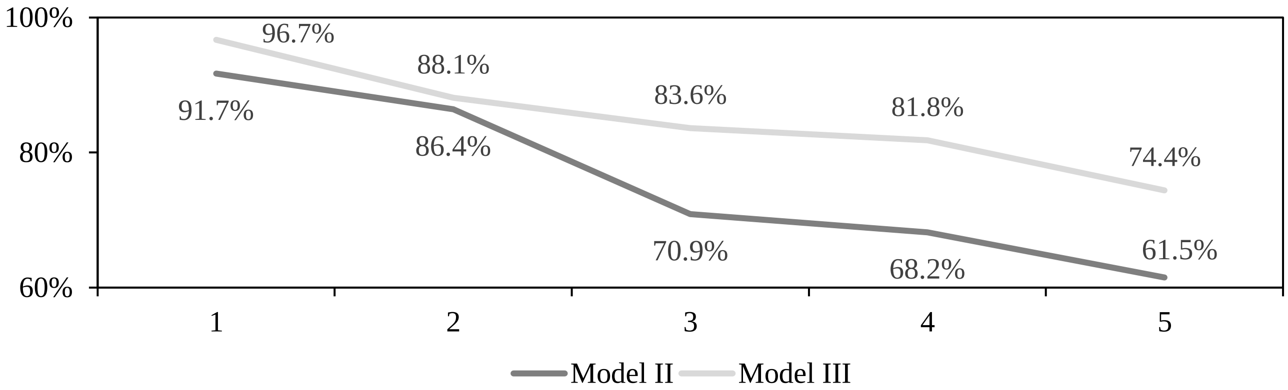

Figure 15. Comparison of Long-term Prediction Accuracy between Model II and Model III; one to five years prior to bankruptcy. Development of prediction accuracy for the estimation sample. The vertical axis indicates the prediction accuracy expressed in percent, while the calendar year is shown on the horizontal axis. Source: Own Analysis based on SPSS Statistics

Findings in line with recent studies

Our findings are complemented by several recent studies. For example, a paper by Liang et al. (2016) on the Taiwanese market similarly showed better prediction results for models using a combination of corporate governance indicators and financial ratios, also noting increased effectiveness. Additionally, Fich and Slezak (2008) also note enhanced predictive power in their analysis using US firms in 1991. Similarly, Chen et al. (2016) find improved prediction accuracy when including governance variables in their sector-agnostic study of US firms in the early 2000s. Hence, across the research conducted regarding corporate governance and bankruptcy prediction, albeit limited, the conclusion is one-sided: the predictive power of bankruptcy models is improved when including corporate governance-related metrics. To summarise, we find that our re-estimated model with corporate governance indicators (Model III) *shows superior long-term prediction power* compared to the re-estimated model (Model II), which only includes financial variables. On this basis, we find sufficient evidence to support **Hypothesis 2**.

Contributions of predictor variables confirm importance of corporate governance metrics

When considering the loading factors associated with our Model III, we observe that the variables holding the strongest classification power are Variable Compensation (X_9), Director Ownership (X_{11}), EBIT to Total Assets (X_3), Independent Directors (X_4) and Working Capital to Total Assets (X_1). Interestingly, as we introduce corporate governance variables to the bankruptcy prediction model several of Model II's variables become less important with the remaining three variables (X_5, X_2 and X_4) occupying contribution rank 8, 10 and 12 respectively. The strongest discriminating variable in Model III, by a considerable margin, is Variable Compensation (X_9). In line with theory, the larger performance-linked compensation the CEO benefits from, the greater incentive they have to perform well and hence reduce the likelihood of bankruptcy. This conclusion is also supported empirically by Hall and Liebman (1998), and more recently by Chen and Ma (2011), who similarly find a strong positive association between variable pay and firm performance. However, as stated in our literature review, other studies, such as Coles et al. (2006), have shown that higher executive pay can lead to greater risk-taking, which can harm firm value. Therefore, the empirical findings on this relationship are still mixed and inconclusive.

