HELLENIC REPUBLIC
UNIVERSITY OF MACEDONIA

SCHOOL OF BUSINESS ADMINISTRATION

DEPARTMENT OF ACCOUNTING AND FINANCE

POSTGRADUATE STUDIES PROGRAM IN APPLIED ACOUNTING AND AUDITING

Master Thesis

ESTIMATING CORPORATE FAILURE AS AN AUDITOR'S GOING CONCERN EVALUATION FACTOR

by

DIMITRIOS G. GLOUBOS

Supervisor: Livanis Efstratios

This thesis has been submitted in fulfillment of the requirements for the Master Degree in Applied Accounting and Auditing

November 2016

Dedication

This study is dedicated to the people who supported me during the process of writing it, to whom I am greatly indebted. My parents who are my first teachers, Alexandra, my uncle Theoharry and my friends, were the basic source of my inspiration during that working period. Their confidence, encouragement, assistance and faith, gave me the persistence I needed, without which this thesis would not be the same.

"Fast is fine, but accuracy is everything"

Xenophon
(Historian of the 4th century BC)

Acknowledgments

I would like to show my appreciation to all of the respondents who enabled this thesis. I would also like to thank my supervisor Efstratios Livanis for the guidance and the support during the course of writing this thesis. Finally, I would like to thank all anonymous individuals who provided me with insightful comments and critique on this work.

Dimitrios G.Gloubos

Thessaloniki, 20 November 2016

Abstract

One of the most important tasks of the audit profession is the assessment of their going concern opinion. Among many issues an auditor has to examine before issuing an opinion, is the ability of an entity to support its operations financially, in other words, to not be in danger of failure due to liquidity problems. During the last decades, finance literature has examined potential methods to estimate the probability of a firm to fail, exploiting financial as well as market indicators, through bankruptcy prediction models. The purpose of this study is to test the predictive accuracy of MDA, Probit and ANN in foreseeing an entity's bankruptcy, applied in a dataset of 81 bankrupt and 81 healthy US firms. MDA proved to be the optimum model to predict bankruptcy, right before its occurrence, while Probit and ANN can also be used as capable tools to assist auditors with their judgement.

Key-words: Going concern, auditors, corporate bankruptcy prediction, MDA, Probit, ANN

Table of Contents

List of Tables

List of Figures

1 Introduction

Auditors are considered to be a reliable and stabilizing factor of the economy, as they are obliged to execute their work under specific guidelines while using at the same time their objective judgement. One of the fundamental responsibilities an auditor has to follow, is the ability of a company to continue as a going concern. In other words, auditors must evaluate the financial position of a client to determine whether or not the firm's operating ability is endangered (Altman, 1982).

Nowadays, according to that assumption, auditors have to evaluate substantial doubt regarding an entity's ability to continue as a going concern, for the forthcoming one-year period, during the whole process of their audit control. They are also obliged to assess possible financial effects and determine the implications for the auditor's report (AICPA, 2012). Nevertheless, for the assessment of an entity's going concern, the most crucial auditors' tool is their judgment, an ability formed by their morality and their knowledge of conditions and events related to the examined entity.

According to relevant literature, the going concern evaluation has proven to be one of the most difficult and ambiguous audit tasks (Carcello & Neal, 2000). It is not difficult only because it involves auditor's judgement, but also because the consequences of auditor's opinion, on that issue, can be catastrophic for the existence of an entity, in case it is not favorable for it. As a matter of fact, it has been proven several times that auditors do not always succeed in their assessment about an entity's going concern. The high rate of audit failures, revealed during the last decades, indicates that it is difficult to predict a company's future and to be accurate on going concern assessment (Martens, et al., 2008), although it is irrefutable for many cases that we are talking about intentional frauds[1].

During the last decades, corresponding institutions as well as researchers' community, endeavor to find effective ways of ensure auditors' trustiness and objectivity. Institutions introduce regulations for auditors, recently for management as well, and researchers try to find out the reasons that provoke auditors' failures or tools that can contribute to the reliability of their work. A representative research example, in that direction, is the examination of the usefulness of corporate bankruptcy prediction models in assisting auditors with their going concern assessment.

[1] One of the most shocking audit frauds in the US it the case of Enron, occurred in 2001, under the control of Arthur Andersen auditing firm, that caused the introduce of strict regulations on auditor's working procedures and reliability, starting from US and continuing all around the globe (i.e. the .SOX Act of 2002).

The idea was initially introduced by Altman and McGough (1974), whose pioneer work concluded that bankruptcy prediction models were more effective in foreseeing bankruptcies than audit reports[2]. Similarly, many researchers examined the usefulness of those models as a tool that can contribute in auditors' assessment of an entity's going concern, by comparing their accuracy to the accuracy of audit going concern qualifications, supporting the models' superiority (Levitan & Knoblett, 1985; Mutchler, 1985; Koh & Killough, 1990; Cormier, et al., 1995).

Prior to the evolution of this scientific hypothesis, and in parallel to that, other studies concentrated on the development of bankruptcy prediction models, as techniques to estimate financial distress and foresee corporate failure. Starting from Beaver (1966) and till today, literature has to show many models that use financial and market variables, along with other parameters related to an entity's viability. Some of the most cited methods for bankruptcy prediction include the Z-Score model (Altman, 1968), Logit model (Ohlson, 1980), Probit model (Zmijewski, 1984), Shumway model (Shumway, 2001) and BSM-Prob model (Hillegeist, et al., 2004). Furthermore, many researchers attempted to exploit the computational power of modern technology, for the same purpose.

Contributing to previous research, this study tests three bankruptcy prediction models, namely MDA, Probit and ANN, on a set of 81 bankrupt and healthy US firms, with the main objective to answer the following research questions:

1. Which one of the examined models has the highest predictive accuracy, being tested on bankrupt companies, right before the occurrence of the bankruptcy event?
2. Are bankruptcy prediction models able to assist auditors (or management) to their assessment of an entity's going concern?

The structure of this text will be as follows: Firstly will be presented related literature in corporate bankruptcy prediction models. Secondly follows a detailed review of the going concern assumption and relevant regulation. The third part describes the dataset used in this study as well as further insights about the tested prediction models. Subsequently, the fourth part presents and comments on empirical findings of this research, while mentioning certain drawbacks. The fifth and last part presents our conclusions on the summarized findings and proposes further areas of research.

[2] The results of this study, indicated that their model was 82% accurate in predicting bankruptcy when compared to auditors' reports of 46%.

2 Background

The relevant literature of this study allude to two major fields of research: the going concern assumption and the corporate bankruptcy prediction models. In the following chapters we present a thoroughly detailed picture of those two fields, unfolding the background for the empirical research that comes next.

2.1 Going Concern Assumption

Along with the development of accounting, as a mean to codify the financial transactions of corporations and their economic state at a given time, arose the need to come up with specific accounting guidelines (principles), which would be followed by everyone, in order to give uniformity and objectivity to the presentation of financial information. Today, in USA those rules are known as the basic Generally Accepted Accounting Principles (GAAP or US GAAP) or as the "conceptual framework of financial reporting" and they consist of Assumptions, Principles and Constraints, as shown below:

Table 1 – Conceptual Framework of Financial Reporting (US GAAP)

Assumptions		
1	Economic Entity	For accounting purposes, a company is considered to be a separate economic entity.
2	Going Concern	A company will operate indefinitely, unless there is substantial evidence for the opposite.
3	Monetary Unit	Financial statements must be reported in the national currency.
4	Time Period	Financial reports cover a specific period of time.
Principles		
1	Historical Cost	Initial recording of financial transactions (assets and liabilities) must be at their original cash equivalent cost.
2	Full Disclosure	Companies must reveal enough information to the users of financial reports, in order to foster their sound judgment.
3	Revenue Recognition	Revenues must be recorded when services are completed and goods are delivered to customer, not at the time of payment.
4	Matching	Expenses must be recorder at the period they helped create revenue.
Constraints		
1	Materiality	An item is material if its inclusion or omission would influence the judgment of a reasonable person.
2	Conservatism	A company should use the accounting method that affects financial statements in the least favorable immediate way
3	Cost-Benefit	Companies must weigh the costs of providing the information against the benefits that can be derived from using them.
4	Industry Practices	Financial statements of companies in specific industries, in some cases, should follow reporting practices of the industry they operate.

One of the basic assumptions, that was needed to detect from the very beginning of the accounting profession, refers to the ability of an entity to continue as a going concern. According to the American Institute of Certified Public Accountants (AICPA) "The auditor has a responsibility to evaluate whether there is substantial doubt about an entity's ability to continue as a going-concern for a reasonable period of time, not to exceed one year beyond the date of the financial statements being audited". In other words, a going concern confirmation ensures that the entity will not be driven to halt its operations and liquidate its assets in the subsequent year (AICPA, 1988).

This information is crucial for everyone who is involved to the financial activities of an entity, like investors, shareholders and creditors, as the ability of a company to continue meeting its objectives and obligations is the first condition someone has to reassure before entering or keeping his position to the capital investment or operating cycle of a company.

Under that fulfilment, auditors were called to play a significant role to the process of evaluating companies' going concern, under the guidance of institutions that formed the corresponding framework, with the main purpose to inform public with reliable corporate financial information, beyond occasional management's intentions to the opposite.