Variable		Coefficient	Rank
X_9	Variable Compensation	2.389	1
X_{11}	Director Ownership	-1.940	2
X_3	Earnings Before Interest and Tax (EBIT) / Total Assets	1.130	3
X_8	Independent Directors	0.949	4
X_1	Working Capital / Total Assets	0.795	5
X_7	Female Directors	0.599	6
X_6	Blockholders	0.184	7
X_5	Sales / Total Assets	0.140	8
X_{12}	Board Size	0.107	9
X_2	Retained Earnings / Total Assets	-0.077	10
X_{10}	CEO Tenure	0.054	11
X_4	Market Value of Equity / Book Value of Debt	0.052	12

Unstandardized coefficients

Table 40. Ordinal Ranking of the Contribution of Variables in Model III. The table shows the ordinal ranking of the contribution the model variables have in predicting bankruptcy. Source: SPSS Statistics

It is particularly noteworthy that we find that the loading direction obtained for the Director Ownership variable is negative, which implies that a higher percentage of director ownership contributes to bankrupt classification. This stands in contrast to prior studies, which have shown negative associations between board ownership and the probability of default Manzaneque et al. (2016). Upon closer inspection of our analysis of variance in Table 27, we note that the bankrupt group on average contains a lower percentage of independent directors, whilst also having a higher board ownership percentage, compared to the non-bankrupt group. Therefore, it can be argued that the benefits associated with independent directors, as highlighted in Section 5 are neutralised due to material ownership stakes reducing such level of independence. As a result, a greater number of these independent directors, which in fact are not independent, contribute to a higher likelihood of bankruptcy.

Finally, we note that the two financial ratios EBIT to Total Assets (X_3) and Working Capital to Total Assets (X_1), which were the best discriminating variables in Model II, still hold notable classification power after introducing corporate governance variables. Hence, we conclude that these ratios are robust in predicting bankruptcy across models, industries and years.

10.3 Hypotheses overview

We recall the hypotheses formulated in Section 6 and summarise our empirical findings in relation hereto.

Hypothesis	Description	Analysis
H_1	Altman's original model has different coefficients and a lower prediction accuracy than the re-estimated model	Supported
H_2	Including corporate governance indicators in the bankruptcy prediction model decreases the number of Type I and Type II errors relative to Altman's original model	Supported
H_{2a}	Bankrupt firms will have a lower number of blockholders compared to non-bankrupt firms	Supported
H_{2b}	Bankrupt firms will have a lower percentage of board ownership compared to non-bankrupt firms	Unsupported
H_{2c}	Bankrupt firms will have larger boards compared to non-bankrupt firms	Unsupported
H_{2d}	Bankrupt firms will have a lower ratio of independent board directors compared to non-bankrupt firms	Supported
H_{2e}	Bankrupt firms will have a lower ratio of female board directors compared to non-bankrupt firms	Supported
H_{2f}	Bankrupt firms will have a higher incidence of CEO duality compared to non-bankrupt firms	Unsupported
H_{2g}	Bankrupt firms will have higher CEO tenure compared to non-bankrupt firms	Unsupported
H_{2h}	Bankrupt firms will have a higher incidence of CEO turnover compared to non-bankrupt firms	Supported
H_{2i}	Bankrupt firms will have a lower degree of performance-based CEO compensation compared to non-bankrupt firms	Supported
H_{2j}	Bankrupt firms will have a lower percentage of CEO ownership compared to non-bankrupt firms	Unsupported

Table 41. Hypothesis Test Summary. The table provides an overview of the hypothesis tests conducted in the paper and illustrates if the hypothesis has been supported or not.

Blockholders

In comparing our findings with our corporate governance hypotheses, we observe that bankrupt firms have a lower presence of blockholder owners relative to non-bankrupt firms, thus providing support for **Hypothesis 2_a**. This is also consistent with the prior study by Parker et al. (2002), which found blockholder ownership was negatively associated with the likelihood of bankruptcy. As such, this reinforces the notion that blockholders' sizeable stakes give them a sufficiently large economic incentive to bear the cost of monitoring managers and exert their influence to ensure a firm does not 'lose its way'. This is further supported by the positive loading factor in the discriminant function for Model III.