2.1.1 Operating Framework

The framework under which auditors are called to execute their profession, is fully designated and guided via specific procedures, defined by authoritative institutions. Depending on which country an auditor and the audited company operates, the auditor is obliged to follow the relevant auditing standards and the audited company the relevant accounting standards, as well as relevant laws that apply for both of them.

2.1.1.1 Authoritative Bodies

In USA, the national professional organization of Certified Public Accountants (CPAs) is the AICPA, founded in 1887, which lead to the establishment of accountancy as a profession distinguished by rigorous educational requirements, high professional standards, a strict code of professional ethics, a licensing status and a commitment to serving the public interest (AICPA, 2016). AICPA's mission, as an authoritative body, is to develop standards for audits, the so called Statements on Auditing Standards (SAS), provide guidance and knowledge to its members, perform examinations for candidate CPAs, and monitor the compliance with the profession's technical and ethical standards.

Additionally, the authoritative body responsible to establish financial accounting and reporting standards, which follow GAAP, is the Financial Accounting Standards Board (FASB). FASB is an organization, established in 1973, recognized by the Securities and Exchange Commission (SEC), as well as the AICPA, as the designated accounting standard setter for public companies. The main objective of FASB is to issue financial accounting standards, intended to promote financial reporting and management's responsibility.

Throughout the past decades, AICPA has developed numerous SAS, guiding auditors on Generally Accepted Auditing Standards (GAAS) in regard to auditing an entity and issuing a report.

SAS cover every aspect of the auditing profession including auditor's responsibilities audit procedures, documentation, primary and supplementary information needed for every step of the control plan, and reporting methods. One of the first matters that AICPA needed to codify was the going concern assumption and the procedures an auditor had to follow so as to issue a going concern opinion.

2.1.1.2 Relevant Statements on Auditing Standards (SAS)

The first initiative took place in 1981 with the addressing of the going concern qualification issue through SAS No. 34 "The Auditor's Considerations When a Question Arises About and Entity's Continued Existence". Later on, in 1988, AICPA superseded it by issuing SAS No. 59 "The Auditor's Consideration of an Entity's Ability to Continue as a Going Concern", which was also superseded in 2012 by SAS No. 126 "The Auditor's Consideration of an Entity's Ability to Continue as a Going Concern (Redrafted)".

Before 1981, there was not sufficient authoritative guidance on whether auditors should modify their opinion based on substantiated doubts that the audited entity could continue as a going concern. At that time, it was observed that several companies filed for bankruptcy while auditor's opinion was sanguine for the opposite (Altman & McGough, 1974; Altman, 1982). In an effort to reassure the reliability of auditing control and opinion, SAS No. 34 (AICPA, 1981) came to regulate that area.

The new standard was introduced as an effective and detailed regulation, capable of increasing auditors' responsibility and providing information of higher quality to the public.

SAS No. 34 (AICPA, 1981) in paragraph 3 states that auditors should form their opinion based on financial statements, contrary information related to an entity's ability of continued existence, along with any management' plans for dealing with the underlying issues. Paragraph 4 gives examples of contrary information, which include recurring operating losses, default on loan or similar agreements, loss of key management or operations personnel, and legal proceedings. Paragraph 5 highlights factors tending to mitigate the significance of contrary information, such as disposability of assets, credit availability, capability to reduce expenses, and variability of dividend requirements.

Paragraph 6 refers to the entity's capacity to adopt alternative actions in order to cope with dysfunctions that may occur, and paragraph 7 require auditors to consider contrary information and mitigating factors. Following this, paragraphs 8 and 9 refer to management's plans needed to answer evidence that threaten entity's ability to fulfill its obligations and to auditor's consideration of the proposed solutions.

Paragraph 10 requires disclosure of the principal conditions that raise doubts about an entity's going concern and paragraph 11 discusses auditor's judgement on the appropriateness of modifying the audit opinion to point out doubts about the entity's going concern status.

Although this standard was a promising regulation, there were still questions on auditor's responsibility at evaluating an entity's ability to continue in existence (Goldstein, 1989), while many companies that filed for bankruptcy did not receive a modified audit report before the bankruptcy event (Menon & Schwartz, 1987; Hopwood, et al., 1989).

As an aftermath, SAS No. 59 (AICPA, 1988) came to supersede previous regulation, being a part of the nine expectation gap auditing standards issued that year. The main purpose of the new SAS's issuance was to address the gap between auditor's responsibilities and public expectations, though it was considered to be the most controversial of that year's expectation gap auditing standards (Guy & Sullivan, 1988) and that it added little to the authoritative guidance (Geiger, et al., 1998).

SAS No. 59 (AICPA, 1988) brought three main changes compared to the previous standard (Asare, 1990):

- It required auditors to consider an entity's ability to continue as a going concern at every step of the audit process, although without adding any further procedures, while previous SAS required auditors to consider going concern status only when audit procedures would rise such a question.

- In case there of high doubt about an entity's going concern status, new SAS required modifications on the audit report, while the previous one required auditor's qualification in case of uncertainty regarding the recoverability of assets and the classification of liabilities.
- The last difference between the two SAS, relies on an extra explanatory paragraph that the new SAS required in the audit report about auditor's substantial doubts, while previous SAS required only auditor's opinion.

Many studies that investigated the effectiveness of the new standard, in comparison to the era prior to its effectiveness, concluded that auditors became more responsible and were more likely to issue a qualified going concern opinion (Raghunandan & Rama, 1995; Carcello, et al., 1995). Consequently, SAS No. 59 (AICPA, 1988) is the only guidance for auditors on evaluating the going concern assumption, effective till today, redrafted under SAS No. 126 (AICPA, 2012).

2.1.1.3 Relevant General Accepted Accounting Principles (US GAAP)

GAAP, assumed that a company will continue to operate as a going concern until its liquidation becomes imminent (FASB, 2013). Nevertheless, GAAP did not include any further guidelines to management on the substantiation of the going concern assumption, until 2014.

Recently, FASB published the Accounting Standards Update (Update or ASU) No. 2014-15[3] "Disclosure of uncertainties about an Entity's Ability to Continue as a Going Concern", defining management's going concern assessment and disclosure responsibilities. The new standard, requires disclosures when conditions give rise to substantial doubts about an entity's going concern for a reasonable period of time, as even if an entity's liquidation is not imminent there may be events or conditions that may threaten its viability.

Disclosures related to going concern uncertainties is a well-known practice in financial reporting, but before this standard there was not any guidance to management on how to treat these issues upon their occurrence. Also, in accordance to the relevant auditing standards and regulation, which require auditors to evaluate an entity's going concern and to consider management's footnote disclosures, GAAP now line with this practice.

[3] ASU No. 2014-15 applies to all companies and is effective for the annual period ending after 15 December 2016 and all annual interim periods thereafter.

Specifically, the new standard attempts to complete and integrate the existing guidance, compared to SAS, in the following tasks:

- It requires a going concern assessment each interim and annual reporting period, while SAS do not apply to interim periods.
- Substantial doubt is defined and described in detail, while SAS are not that determinate.
- The look-forward period for management is one year starting from the issuance of financial statements, while auditors are required to examine a one-year period starting from the balance sheet date.
- Managers are required to provide disclosures for every issue that may rise substantial doubts and even for the resolved ones, while in these situations SAS motivate auditors to review the effectiveness of management's plans without specifying the disclosure requirements.

Under ASU No. 2014-15, the FASB (2014), guides management in the evaluation process of an entity's going concern, by introducing three key provisions. The first discusses the evaluation of substantial doubt, the second refers to the feasibility of management's plans and the last one describes the required disclosures.

Upon appearance of substantial doubts about a company's going concern, for each forthcoming interim and annual period, management should proceed to the evaluation of the issues that raise doubts and provide related disclosures. According to the new standard, substantial doubt exists when conditions and events indicate that a company will probably not be able to meet its obligations, within one year after the issuance date of financial statements. Except from that, management should also consider all subsequent events relevant to the conditions that threaten company's going concern.

Additionally, the standard indicates that the evaluation of substantial doubts assumes that management considers both quantitative and qualitative information, in order to measure their impact on the company's ability to meet its obligations, as shown below (FASB, 2014, p. 8):

- The company's current financial condition, such as available cash and credit.
- Conditional and unconditional obligations related to the next period or year.
- Funds necessary to maintain operations, considering the projected inflows and outflows for the forthcoming period.

- Other conditions that could raise doubts about the company's ability to meet its obligations, in conjunction with the above, such as negative finance trends, other indicators of financial difficulties, internal and external matters.

In case the evaluation procedure results to issues that give rise to substantial doubt, the standard requires management to consider its plans and their mitigating impact in alleviating substantial doubt. In order to do that, management should examine if its plans will be effectively implemented within the assessment period and verify their ability to mitigate the conditions related to substantial doubts.

Management's plans orientation depend on the problematic situation a company faces and they intend to restore the viability of that company. For example, they could concern disposal of an asset or business, borrowing money or restructuring debt, reducing or delaying expenditure and increasing ownership equity (FASB, 2014, pp. 13-14).