Board size, director independence and female directors

Concerning board size, our results show a significant difference with average board sizes of 7 and 9 members for bankrupt and non-bankrupt firms, respectively. This stands in contrast to the findings of Fich and Slezak (2008) and our **Hypothesis 2$_c$**. Interestingly, this suggests that the agency and resource dependency theories involving increased monitoring, controlling and broader expertise associated with a higher number of directors, outweigh the stewardship theory (i.e. that managers perform better with less board influence). Our findings also show a significant, lower percentage of both independent and female board directors present within bankrupt firms compared to non-bankrupt firms, thus providing support for **Hypothesis 2$_d$** and **Hypothesis 2$_e$**. This is also reflected in Model III where both variables have positive loadings. With respect to **Hypothesis 2$_d$**, this reinforces the idea that strong outsider representation creates higher efficacy and a more active approach in strategic decision-making, as inside directors involve a greater likelihood of conflicts of interest with shareholders relating to rent-seeking. This finding is in line with prior studies by Fich and Slezak (2008) and Parker et al. (2002). For **Hypothesis 2$_e$**, this supports the idea that increased gender-diversity results in better monitoring and earlier implementation of bankruptcy-preventative measures, as opposed to the occurrence of marginalisation and delayed decision-making.

CEO duality, variable compensation, and director ownership

Interestingly, our analysis of variance test does not find any significant difference in terms of CEO duality between bankrupt and non-bankrupt firms (30 percent vs. 37 percent) as would otherwise have been expected. This finding stands in contrast to Daily and Dalton (1994), who noted the opposite findings: 54 percent and 38 percent for bankrupt and non-bankrupt firms. One possible explanation for this could be because the general presence of CEO duality has fluctuated markedly over time, as noted by Krause et al. (2014), and the time-period may, therefore, be subject to cyclicality, which could distort our findings. Hence, we do not find support for **Hypothesis 2$_f$**. Performance-based (variable) CEO compensation is the greatest contributor to classifying firms. This supports the notion proposed by Sun et al. (2013), that is, firms which have CEO's with significant '*skin in the game*' in the form of performance-contingent compensation are less associated with bankruptcy. As such, we find evidence that supports our **Hypothesis 2$_{i}$**. Another possible explanation is that CEOs managing firms which are more bankruptcy-prone negotiate their compensation packages to place a lesser weight on performance-based pay, as argued by Fich and Slezak (2008). Our analysis of variance test does not find any significant difference in terms of director ownership or CEO duality across bankrupt and non-bankrupt firms. Therefore, it follows that there is no support for **Hypothesis 2$_{b}$**, which stands in contrast with Gueyie and Elloumi (2001), who note a decreased likelihood of bankruptcy associated with director ownership.

CEO tenure, turnover, and ownership

In terms of CEO tenure, our results show a significant difference with average CEO tenure of 5.5 and 11 years for bankrupt and non-bankrupt firms, respectively. Interestingly, this stands in contrast to Luo et al. (2014), and does not provide support for **Hypothesis 2$_{g}$**, suggesting that CEOs do not become complacent and are reluctant to adapt to secular changes, which leads to firm deterioration. Related to this, our results provide evidence that bankrupt firms experience a significantly higher degree of CEO turnover, thus supporting **Hypothesis 2$_{h}$**. This is consistent with the notion that turnover within a management team can serve as an early indicator for business troubles. It is also aligned with the findings of Parker et al. (2002), who found that firms, which experienced changes in CEO were significantly more likely to experience bankruptcy. This is further supported by the loading factor in the discriminant function for Model III. Finally, there was no significant difference in CEO ownership between the two groups, and thus we do not find supporting evidence for **Hypothesis 2$_{j}$**.