The last provision discussed in this standard has to do with the required disclosures on information about issues that raise substantial doubts. No matter if those issues are alleviated by management's plans, disclosures are required for all conditions related to substantial doubts.

In case management's plans are considered to be effective in overcoming problematic situations, the company should disclose information that enables users of financial statements understand the issues that initially gave rise to substantial doubts, management's consideration on the criticalness of those issues, the company's ability to meet its obligations and the management's plans that alleviated substantial doubt.

If substantial doubt is not alleviated according to management's consideration, a company should include a statement indicating that there is substantial doubt the entity will continue as a going concern for the upcoming one-year period. Moreover, management should provide disclosures able to inform users of financial statements about the conditions that caused uncertainty, including (FASB, 2014, p. 28):

- The principal conditions that gave rise to substantial doubts.
- Management's evaluation of the impact of those condition to the company's ability to meet its obligations.
- Management's plans for the mitigation of the adverse conditions.

The detailed full process, as described in this ASU is visually presented at the attached Appendix A: Decision flowchart on going concern evaluation by management.

2.1.1.4 Relevant Case Law - The SOX Act of 2002

As mentioned above, all institutions responsible of guiding and monitoring the work of auditors and management have created a comprehensive set of rules and guidelines, intended to ensure the reliability of financial information. Yet, many flagrant cases that have been revealed and led to bankruptcies, such as Enron (2001) and Arthur Andersen (2002)[4], revealed certain gaps and weaknesses of the audit profession, able to mars auditors' or audit firms' trustiness. The shock of those scandals came as the final twist of the screw, leading to the enactment of the famous Sarbanes-Oxley Act (SOX) of 2002.

Its main purpose was to fix and enhance the quality of corporate governance and financial statements information of the US listed firms (Coates, 2007) and as a result, it came to redefine both management's and auditor's responsibilities. The Act, also, brought a new quasi-public institution to oversee audit firms, the Public Company Accounting Oversight Board (PCAOB), while SEC kept the competence to oversee public companies.

The SOX Act contains 11 titles that describe specific mandates and requirements related to financial reporting. Specifically, the Act concentrates on the role of management, executive analysts, auditors and internal control, with the aim to reassure the validity of financial information provided to public.

The basic topics discussed in this law are presented in the following table, as categorized by Coates (2007):

Table 2 – Summary of SOX Act's Topics

Sections	Topics
101-109	PCAOB's creation, oversight, funding and tasks
302, 401-406, 408-409, 906	New disclosure rules, including control systems and officer certifications
201-209, 303	Regulation of public company auditors and auditor-client relationship
301, 304, 306, 407	Corporate governance for listed firms
501	Regulation of securities analysts
305, 601-604, 1103, 1105	SEC funding and powers
802, 807, 902-905, 1104, 1106	Criminal penalties
806, 1107	Whistleblower protections
308, 803-804	Miscellaneous (time limits for securities fraud, bankruptcy law, fair funds)

[4] There are numerous scandals, reported during the last 40 years, which involved audit firms on the manipulation of accounting data. Enron & Arthur Andersen are two of the most discussed cases, occurred in 2001 and 2002 in USA, that led to shutdown these companies, to damage the reputation of audit firms, and to the introduction of further accounting reform regulations all over the world.

The most radical measure taken with this initiative was the enhancement of PCAOB, an institution responsible to oversee auditing firms and to protect investors and public interest through effective and independent evaluation of auditors' work. Auditor's independence is another crucial matter that suffered criticism due to the increasing number of fraud cases, and the response of the SOX Act was to impose strict rules and criteria on the audit control in order to ensure auditor's independence.

Additionally, the SOX Act brought further responsibilities for management regarding the accuracy and completeness of financial information, which can lead to serious penalties in the case of fraud. Except from that, disclosure requirements became mandatory for even more situations, such as intra-group transactions and associated enterprises, and there was significant improvement on the organization and the role of internal control.

After the effectiveness of the SOX Act, audit firms claim that they have become much more conservative with respect to client retention and acceptance decisions because the risks associated with auditing increased significantly as a result of the SOX Act (Rama & Read, 2006). Particularly, the change of auditor's view on issuing audit opinions, since the enactment of SOX Act, is related to the transfer of their oversight to PCAOB and to the significant increase of insurance and other liability related costs (Ryu, et al., 2009).

Although the Act concentrates on the conservatism constraint for the reporting and auditing of financial information, the going concern assumption is the core of auditing evaluation as it is linked to the accuracy of financial information as well as to auditor's and management's reliability.

Many researchers investigated the impact of the SOX Act on the issuance of auditor's going concern opinion and on the quality of financial information, with the majority of them indicating that the Act contributed to the improvement of auditor's responsibility and financial statements' reliability. Geiger, et al. (2005) examined 226 companies that entered into bankruptcy from 2000-2003 and found out that auditors were more likely to issue going concern opinions after the effectiveness of the SOX Act. Furthermore, Kogan, et al. (2009) in their research on stock volatility prediction of US firms from the text of 10-K reports, found that stock volatility was more accurately predicted in the years 2004-2006 than in 2001-2002, suggesting that the SOX Act led to more informative reports.

Other studies, such as Fargher & Jiang (2008) and Feldmann & Read (2010) , although they mention the impact of SOX to auditor's going concern opinion, during the first years after the SOX enactment, they doubt about its effectiveness after the year 2004 or 2005.

2.1.2 Auditor's Objectives & Responsibilities

The current auditing standards are explicit about auditor's role in the process of evaluating an entity's going concern and providing information to the users of financial statements, although during that process auditors frequently have to face various obstacles.

2.1.2.1 Auditor's Consideration

Auditors' objective, in general, is to reassure the users of financial statements and auditing reports that published financial data, certified by auditors, are accurate, relevant and reliable. More specifically, SAS No. 126 (AICPA, 2012, p. 574) describes three basic auditors' objectives regarding the going concern assumption, which are:

- to evaluate and conclude, based on the audit evidence obtained, whether there is a substantial doubt about the entity's ability to continue as a going concern for a reasonable period of time (not to exceed one year beyond the date of the financial statements being audited),
- to assess the possible financial statement effects, including the adequacy of disclosure regarding uncertainties about the entity's going concern, and
- to determine the implications for the auditor's report.

As a general rule, auditors' evaluation and opinion is formed based on their knowledge of relevant conditions and events that took place prior to the date of the audit report. Such information, are obtained via audit procedures planned to achieve audit objectives that are related to management's assertions embodied in the financial statements being audited (AICPA, 2012, p. 573). Examples of procedures that may identify useful information for auditors, summarize as follows (AICPA, 2012, p. 578):

- Analytical procedures
- Review subsequent events and subsequently discovered facts
- Review of compliance with the terms of debt and loan agreements
- Reading of minutes of meetings of stockholders, board of directors and important committees of the board
- Inquiry of an entity's legal counsel about litigation, claims, and assessments
- Confirmation with related and third parties of the details of arrangements to provide or maintain financial support

After the auditor gets all information needed to form an audit opinion on an entity's ability to continue as a going concern for a reasonable period of time, the findings may rise substantial doubt about this ability. Auditor's responsibility, in this case, is to include the crucial ones to the emphasis-of-matter paragraph in the audit report, so as to meet the obligation inform the users of financial statements about factors that may threaten an entity's viability.

In case the auditor is asked to reissue the audit report without the emphasis-of-matter paragraph thaw was originally included, the auditor has to reassure that conditions and events that initially gave raise to substantial doubts about the entity's ability to continue as a going concern have been resolved (AICPA, 2012, p. 581).

2.1.2.2 Auditing Beyond Guidelines

Auditing is a necessary monitoring device because potential conflicts of interest may arise between owners and managers and among different classes of security holders (DeAngelo, 1981). Although the framework under which an auditor performs his activities and concludes to his judgement is concrete, it is an actual fact that auditors often face the dilemma either to act with responsibility or to start a conflict and probably lose a client.

For instance, auditor's judgment on a company's going concern, has potential consequences for both the auditor and the audited company. Auditors are obliged to report any important factor may threaten an entity's going concern, because if those clues are not revealed in the audit report and the company goes bankrupt, he will then face legal actions against him. On the other hand, managers are reluctant to hire an auditor who may not provide a going concern qualification to their company, even if there are indicators that obligate him to do so. It has been, also, noticed that auditors' reputation declines when they provide massive audit reports with qualified opinions, and as a result they may attempt to cooperate with the audited company to present financial results as favorably as possible to the potential detriment of the outside users (Bolten & Crockett Jr., 1979).

Additionally, Uang, et al. (2006) highlight the main factors that determine the credibility of going-concern disclosures such as the impact of board structure on managerial behavior, the impact of audit committee on managerial behavior and external audit, the influence of institutional stockholders, the lender monitoring on management, and the wider impact of corporate governance.

In any case, when there is a difference between the interests of managers and users of financial statements, auditor's responsibility is to provide sound and reliable information to the users of financial statements.

2.1.3 Financial Distress

Companies' basic and most important task is to ensure their ability to survive. As described in previous sections of this study, responsible for the reassurance of an entity's ability to continue in existence are management and auditors, who are designated to examine potential conditions for substantial doubts.

Literature mentions various words to particularize financial distress cases. The term *default* usually refers to the financial inability of a debtor to pay its debt, while the legal term for this situation is *insolvency*. Additionally, *bankruptcy* is a legal term ratifying that an insolvent entity cannot repay its debts, imposed by a court order.

A problematic situation able to threaten an entity's viability can be caused due to financial or non-financial, qualitative and quantitative, as well as internal or external factors. Under an initial wide perspective, the basic indication of a firm's viability lies on two key factors, the ability to meet its obligations and its access to funding. In other words, an entity can be viable if there are no liquidity problems. Nevertheless, there are plenty of conditions that indicate companies' financial problems, which influence auditors' going concern opinion and can lead to financial distress and even bankruptcy.

Although auditor's assessment on a company's going concern derives from a complicated process, which implies the investigation of many factors, this study is concentrated to the financial indicators related to that process.

2.1.3.1 What Default Means

Corporate default is another word for corporate failure and it is connected to financial distress factors. It is often associated with potential negative events in a situation where credit risk is present and can be defined as the failure to make required payments (Law & Smullen, 2008).

In practice, however, corporate default does not unavoidably lead to bankruptcy, as many companies face liquidity problems but eventually manage to settle their obligations and rearrange their payments. That's because their bankruptcy could affect their lenders in a no return way that is not always a solution to the problem.

There are many interpretations for the word default, depending on the point of view of the one that uses it or its profession. It is usually defined as the inability of a firm to pay its financial obligations as they mature (Beaver, 1966), a definition which is consistent to the current relevant SAS. Alternatively, it is a term used in a legal perspective on companies that have filed for bankruptcy (Altman, 1968; Ohlson, 1980), or in a sociological perspective as an undesirable inability related to the reallocation of resources (Aharony, et al., 1980).

2.1.3.2 Legislation of Corporate Bankruptcy in United States

Bankruptcy cases in USA follow a specific process, codified in the Tittle 11 of the United States Code, namely the Bankruptcy Reform Act of 1978. That process has been amended several times, with the most noteworthy changes enacted in 2005 through the Bankruptcy Abuse Prevention and Consumer Protection Act (BAPCPA) of 2005. Specifically, corporations unable to fulfill their obligations to creditors can file with a federal bankruptcy court for protection under Chapter 7 or Chapter 11.

The most common form of bankruptcy is the liquidation of a company under Chapter 7. Under this process, the company ceases operations and appoints a trustee in order to sell debtor's property and pay out creditors. The alternative for corporations, given by the Tittle 11 Code, is Chapter 11, under which they can implement a reorganization plan and eventually survive, although it can also be used as a mechanism of liquidation.

Nevertheless, the procedure of filing in either of two Chapters of the Bankruptcy Code is costly and is not the first step an entity has to take in the case it is facing financial distress issues. On the contrary, and in accordance to the existing SAS, auditors are obliged to examine risk factors in every detail, before issuing their opinion on a company's going concern, and management should create a plan to overcome potential risks.

2.1.3.3 Financial Data Concerning Auditors' Going Concern Evaluation

There are several factors able to threaten an entity's ability to continue as a going concern, both financial and non-financial, related to the company's performance or to market's fluctuations. As auditor's and management's responsibility is to predict and identify such factors, many researchers have tried to analyze the process of financial distress. Complementary, others, often from the perspective of users of financial statements, have identified specific financial variables and developed models to calculate failure probability.

Financial distress reaction to financial values is often observed in different stages, during the operation of an entity, as mentioned by Laitinen (1991):

- Early stage, where financial statements indicate decreased profitability.
- Late stage, where financial statements indicate decreased profitability and increased leverage.
- Final stage, where financial statements indicate decreased profitability and increased leverage and decreased liquidity.

At any of these stages, signs of uncertainty can be measured to determine the financial situation of a firm. This practice has been extensively studied in finance and accounting literature through bankruptcy prediction models, that utilize financial and market ratios as predicting indicators. Auditors, management, creditors and shareholders have high interest in reassuring the ability of a company of their interest to continue as a going concern. In this context, analysis of the probability of a firm to fail can be a helpful tool to identify risk factors, and can be a supplementary assistance for auditors on their going concern assessment.

Auditors, in particular, have to examine many qualitative aspects of a firm's operational environment that influence their opinion, but the most important are the quantitative (financial) ones as they reflect the past financial performance, which will affect the future either in positive or in a negative manner.

In accordance with that, Asare (1990) noted that going concern opinions can be predicted successfully using financial variables. For example, Mutchler (1985) managed to classify correctly 83% of her sample using financial variables. Also, Menon & Schwartz (1987) examined if it is possible to predict the possibility of a company to receive e going concern opinion, via financial variables, and concluded that liquidity and operating loss are the two key financial indicators related to auditor's opinion. Furthermore, Koh & Tan (1999) utilized Neural Networks as a method to predict going concern status, utilizing six ratios, and proved that all of them were significant to auditor's opinion.

Consequently, literature shows that the relationship between financial variables and auditors opinion on going concern assumption is high and as a result it could also work backwards. In other words, financial indicators related to an entity's probability to fail can be exploited through prediction models, in order to assist auditors to the assessment of their going concern opinion. Those models have been introduced and tested by a large number of researchers and are presented in the following chapter.

2.2 Corporate Bankruptcy Prediction

Corporate bankruptcy prediction is one of the core areas of finance and accounting research. Various models have been developed widely during the last decades, in academic and business society, in quest of predicting bankruptcy events and verifying the significant value of financial ratios as indicators of a firm's capability to outlast. The developed models have been used by investors, creditors, managers and auditors, who need to have accurate knowledge on a firm's performance and its probability to fail.

This chapter aims at presenting an integrated overview of the most distinguished bankruptcy prediction models that have been built and applied widely in the last decades. We focus on highlighting the key points of the presented models while also showing up the relevant literature references, in order to appear the whole picture.

Some notable contributors in accounting models[5] development are Beaver (1966), Altman (1968), Deakin (1972), Ohlson (1980), and Zmijewski (1984). Other, more sophisticated methods to predict corporate failure, that count not only a firm's performance ratios but also the overall economic environment, have been introduced by Shumway (2001), Hillegeist (2004) and Wu et al. (2010). Along with these, we also mention alternative applications for corporate bankruptcy prediction that exploit modern computer science, such as Artificial Neural Networks (ANN) and Support Vector Machines (SVM), developed by an extensive number of researchers.

2.2.1 Accounting-Based Models

Scientific community started expressing their interest in bankruptcy prediction back in the 1930's trying to benefit from the information they could export from accounting data and financial ratios. At that time, the Bureau of Business Research (BRB) presented the key ratios of industrial companies that went bankrupt[6]. Subsequently, numerous researchers analyzed bankrupt firms' ratios and published relevant studies trying to contribute to the prediction of future corporate failures and to identify the major financial weaknesses causing a bankruptcy (FitzPatrick, 1932; Smith & Winakor, 1935; Chudson, 1945; Jackendoff, 1962). Beaver (1966) following the path of previous researchers,

[5] The term "accounting-based models" for predicting bankruptcy events refer to statistical methods that use mainly static accounting data from financial statements.

[6] The study analyzed 29 companies using 24 key ratios in order to identify their common characteristics that may have caused their failure, concluding to 8 ratios that could foresee the event.

analyzed 30 ratios of 79 bankrupt and 79 healthy companies in 38 industries and reached to a comprehensive univariate model to predict bankruptcy events.

The initial introduction of a multivariate prediction model was by Altman (1968) who objected the univariate technique and came up with a multiple discriminant analysis (MDA) function, by combining 5 specific financial variables under a linear multivariate model, which calculates the so called Z-Score as an indicator of corporate failure.

Several researchers attempted to evaluate or advance the MDA technique, by adding or varying financial ratios, while others disagreed on its effectiveness (Deakin, 1972; Blum, 1974; Altman, et al., 1977; Dambolena & Khoury, 1980; Gloubos & Grammatikos, 1988; Piesse & Wood, 1992; Gerantonis, et al., 2009; Wu, et al., 2010; Bauer & Agarwal, 2014).

Ohlson (1980), criticizing the assumptions of MDA, proposed a logistic regression method (Logit) and modeled various financial ratios in order to design a more accurate predicting pattern than the previous ones, introducing the O-Score as a measure of bankruptcy prediction. The Logit bankruptcy prediction method was probed by a number of researchers who highlighted the weaknesses and the strengths of that approach (Lau, 1987; Johnsen & Melicher, 1994; Weiss, 1996; Low, et al., 2001; Chi & Tang, 2006 ; Lacerda & Moro, 2008; Muller, et al., 2009).

Alternatively, Zmijewski (1984) arguing researchers use non-random samples to estimate financial distress, introduced the Probit (probability + unit) analysis in corporate bankruptcy prediction, which was also tested and criticized by future researchers mainly due to its lack of variables (Shumway, 2001; Grice & Dugan, 2003; Wu, et al., 2010).