10.4 Contribution to literature

Our paper distinguishes itself from the general approach of constructing bankruptcy prediction models solely from financial indicators by proposing the inclusion of several corporate governance metrics to enhance predictive ability. In addition to this, to our knowledge, no other studies regarding bankruptcy prediction and corporate governance have been performed using MDA as a methodology. It therefore follows, given the historical popularity of this methodology, our study provides an extension of the classic model. As established in our introduction, the practice and ability to evaluate corporate bankruptcy is of economic and social relevance to a wide range of stakeholders. Over the past decades, the importance of appropriate corporate governance measures has permeated large parts of the corporate world, and as such, we argue the inclusion of corporate governance indicators in bankruptcy models, such as those explored in this paper, is highly relevant and should be common practice. We argue that the findings may be relevant in designing and implementing corporate governance mechanisms and executive compensations schemes. Finally, we note that our extended Z-score (Model III) can be used as an alternative to paid, subscription-based default prediction models offered by credit agencies. The model is intuitive, straightforward to operate and can be used independently of complex statistical software, making it highly relevant for a broad user base.

10.5 Limitations of paper and recommendations for further research

Although the inclusion of corporate governance-related metrics yields impressive results, they should be interpreted with a certain level of healthy scepticism and not be extrapolated outside the scope provided in this study. In extension of this point, a limitation of the paper relates to the geographical focus of our analysis. Our paper analyses US firms only due to comparatively higher data quality and availability. Liang et al. (2016) also argue that the inclusion of corporate governance indicators and their usefulness in bankruptcy prediction should be dependent on the particular market being analysed, the same way there must be homogeneity in the definition of bankruptcy being applied. To draw more general conclusions regarding the role of corporate governance in bankruptcy prediction and mitigation, future studies could fruitfully explore this issue by broadening the geographical scope. In particular, the existence of differences between corporate governance structures, driven by varying regulatory principles, may result in different findings and relationships.

Another source of limitation relates to our sector-agnostic approach, except financial sector companies and REITS, with respect to our firm sample. Hence, a potential area for further research would involve investigating the model's applicability within individual industries, as well as tailoring industry-specific models, as has been done with Altman's original model.

Further, the developed model can only be applied to listed equities. Future research could construct a model that also looks at private companies. However, data limitations on financial and particularly corporate governance variables could pose an issue.

Our study is limited to a total sample of 102 firms spilt equally between bankrupt and non-bankrupt statuses. An interesting addition to our paper would be to test the robustness of our model across a wider sample to confirm that the impressive prediction accuracies we observe also hold true as the sample size is increased. We note, however, that manually collecting corporate governance variables from individual 10-K statements is a cumbersome task and thus, increasing the sample size significantly would considerably lengthen the data collection process. Another interesting research topic related to model robustness would be to test the performance of our extended model when exposed to an exogenous shock, for instance the COVID-19 pandemic or the like.

We note that the application of statistical models has its own limitations, such as the potential violation of certain assumptions which can influence the occurrence of Type I and Type II errors and result in over- or under-estimation.

Finally, as established in our literature review, several different approaches and methodologies have been developed subsequent to Altman's original paper. Although the use of MDA in bankruptcy prediction has remained relevant since its first use, the application of other, more statistically advanced, methodologies, such as random forest or neural networks, incorporating corporate governance variables warrants further investigation.

11 Conclusion

Bankruptcy prediction has emerged as an important topic within financial academia and become a critical tool for many stakeholders, including policymakers, financial market participants and individuals. However, the existing research regarding prediction models which include both financial ratios and corporate governance variables is limited.

The purpose of this paper was twofold: (i) to examine the validity and accuracy of Altman's seminal Z-score model in predicting corporate bankruptcy of US-listed companies in the post-Global Financial Crisis period; and (ii) determine whether the inclusion of corporate governance indicators would lead to enhanced performance. We analysed these issues by formulating a string of hypotheses derived from our examination of conceptual corporate governance theories and empirical research, which we subsequently quantified and tested.

We utilised multiple discriminant analysis to estimate two multiple discriminant models (Model II and Model III). Model II re-estimated Altman's five-factor model based on a non-industry specific, post-Global Financial Crisis data set. Model III extended Altman's original model to include a set of corporate governance-related indicators. These models were constructed from a unique data set sourced from EDGAR (SEC) and Bloomberg. A comparative assessment of the model performances was conducted by examining overall accuracy via the occurrence of Type I and Type II errors and receiving operating characteristic plots.