2.2.1.1 Altman Model

The Z-Score, developed by Edward Altman, is perhaps the most popular and widely recognized model for predicting corporate failure. He inspired his model, influenced by Beaver (1966), doubting that previous models predict bankruptcy using specific variables and non-bankruptcy events using different ones, resulting to non-impartiality and questionable outcomes. He began from a list of 22 financial indicators and finally concluded to 5 representative ratios, which ultimately outperform Beaver's ratio (Cash Flow/Total Debt). Those where selected with restrictive assumptions, based on empirical evidence, following the next procedures (Altman, 1968, p. 594):

- "Observation of the statistical significance of various alternative functions including determination of the relative contributions of each independent variable",

- "Evaluation of inter-correlations between the relevant variables",
- "Observation of the predictive accuracy of the various profiles", and
- "Judgment of the analyst".

He worked on a sample of 66 manufacturing firms, half of which were bankrupt. Using the MDA technique he came up with the following equation, consisting of 5 discriminant coefficients and 5 independent variables, which give the Z-Score that measure the probability of bankruptcy:

$$Z = .012 * \chi 1 + .014 * \chi 2 + .033 * \chi 3 + .006 * \chi 4 + .999 * \chi 5$$

The independent variables used in this equation are presented and described in the following table:

Table 3. - Variables of the Altman Model

Variable		Description
χ1	WC/TA	Working Capital / Total Assets
χ2	RE/TA	Retained Earnings / Total Assets
χ3	EBIT/TA	Earnings Before Interest Expense and Taxes / Total Assets
χ4	MVE/BKD	Market Value of Equity / Book Value of Total Debt
χ5	S/TA	Sales / Total Assets

According to Altman (1968) the Z-Score that discriminates the bankrupt and non-bankrupt firms is equal to 2.675, while the area between 1.81 and 2.99 is considered as a "zone of ignorance" (Altman, 1968, p. 606) due to possible classification errors by the discriminant model. Firms that score above 2.99 are considered to be healthy, while those of under 1.81 have a high probability of default.

This technique, as described above, have been used mostly for small samples of manufacturing firms, as well as bankrupt and non-bankrupt firms of equal sizes (Grice & Ingram, 2001). As stated by Altman (1968) the accuracy of his technique is 95%[7], while Deakin (1972) shows that this model can classify correctly 90% of all firms that failed or did not fail in the next one to three years doubting for its effectiveness on predictions 3 years prior the failure event.

Others studies doubted about the models' effectiveness and tried to improve it by varying the sample of firms and its size, or by applying different financial ratios (Altman, et al., 1977; Agarwal & Taffler, 2008; Wu, et al., 2010; Tinoco & Wilson, 2013).

[7] The percentage of 95% refers to those firms that would go bankrupt the next year, while for those that failed the year after the prediction accuracy fell to 83%.

2.2.1.2 Ohlson Model

Ohlson (1980), influenced by Santomero & Vinso (1977) and Martin (1977), applied a logistic regression method (Logit) with the intention of overcoming the MDA's malfunctions. He suggested that the effectiveness of previous methods is uncertain due to their assumptions that do not correspond to real and timely conditions. In particular, he criticized Altman's (1968) model, mentioning the problems of strict statistical requirements, low intuitive interpretation of the Z-Score and non-reliable matching of bankrupt and non-bankrupt firms (Ohlson, 1980, p. 112).

In order to discover a more accurate predicting model he used the Logit model that according to him, could overcome the MDA problems. In his model, he tested 9 independent variables, in a sample of 2.163 industrial firms traded in US stock exchange[8], during the period 1970-1976, using the following logistic function:

$$Y = B0 + B1 * \chi 1 + B2 * \chi 2 + B2 * \chi 3 + B4 * \chi 4 + \ldots + B9 * \chi 9$$

His intention was to build three models, one that could predict corporate failure within one year, the second could identify firms that will go bankrupt the second year, and the last one could contain firms that may fail within one year or the next one. The O-Score is estimated using the following equation that indicate the weight of each independent variable:

$$y_i = -1.32 - 0.4071\chi 1 + 6.03\chi 2 - 1.439\chi 3 + 0.0757\chi 4 - 2.37\chi 5 - 1.83\chi 6 + 0.285\chi 7 - 1.72\chi 8 - 0.521\chi 9$$

The independent variables used for predicting corporate failure, are described above, though no theoretical justification was provided, by the author for their selection (Jouzbarkand, et al., 2013, p. 90):

Table 4. - Variables of the Ohlson Model

Variable		Description
χ1	SIZE	Log (Total Assets / GNP Price-Level Index)
χ2	TL/TA	Total Liabilities / Total Assets
χ3	WC/TA	Working Capital / Total Assets
χ4	CL/CA	Current Liabilities / Current Assets
χ5	OENEG	1 if Current Liabilities exceed Total Assets, 0 otherwise
χ6	NI/TA	Net Income / Total Assets
χ7	FU/TL	Funds from Operations / Total Liabilities
χ8	INTWO	1 if Net Income was negative for the last two years, 0 otherwise
χ9	CHIN	$(NI_t - NI_{t-1})/(\lvert NI_t \rvert + \lvert NI_{t-1} \rvert)$

[8] From those, 105 were bankrupt and 2058 were non-bankrupt firms.

For the evaluation of a firm's probability to fail, the O-Score is interpreted as follows: $P = (1 + exp\{-y_i\}^{-1})$

Ohlson's (1980) accuracy in predicting corporate failure, according to his study, is higher than Altman's (1968) Z-Score. However, many researchers attempted to improve his model, using Logit regression with more effective independent variables (Lau, 1987; Shirata, 1995; Low, et al., 2001; Tseng & Lin, 2005).

2.2.1.3 Zmijewski Model

The third most popular accounting bankruptcy prediction model was developed by Zmijewski (1984), using the Probit regression method and 3 independent financial variables.

He identified two main problems with previous bankruptcy predicting methods that affect their credibility. The first is that "researchers typically estimate financial distress prediction models on nonrandom samples", which can result in "biased parameter and probability estimates if appropriate estimation techniques are not used" (Zmijewski, 1984, p. 59). The second one refers to a sample selection bias and specifically to companies with incomplete data that are often removed from the sample, resulting to a nonrandom dataset. This argument is also supported by the fact that companies with incomplete data usually are new and small firms, and their probability to default may be higher than others. The Probit regression function that Zmijewski (1984) came up with, combining the 3 independent variables, is shown below:

$$z_i = -4.336 - 4.513\chi1 + 5.679\chi2 - 0.004\chi3$$

The dataset used in this study consisted of 40 bankrupt and 800 nonbankrupt industrial firms, during the period 1972-1978, though the author tried different sample sizes in this research, so as to face with the first problem (dataset bias) as mentioned above.

In order to cope with the second problem, he concluded to only 3 independent variables which, by exploring previous relevant studies, found to be the most representative indicators of a firm's going concern. The following table describes those variables:

Table 5. - Variables of the Zmijewski Model

Variable		Description
χ1	NI/TA	Net Income/ Total Assets
χ2	TL/TA	Total Liabilities / Total Assets
χ3	CA/CL	Current Assets/ Current Liabilities

Similarly to the Logit model, the Probit outcome is also between 1 and 0. A probability of less than 0.5 indicates a healthy firm, while a probability of greater than 0.5 disclose a bankrupt firm. The overall accuracy of Zmijewski's (1984) model, as calculated in his study, is 95.29%[9]. The Probit method is not so popular in bankruptcy prediction literature compared to the previous ones, although it is similar to the Logit method, due to its non linear estimations that require complex calculations, making it costly and hard to use (Gloubos & Grammatikos, 1988).

Many researchers criticized this model, showing a less effective outcome compared to the initial that was presented by the author, while in some other cases the score of this model outperform previous ones[10] (Chen & Wei, 1993; Chen & Church, 1996; Dichev, 1998; Shumway, 2001; Jr. & Dugan, 2003).

2.2.2 Market-Based Models

Many researchers, concluded that traditional accounting-based bankruptcy prediction models (as described above) are suffering serious weaknesses and their place should be taken by more sophisticated models that could predict corporate failure accurately, by exploiting valuable information that previously have been left aside.

Literature shows that accounting-based models suffer major weaknesses, which forced researchers come up with new more consistent ones, in the need to improve the efficiency of failure prediction. The most crucial of them are presented as follows:

- Accounting-based models measure a set of specific variables for each firm at a given time ignoring the fact that firms' characteristics change through time and not taking into account its future prospects, resulting to biased and inconsistent estimates of failure probability (Shumway, 2001; Vassalou & Xing, 2004; Agarwal & Taffler, 2008).
- Accounting rules, such as conservatism constraint and going concern assumption, lead to biased or not informative data in accounting documents (Hillegeist, et al., 2004; Agarwal & Taffler, 2008)[11].

[9] Noting that none of the bankrupt firms was accurately predicted to fail. Also 95% of the firms in the dataset were non-bankrupt firms, since for every bankrupt firm there were 20 non-bankrupt ones.
[10] Some of the characteristics affecting the outcome are the sample size, the industry classification, the time of accounting data collection, etc.
[11] For instance, due to the conservatism principle book values underrate company assets, or due to the going concern assumption that bears out a firms' capability to last accounting statements should not be able to be used on foreseen a bankruptcy event.