The main conclusion is that a prediction model including corporate governance variables has greater predictive ability than a model solely based on financial indicators. This is particularly evident in the long-term accuracy rates. This finding also holds true across an extended timeframe and in- and out-of-sample data, further underscoring its robustness. Secondly, we find evidence supporting the idea that Altman's model remains accurate in a post-Global Financial Crisis period, even when using a non-manufacturing sample.

Our results show that firms in which CEOs receive a greater degree of variable compensation are less associated with bankruptcy, supporting the idea that CEOs with significant '*skin in the game*' lead to better firm management. Also, our findings suggest bankrupt firms are associated with a higher degree of director ownership, supporting the theory of '*entrenchment*'. Lastly, we observe that two of the five variables Altman originally included in his study (EBIT to Total Assets and Working Capital to Total Assets), continue to carry strong discriminating power in the extended model (Model III).

Part VII

Reference List and Appendix

12. Reference List

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13. Appendix

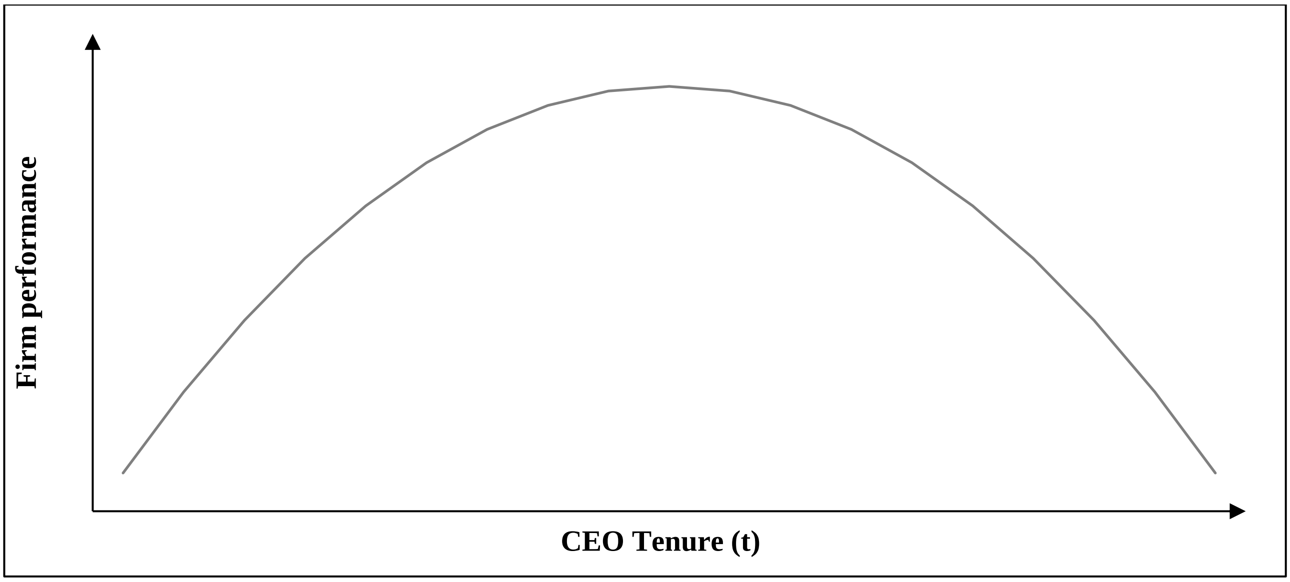
A. Literature review

Author(s)	Date published	Study period	Geography	Industry
Altman	1968	1946-1965	US	Manufacturing
Deakin	1972	1964-1970	US	General
Lis	1972	1964-1972	UK	Manufacturing
Altman	1973	1939-1970	US	Railroad
Blum	1974	1954-1968	US	General
Taffler	1974	1968-1973	UK	Manufacturing
Sinkey Jr	1975	1969-1972	US	Banking
Altman	1976	1971-1973	US	Broker-dealers
Tisshaw	1976	1975-1976	UK	Manufacturing
Deakin	1977	1964-1970	US	General
Moyer	1977	1965-1975	US	General
Santo	1977	1965-1974	US	Banking
Taffler	1977	1968-1976	UK	Manufacturing
Ketz	1978	1970-1975	US	General
Mason & Harris	1978	1976-1977	UK	Construction
Earl & Marais	1979	1974-1977	UK	Manufacturing
Norton & Smith	1979	1971-1975	US	General
Levallee & Altman	1980	N/A	Canada	General
Dambolena & Khoury	1980	1969-1975	US	General
Marais	1980	1974-1980	UK	Manufacturing
Pettway & Sinkey Jr	1980	N/A	US	Banking
Sharma & Mahajan	1980	1970-1976	US	Retail
Taffler	1980	1974-1978	UK	Distribution
Castanga & Matolcsy	1981	1963-1977	Australia	General
Betts & Belhoul	1982	N/A	UK	General
Taffler	1982	1978-1981	UK	Construction
Betts & Belhoul	1983	1977-1982	UK	General
El Hennway & Morris	1983	1955-1974	UK	Construction
Mensah	1983	1971-1979	US	Manufacturing
Springate	1983	N/A	Canada	General
Appetiti	1984	1979-1980	Italy	Manufacturing
Fulmer et al.	1984	N/A	US	SME
Izan	1984	1963-1979	Australia	General
Takahasi, Kurijawa & Watase	1984	1961-1977	Japan	General
Casey & Bartczak	1985	1971-1982	US	General

Frydman, Altman & Kao	1985	1971-1981	US	General
Levitan & Knoblett	1985	1980-1981	US	General
Rose & Kolari	1985	N/A	US	Banking
Keasey & Watson	1985	1975-1981	UK	SME
Lane, Looney & Wansley	1986	1979-1983	US	Banking
Scaggs & Crawford	1986	N/A	US	Airlines
Gombola et al.	1987	1967-1981	US	Manufacturing
Karels & Prakash	1987	1972-1976	US	General
Mahmood & Lawrence	1987	before 1982	US	Retail
Moses & Liao	1987	N/A	Other	Small contractors
Pantalone & Platt	1987	1976-1984	US	S&L Associations
Gloubos & Grammatikos	1988	N/A	Greece	General
McNamara, Cocks & Hamilton	1988	1980-1983	Australia	Private firms
Unal	1988	N/A	Turkey	General
Koh & Killough	1990	1980-1985	US	General
Cadden	1991	N/A	US	General
Espahbodi	1991	1983	US	Banking
Goudie & Meeks	1991	N/A	UK	General
Laitinen	1991	1987-1990	Finland	SME
Luoma & Laitinen	1991	1983-1988	Finland	General
Tam	1991	1985 - 1987	US	Banking
Baldwin & Glezen	1992	1977-1983	US	Quarterly models
Coats & Fant	1992	N/A	US	General
Agarwal	1993	N/A	US	General
Bukovinsky	1993	1987-1990	Other	General
Guan	1993	N/A	US	General
Odom & Sharda	1993	1975-1982	US	General
Bortiz & Kennedy	1995	N/A	US	General
Rujoub, Cook & Hay	1995	1987-1992	US	General
Alici	1996	N/A	UK	Manufacturing
Gardiner, Oswald & Jahera	1996	1986-1986	US	Hospitals
Lindsay & Campbell	1996	1983-1992	US	General
McGurr	1996	1991-1994	US	Retail
Kiviluoto	1998	N/A	Finland	SME
Dimitras et al.	1999	1986-1990	Greece	General
Gao	1999	1987-1998	US	Hospitality
Kahya & Theodossiou	1999	1974-1991	US	General