- Asset volatility is not measured in the calculation of a firms' bankruptcy probability within accounting-based models. Yet, this is a factor that according to Hillegeist, et al (2004) is very important as it has a key impact on a firm's ability to pay its debt.
- Accounting numbers may not be reliable as, in actual fact, they can be manipulated by the management (Agarwal & Taffler, 2008).
- The effectiveness of particular financial ratios in predicting a bankruptcy event varies through different industries, as different ratios are significant for specific industries and other ratios for other ones (Grice & Dugan, 2001).

On that perspective common literature presents two highlights, the Hazard model (Shumway, 2001) that integrates accounting and market variables, and the BSM-Prob model (Hillegeist, et al., 2004) based on the theoretic groundwork of Black & Scholes (1973) and Metron (1974) option pricing model.

2.2.2.1 Shumway Model

The innovation that Shumway (2001) introduced lies to a multi-period approach of calculating a firms' bankruptcy probability, which takes into account both financial ratios and market variables. This model uses available data to estimate bankruptcy probability for each period, resulting to a non-biased period or data selection, unlike previous static models. The hazard model can be interpreted either as a logit model done by firm year, or it can be viewed as a discrete accelerated failure-time model (Shumway, 2001, p. 123).

The Hazard model uses accounting variables, as they were applied by Altman (1968) and Zmijewski (1984), along with market-driven ones to identify bankrupt firms. Those variables are presented in the following table:

Table 6 – Variables of the Shumway (Hazard) Model

Variable		Description
$\chi 1$	NI/TA	Net Income/ Total Assets
$\chi 2$	TL/TA	Total Liabilities / Total Assets
$\chi 3$	Relative Size	Log((Outstanding Shares * Year-End Share Price)/Total Market Value)
$\chi 4$	Excess Return	Cumulative annual return in year t-1 – value-weighted NYSE/AMEX[12] index return in year t-1
$\chi 5$	SIGMA	Regressing monthly stock return on NYSE/AMEX index return for the same year

[12] New York Stock Exchange (NYCE), American Stock Exchange (AMEX).

The first two variables are borrowed from previous static models while the rest of them are market variables devised by Shumway. NI/TA variable shows firms' profitability, while TL/TA is included in this set as a credible leverage variable.

The first of the three market variable refers to the firms' size which is not measured using accounting data from financial statements but the firms' market capitalization divided by the value of NYSE/AMEX index. The next variable measures the firms' past excess return measured as a return in year t-1 minus the value weighted NYSE/AMEX index. The last market variable, called SIGMA, is the idiosyncratic standard deviation of each firm's stock returns, included in this set as a liquidity indicator.

According to this hazard model, the dependent variable is the time that the firm will remain healthy, while the independent variables consist of accounting and market data. In his study, the author, tested 300 bankrupt companies using corporate data for a 30year period[13].

Chava & Jarrow (2004), tested the performance of the Shumway model in comparison to Altman and Ohlson models, concluding that the first one outperforms the accounting-based models. Following this, Wu et al. (2010) agrees that this model is more accurate compared to the accounting-based ones. Hazzard models, in general, are proven superior to static models, both theoretically and empirically, for forecasting bankruptcy. In practice, however, many hazard models are difficult to estimate because of their nonlinear likelihood functions and time-varying covariates (Shumway, 2001, pp. 103, 111).

2.2.2.2 BSM-Prob Model

Another popular technique for measuring financial distress as a mean to predict corporate failure, using market data, was proposed by Hillegeist et al. (2004). They came up with a discrete hazard model, based on the Black & Scholes (1973) and Metron (1974) option-pricing theories. Under this framework, equity is viewed as a call option on the value of a firm's assets, considering that when the asset value falls below the face value of liabilities the call option is not exercised and the firm is turned over to its debtholders (Hillegeist, et al., 2004, p. 1).

[13] The dataset included firms that started trading during 1962 and 1992. Firms that started trading before or after this period were excluded from the sample, along with financial firms (SIC code 6.000 – 6.999).

In order for this model to be valid, the following list of assumptions is taken as granted, which are essential to note for a deeper understanding of the model's structure (Hillegeist, et al., 2004, pp. 5-6):

- Financial markets are liquid, have continuous trading, no transaction costs or taxes, perfect asset divisibility and no arbitrage opportunities.
- Asset values follow a geometric Brownian motion process.
- A constant risk-free interest rate that is identical for borrowing and lending.
- Short selling with the full use of proceeds.
- No bankruptcy costs.
- The firm issues only zero-coupon bonds, so bankruptcy occurs at bond maturity.

The data used in this study were taken from the CRSP Daily Stock Return File. After excluding financial firms and firms with no available data, from an initial sample of 156.489 firm-year observations, the final sample consisted of 65.960 firm-year observations, 10.845 firms and 516 total bankruptcies.

Hillegeist et al. (2004) meassured the effectiveness of his BSM-Prob model compared to Altman and Ohlson models and found out that his model outperforms significantly the two previous ones. On the other hand, Wu et al. (2010) showed that both market-based models as presented in this paper outperform the accounting-based ones while the Shumway (Hazzard) model's predictive accuracy is higher than the BSM-Prob model.

A similar research conducted by Vassalou & Xing (2004) adopted the option pricing theory to estimate bankruptcy probability using equity data. They found out that default risk is related to the size and book-to-market characteristics of a firm, that firms with high risk of default earn higher returns and that this risk is systematic (Vassalou & Xing, 2004, pp. 832-833).

2.2.3 Modern Computational Methods

In the last decades, literature on bankruptcy prediction is attempting to show alternative approaches that are innovative as well as reliable. Many researchers, exploited the computational power and the new capabilities that modern technology provides us, in order to make bankruptcy prediction more accurate. Most of them make use of Artificial Neural Networks (ANN), Support Vector Machines (SVM), Decision Trees (DT) and

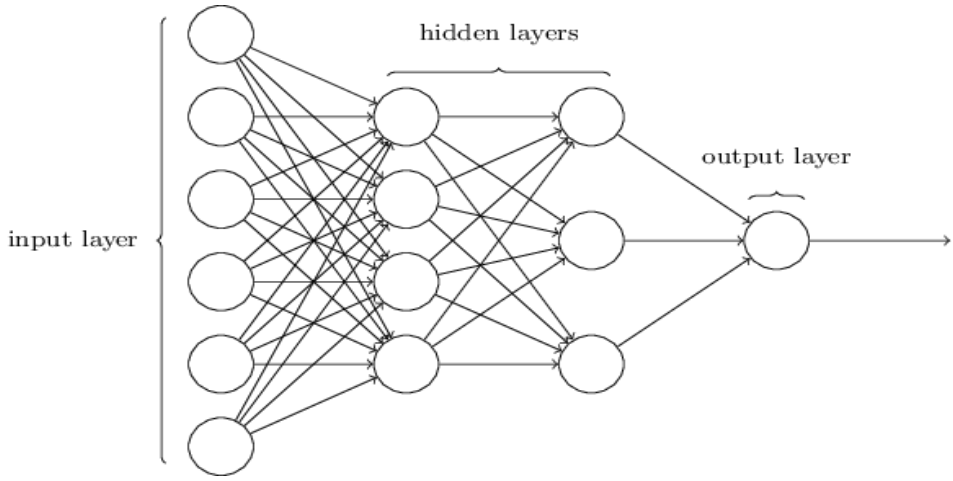
Case-Based Reasoning (CBR), whereas the first two are the most popular and will be revealed in this chapter.

2.2.3.1 Artificial Neural Networks

Artificial Neural Networks (ANN), also called Neural Networks (NN), are algorithms that emulate specific functions of the human brain nervous system. The history of scientific brain exploration is perennial, whereas the first to introduce the application of NN to artificial intelligence were McCulloch & Pitts (1943). Since then, this technique has been used in many areas of scientific research such as neuroscience, biology, medical engineering, robotics mathematics and finance. Especially in the areas of prediction and classification problems, ANN proved to be highly effective (Wilson & Sharda, 1994).

An ANN is a computational model, which mimics human brain's functions, using highly interconnecting processing elements, the so called neurons, that operate in parallel (Al-Shayea, et al., 2010). The structure of such a model, usually consists of an input layer, one or more hidden (processing) layers and an output layer. Each layer includes one or more elements depending on the number of input variables, hidden units and data to be extracted. The following figure shows the structure of a four layer model[14]:

Figure 1 – Illustration of a Four Layer Network with a Single Output



As seen on the figure above, every element, also called neuron or node, receives information which is been processed and then transferred to the next stage. Each neuron operates independently, while they are all interconnected. When the neural network is at the stage of training, each element connection multiplies with a specific weight, which is calculated by the machine learning process using the available knowledge. The

[14] Source: http://neuralnetworksanddeeplearning.com/chap1.html

consecutive training of a neural network adjusts those weights, making it possible for the researcher to identify the proper function in order to estimate a valid outcome.

ANN are learning machines, meaning that they are molded using external and internal information. The learning process defines how the model uses the input information, how additional information will be created and eventually how the neuron weights will be formed. Usually, the process of training an ANN follows a straightforward flow of information, the so called feed-forward network, beginning from the input layer, moving to the hidden layer(s) and ending to the output layer. There are three major learning paradigms, supervised, unsupervised and reinforced learning, each one referring to a unique process, as described below:

- Supervised learning is the machine learning task of inferring a function from labeled training data (Mohri, et al., 2012). In this paradigm the ANN is trained through representative input and output patterns. Under this procedure the ANN adjusts the neuron weights so that the output it generates matches with the output needed as a valid outcome. The most common supervised learning technique is backpropagation (BPN), which uses an algorithm to form element weights so as to minimize calculation errors. Usually, this technique is applied using multiple layers of computational elements, the so called multi-layer perceptron (MLP).
- Unsupervised learning paradigm, on the contrary, receives inputs but gets no specific output patterns or rewards from its environment (Ghahramani, 2004). In other words, the learning machine process does not receive any feedback while training but uses input data to create patterns itself. A widely used technique that utilizes unsupervised learning for its training is the self-organizing map (SOM). The SOM is an algorithm, developed by Kohonen (1982), which visualizes high-dimensional input data to low-dimensional views with accuracy, maintaining the initial topological order.
- Reinforced learning can be considered as an intermediate paradigm of supervised and unsupervised learning, where every action of the training procedure gives a feedback response which is evaluated by the system in order to adjust the parameters accordingly (Singh & Chauhan, 2009). Recurrent neural networks (RNN) is a representative technique for this type of learning, that uses internal memory to transmit information from element to element, in order to evaluate its own performance and process input data accordingly.

ANN are used mainly in the areas of prediction and classification, seeking to substitute or replace regression and other statistical models that conventionally dominate these areas. For instance, Ripley (1994) examined neural networks and related classification methods and reached the conclusion that ANN are one of a class of flexible non-linear regression methods. Additionally, Warner & Misra (1996) compared neural networks to regression models, in terms of notation and implementation, and showed that ANN behave as a non-parametric regression model.

A great number of ANN literature centers on finance and accounting applications, essentially on evaluation and prediction. In bankruptcy prediction, ANN use mainly the input variables used in accounting and market based models. Several studies compare the performance of ANN in comparison to traditional and modern classification methods, such as MDA, Logit, Probit, decision trees and SVM. The same models, have been used to resolve prediction issues involved to the auditing profession, such as the auditor's opinion on a company's going concern or management frauds.

Odom & Sharda (1990) tested the predictive accuracy of MDA and ANN in corporate failure and concluded that artificial neural networks perform better on small a sample size. By the same token, Wilson & Sharda (1994) confirm that ANN perform significantly better, compared to MDA, at predicting firm bankruptcies, while Tsukuda & Baba (1994) showed equivalence between the two methods for listed firms and better performance of ANN for unlisted ones.

Similarly, Fletcher and Gross (1993) compared a BPN neural network model with Logit model, on a small sample size of 18 bankrupt and 18 non-bankrupt firms, deducing that ANN was more accurate in predicting bankruptcy than Logit regression.

Zhang, et al (1999), using six input variables on a matched sample of 220 firms, agreed that the BPN neural network performs significantly better than the Logit model in bankruptcy prediction. They also note that ANN are robust to sampling variations in overall classification performance. On the contrary, Boritz & Kennedy (1995), tested the predictive accuracy of four BPN neural network techniques in comparison to traditional bankruptcy prediction techniques, namely MDA, Logit and Probit. They demonstrated that the performance of ANN is sensitive to the choice of variables selected and that the networks cannot focus on the most important variables, noting that ANN does not always show significant improvement on their prediction ability, compared to the traditional models.

Jo, et al. (1997), used three different techniques on Korean firms' probability to go bankrupt, namely MDA, case-based forecasting and neural networks. They showed that the average hit ratios of the three methods ranged from 81.5% to 83.8%, while ANN proved to be the most accurate one. Additionally, Lee, et al. (2005) tested supervised (BPN) versus unsupervised (Kohonen self-organizing feature map) ANN learning techniques on their accuracy to predict failure events of Korean firms, using as benchmark MDA and Logit models. Their findings suggest that the BPN network is the better choice when a target vector is available.

In a wider perspective review, Adnan Aziz & Dar A. (2006) tested numerous bankruptcy prediction models across ten different countries, showing that ANN perform marginally better in comparison to traditional statistical and theoretical models.

Being one of the most crucial objectives of the audit profession, the going concern assumption is fully related to a company's probability to fail. On that perspective, Udo (1993) used ANN to predict the going concern of firms based on financial ratios of 300 companies, resulting that they are as accurate or more accurate as a multiple regression model in predicting bankruptcy, in addition to being easier to use and readily adapting to the changing environment. Correspondingly, Lenard, et al. (1995) used the generalized reduced gradient (GRG2) optimizer for neural network learning, a BPN neural network, and a Logit model to predict which firms would receive audit reports reflecting a going concern uncertainty modification for firms that are in danger of failure. They resulted that the ANN model formulated using GRG2, scores a prediction accuracy of 95%, recommending it as a robust alternative model for auditors to support their opinion on a company's going concern.

2.2.3.2 Support Vector Machines

Although it is proven that ANN, and specifically BPN neural networks, perform effectively in data classification and pattern recognition tasks, they suffer limitations, that make it complicated to use them and produce a valid outcome, as they are presented above (Shin, et al., 2005, p. 127):0

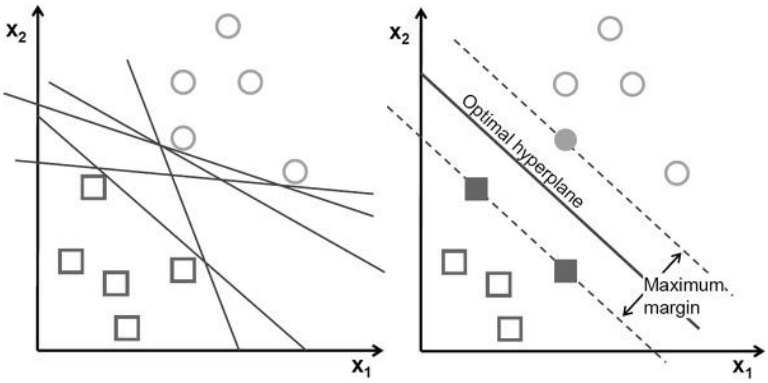
- It is hard to find the appropriate ANN model, which can adopt all problem characteristics, due to the large numbers of controlling parameters and processing elements in every layer.

- The search process of calculating element weights could converge to a local minimum result that is applicable for the training samples.
- The principle of minimizing empirical risk, in other words training error, does not guarantee good generalization performance.
- The size of the training set is also an issue to be resolved in the generalization, as the sufficiency of the training set is a crucial factor for the final outcome.

Recently, many studies make use of Support Vector Machines (SVM), also called Support Vector Networks (SVN). This method, as introduced by Vapnik (1995), is an alternative artificial intelligence learning technique, used for regression analysis, classification and pattern recognition. SVMs are machine learning models that construct optimal discrete hyperplanes in a high-dimensional space, in order to map the input vectors effectively. This method uses a linear model to develop a decision function based on non-linear class boundaries.

The purpose of SVMs is to use an algorithm to create an optimal hyperplane and set a maximum margin, in order to separate data appropriately into the maximum distance between the hyperplane and the nearest training points, since the generalization error is reduced inversely to the size of the margin. The hyperplane that minimizes potential errors is called optimal separating hyperplane, as it finds a maximum margin that has the largest separation of data. The training points that are closest to the optimal separating hyperplane are called support vectors, while other training examples are not relevant for the definition of binary class boundaries. Usually, when data are not separated linearly, SVM uses non-linear machines to set a hyperplane that minimizes the errors for the training set (Cristianini & Shawe-Taylor, 2000) .An example of a SVM application is shown in the following figure[15].

Figure 2 – The Structure of a SMV Before (left) and After (right) Classification



[15] Source: http://docs.opencv.org/2.4/doc/tutorials/ml/introduction_to_svm/introduction_to_svm.html

Recently, many studies have used SVM in financial applications, such as credit analysis, corporate bankruptcy prediction and fraud detection. At large, these studies indicate that SVM, in many cases, perform better or similarly to other methods, including ANN, CBR, MDA, Logit and Probit.

In the area of prediction and classification, Tay & Cao (2001) tested the accuracy of SVM compared to ANN, showing the superiority of SVM in time-series forecasting. Additionally, Kim (2003) shows that SVM in comparison to ANN can be a promising alternative to stock market and corporate bankruptcy prediction.

Similarly, Min & Lee (2005) applied SVM to the prediction problem, using the Kernel function to build a stable model with high explanatory performance, comparing it to MDA, Logit and ANN (BPN). Their experiment resulted showing that SVM outperform all the other methods. In the same direction, Boyacioglu, et al. (2009) compared the classification accuracy performance of SVM, ANN and multivariate statistical methods, on a dataset of 21 bankrupt and 44 non-bankrupt banks in Turkey, showing SVM as the most superior model in prediction.

In an attempt to improve the explanatory power of SMV, Min, et al. (2006) combined Genetic Algorithms and SVM, developing a hybrid model, which proved to perform much more effectively than ANN and Logit. Additionaly, Lin, et al. (2013) created a hybrid business failure prediction model using Locally Linear Embedding (LLE) algorithm and SVM, succeeding to achieve the highest rate of accuracy compared to the SVM without the proposed hybrid approach and to the Principal Component Analysis (PCA).