Sung, Chang & Lee	1999	1991-1995	S. Korea	Manufacturing
Yang, Platt & Platt	1999	1984-1989	US	Oil & Gas
Lee	2001	N/A	S. Korea	General
Patterson	2001	1985-1997	US	Hospitality
Grover	2003	N/A	US	Manufacturing
Lee & Anadarajan	2004	N/A	US	General
Galvao et al	2004	1997-2000	UK	General
Lin & Piesse	2004	1985–1994	UK	Industrial
Iwan	2005	2000-2001	Indonesia	General
Kim & Gu	2006	1986-1997	US	Hospitality
S&in & Porporato	2007	1990-1999	Argentina	General
Erkki K. Laitinen	2007	N/A	Finland	General
McKee	2007	1991-1997	US	General
Berg	2007	1996	Norway	General
Agarwal & Taffler	2008	1985-2001	UK	General
Boyaciogu, Kara & Baykan	2008	1997-2004	Turkey	Banking
Xu & Zhang	2008	1992-2005	Japan	General
Chen	2008	1997-2001	Taiwan	Banking
Li & Sun	2010	N/A	China	General
Rashid & Abbas	2011	1996-2006	Pakistan	General
Pervan, Pervan & Vukoja	2011	2010	Croatia	General
Korol	2012	1996-2009	Other	General
Li	2012	2008-2011	US	General
Kiyak & Labanauskaite	2012	2006-2010	Lithuania	General
Serrano-Cica & Gutierrez-Neito	2013	2008-2011	US	Banking
Bee & Abdollahi	2013	2006-2010	Malaysia	General
Tinoco & Wilson	2013	1980-2011	UK	General
Bauer & Agarwal	2014	1979-2009	UK	General
Machek	2014	2007-2012	Czech Rep	General
Kanapickiene & Marcinkevicius	2014	2009-2013	Lithuania	Construction
Kim	2014	1995-2002	S. Korea	Hospitality
Slefendorfas	2016	2007-2013	Lithuania	General
Gavurova et al.	2017	2009-2014	Slovakia	General
Ninh, Thanh & Hong	2018	2003-2016	Vietnam	General
Kovacova et al.	2018	2015	Slovakia	General
Karas & Režňáková	2018	2011–2014	Czech Rep	Construction
Alka et al.	2019	2008-2017	Other	Construction
Singh & Mishra	2019	2006-2014	India	Manufacturing

Appendix 1. Overview of Previous Discriminate Bankruptcy Prediction Studies. The table shows a list of discriminate studies within bankruptcy prediction. The list is not exhaustive.



Appendix 2. Illustrative graph of firm performance and CEO tenure. The vertical axis indicates the firm performance, while CEO tenure is expressed on the horizontal axis. Source: Illustration based on Wu et al. 2015.

B. Data sampling

Code	Industry Title	Number of Businesses
11	Agriculture, Forestry, Fishing and Hunting	378,293
21	Mining	32,231
22	Utilities	44,408
23	Construction	1,484,279
31-33	Manufacturing	638,730
42	Wholesale Trade	697,579
44-45	Retail Trade	1,800,166
48-49	Transportation and Warehousing	587,261
51	Information	355,030
52	Finance and Insurance	791,029
53	Real Estate Rental and Leasing	863,427
54	Professional, Scientific, and Technical Services	2,196,583
55	Management of Companies and Enterprises	71,170
56	Administrative and Support and Waste Management and Remediation Services	1,755,832
61	Educational Services	422,162
62	Health Care and Social Assistance	1,683,584
71	Arts, Entertainment, and Recreation	363,300
72	Accommodation and Food Services	901,005
81	Other Services (except Public Administration)	1,879,818
92	Public Administration	259,799
	Total Business Establishments	**17,205,686**

Appendix 3. North American Industry Classification System (NAICS). The North American Industry Classification System (NAICS) is the standard used by Federal statistical agencies in classifying business establishments for the purpose of collecting, analysing, and publishing statistical data related to the US economy. Source: United States Census Bureau (2020). Available at: www.census.gov/eos/www/naics

Category	Criteria	Search results
World region / Country	United States of America	61,805,308
Status	Active companies	61,559,040
Listed / Unlisted companies	Publicly listed companies	17,415
Industry	Excluding: Real Estate Activities and Financial and Insurance Activities	7,239
Total Assets (USDk)	Max = 5,000	4,225
Year of Incorporation	Before 2000	2,563
TOTAL		**2,563**

Appendix 4. Illustrative sample selection process for the Non-bankrupt group. The table shows how the population of US firms were narrowed down to a smaller sample defined by a set criterion matching the Bankrupt group (Matching-principle). The sample is constructed using Orbis' Boolean search tool. Source: Data adapted from Orbis.

C. Empirical analysis and results

Variable	Coefficient
X_3: EBIT / Total Assets	0.686
X_4: Market Value of Equity / Book Value of Debt	0.611
X_1: Working Capital / Total Assets	0.496
X_2: Retained Earnings / Total Assets	0.496
X_5: Sales / Total Assets	-0.082

Appendix 5. Structure Matrix for Model II. Variables ordered by absolute size of correlation within function. Source: SPSS Statistics

Variable	Coefficient
Box's M	3623.976***

*Significant at a 0.05 level; ** Significant at a 0.01 Level; *** Significant at a 0.001 level

Appendix 6. Box's M Test for Model II. The Box's M tests the null hypothesis of equal population. Source: SPSS Statistics

Variable	Coefficient
Box's M	542.432***

*Significant at a 0.05 level; ** Significant at a 0.01 Level; *** Significant at a 0.001 level

Appendix 7. Box's M Test for Model III. The Box's M tests the null hypothesis of equal population. Source: SPSS Statistics

Actual Membership	Predicted Membership		Total
	Bankrupt Group	Non-Bankrupt Group	
Bankrupt Group	27	3	30
Non-Bankrupt Group	2	28	30
Total	29	31	60

Appendix 8. Prediction Accuracy for Model II Using Separate Groups Covariance Matrix. Source: SPSS Statistics

Actual Membership	Predicted Membership		Total
	Bankrupt Group	Non-Bankrupt Group	
Bankrupt Group	28	2	30
Non-Bankrupt Group	1	29	30
Total	29	31	60

Appendix 9. Prediction Accuracy for Model III Using Separate Groups Covariance Matrix. Source: SPSS Statistics

Variables	X_1	X_2	X_3	X_4	X_5	X_6	X_7	X_8	X_9	X_{10}	X_{11}	X_{12}	X_{13}	X_{14}	X_{15}
X_1	**1.000**	-	-	-	-	-	-	-	-	-	-	-	-	-	-
X_2	0.754	**1.000**	-	-	-	-	-	-	-	-	-	-	-	-	-
X_3	-0.039	0.153	**1.000**	-	-	-	-	-	-	-	-	-	-	-	-
X_4	0.141	0.030	0.089	**1.000**	-	-	-	-	-	-	-	-	-	-	-
X_5	-0.096	0.028	0.208	-0.061	**1.000**	-	-	-	-	-	-	-	-	-	-
X_6	-0.007	0.151	0.127	-0.071	-0.124	**1.000**	-	-	-	-	-	-	-	-	-
X_7	0.038	0.148	0.110	-0.048	0.045	0.068	**1.000**	-	-	-	-	-	-	-	-
X_8	-0.028	0.030	-0.041	-0.085	-0.099	0.152	0.198	**1.000**	-	-	-	-	-	-	-
X_9	0.122	0.056	-0.337	-0.052	-0.275	-0.045	0.156	0.345	**1.000**	-	-	-	-	-	-
X_{10}	-0.065	0.066	0.086	0.106	0.012	0.051	-0.044	0.028	-0.277	**1.000**	-	-	-	-	-
X_{11}	-0.014	0.127	0.181	0.092	0.204	0.236	-0.052	-0.249	-0.359	0.256	**1.000**	-	-	-	-
X_{12}	0.075	0.225	0.025	-0.152	0.072	-0.046	0.281	0.011	0.181	-0.104	-0.131	**1.000**	-	-	-
X_{13}	-0.055	0.024	0.084	0.023	0.056	0.060	-0.009	-0.127	-0.190	0.441	0.215	-0.250	**1.000**	-	-
X_{14}	0.279	0.161	0.037	0.018	-0.025	-0.169	0.100	-0.182	0.334	-0.734	-0.049	0.207	-0.263	**1.000**	-
X_{15}	-0.057	0.038	0.010	-0.012	0.068	0.124	-0.053	-0.164	-0.320	0.419	0.596	-0.125	0.289	-0.149	**1.000**

Appendix 10. Exhaustive correlation matrix. Source: SPSS Statistics