3 Methodology

The main purpose of this study is to evaluate the effectiveness of bankruptcy prediction techniques, using two popular accounting based models and an ANN model, in order to determine if they are able to assist auditors in the assessment process of their going concern opinion. For that purpose, we have gathered accounting data from bankrupt and healthy US firms and used them to evaluate the predictive accuracy of the selected models, solely and in comparison.

3.1 Sample Data

Our dataset consists of 81 bankrupt and 81 healthy US companies[16] who have been active during 2002 – 2015, chosen from an initial set of 188 bankrupt firms[17] and respectively from a much larger one of more than 2,000 operating firms. The rest of the bankrupt firms were not included to the final dataset mainly due to missing data or incomplete information. Our criterion for the selection of those data has to do with the requirements of the prediction models that was chosen to calculate. The accounting data used in this study were collected from COMPUSTAT[18] and in some cases we also used 10-K reports, downloaded from the official website of U.S. Securities and Exchange Commission[19]

As is usual, the final sample does not contain financial, insurance and real estate firms, as their financial structure is not comparable to those of other industries (DeFond & Subramanyam, 1998). Further than that, the sample is not biased towards any other industry sector.

The matching of bankrupt and non-bankrupt firms has been carried following a prioritized process, consisting of 4 criteria. Those where data availability for the reporting period (strict principle), same or similar industry classification, equivalent size and as a last criterion we took equivalent liabilities in that order.

The first criterion pertains to data availability, where, we searched and found for each bankrupt firm a corresponding couple with available accounting data for a 2-year period (year of last observation, plus previous 1 year). The second refers to sector matching (SIC Code), where after our assignment, the most non-bankrupt pairs belong to the exact same sector, while, for some exceptions for which there were no firms listed in the same sector, it was chosen a similar one. The following ranking criterion, in priority, refers to the size of a firm, measured via the Total Assets account. In case there couldn't be achieved a total identification using the previous criteria, we used as supplementary measure the volume of a firms' liabilities (Total Liabilities). Company size and liabilities were taken

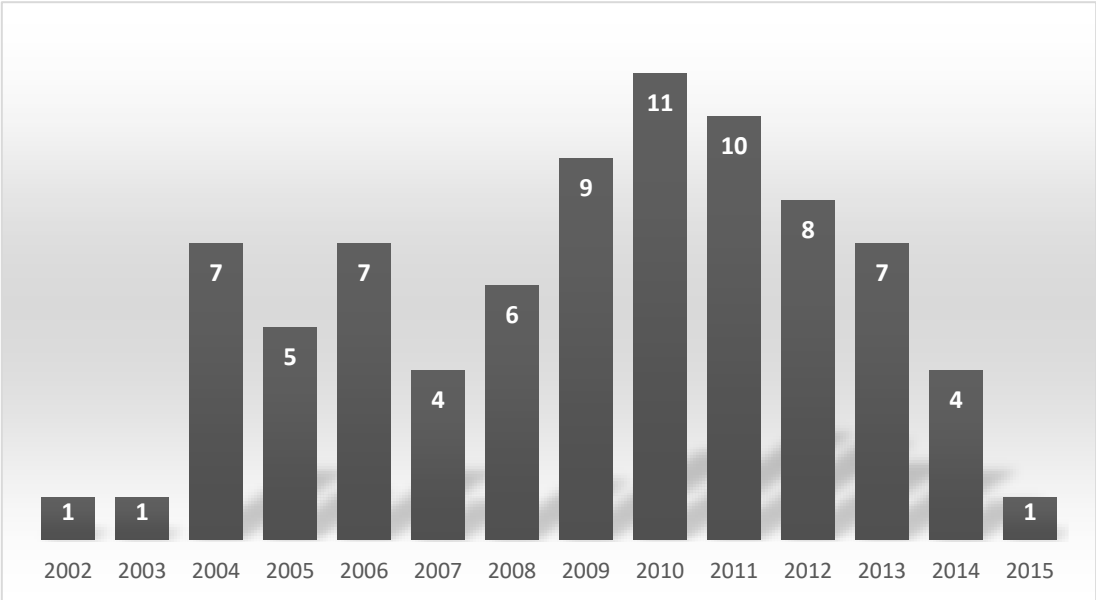
[16] By the term "healthy" we define non-bankrupt companies that were operating at the time this study was conducted and were also operating at the same period with their bankrupt pair.
[17] The term bankrupt refers to firms that have filed for Chapter 7 or Chapter 11 of the US Bankruptcy Code.
[18] In order to locate bankrupt companies in "COMPUSTAT", we used the command "INCO" that refers to inactive companies and "INCOD" that brings the inactivity date. Under the INCO command we chose only the firms that went bankrupt or liquidized (inactive company markers 2 and 3) and shaped the initial set of 188 bankrupt firms.
[19] All company fillings of publicly traded U.S. firms, along with other company information, are accessible through the Edgar platform at http://www.sec.gov/edgar/searchedgar/webusers.htm.

as an average of the last 14 years (2002–2015) for the non-bankrupt firms compared to the corresponding average of the last 2 years for the bankrupt ones.

This process was applied to the last two years of available financial information[20] for the bankrupt firms and respectively for their non-bankrupt pairs (t = 0, t = -1), ending up to two training samples for the two years of investigation, The full list of both bankrupt and non-bankrupt firms selected for this study can be found on Appendix B: US Firms Included in the Dataset.

Basic characteristics of our dataset, such as yearly bankruptcies and sectoral diversification, are analyzed above for the better understanding of the utilized data. The following figure presents the number of bankruptcies per year of our sample:

Figure 3 – Number of Bankrupt Firms per Year



Our data are relatively recent as most of our dataset companies went bankrupt after 2009. The period between 2009 and 2012 sums the highest rate of bankruptcies, from 8 to 11 observations per year, while the less number of bankruptcies are noted in 2002, 2003 and 2015. Of course, this is not a representative depiction of the number of bankruptcies that occurred in US during that period, but it signifies the specific characteristics of our sample.

Another important characteristic of our interest is the sectoral diversification of the bankrupt firm's sample, as seen in the following table:

[20] Usually, financial information for bankrupt companies were available until the bankruptcy event occurred. Nevertheless, in some observations the date of bankruptcy did not match to the year of the last available information and this may have caused discrepancy to the investigated period of their healthy pair.

Table 7 – Sectoral Diversification of Bankrupt Firms Sample

SIC Code	Description	No. of Bankruptcies
1000-1499	Mining	2
2000-3999	Manufacturing	43
4000-4999	Transportation, Communications, Electric, Gas and Sanitary service	5
5000-5199	Wholesale Trade	3
5200-5999	Retail Trade	8
7000-8999	Services	19
9900-9999	Non-classifiable	1

The vast majority of the sample's bankrupt firms belong to the manufacturing sector with 43 observations, followed by the services sector with 19 observations and trade with 11 observations. At the same time, there are 5 firms operating in the transportation, communications, electric, gas and sanitary services, as well as 2 firms operating in the mining sector.

As mentioned before, the relevant dataset of healthy firms is in consistency with the one presented above and both datasets do not include firms of finance, insurance and real-estate sectors.

3.2 Research Design

We use three bankruptcy prediction models, to evaluate their predictive accuracy and determine which one to suggest as an assisting tool to auditor's going concern assessment. The basic hypothesis of this study is that an effective tool, able to measure financial distress and even predict a bankruptcy, can be very helpful to auditors in supporting their opinion or even using it as an alarming signal for deeper investigation of accounting data.

We chose to use two accounting-based models and one from the modern computational methods. Specifically, from the first category we picked Altman's and Zmijewski's models, and ANN from the other one.

Ohlson's model and market-based models were excluded because we would need more data for our calculations resulting to shrink our dataset even more. The financial ratios used in the selected accounting-based models are completely different, ensuring that we use two unique accounting techniques, able to produce a single outcome. Also, market variables are not practically utilized by auditors on their going concern assessment and as a result market-based models would not be consistent with auditor's exploratory objectives.

Furthermore, ANN were chosen as an identical representative of this scientific field, in accordance to relevant literature. Besides, it is not an objective of this study to deepen in bankruptcy prediction models, but rather to evaluate some of the most cited techniques, in order to provide the scientific evidence needed to support the considerations of our main hypothesis.

3.2.1 Accounting-Based Models

In respect to the scientific tradition and to the effectiveness of Altman's Z-Score model, according to literature, it was the first technique chosen for evaluation. We used the improved Altman's function, because according to our calculations it is more effective than the initial one (Altman, 1968), as shown below:

$$Z = 1.02 * \chi 1 + 1.4 * \chi 2 + 3.3 * \chi 3 + 0.6 * \chi 4 + 1 * \chi 5$$

We kept the same coefficients ($\chi 1$-$\chi 5$), as presented previously on Table 3. - Variables of the Altman Model, but instead of using the market value of equity we changed it to the book value of equity. This is a decision we made taking into consideration that markets today are highly volatile plus there can be major discrepancies between these two variables leading to misrepresenting results on a firm's financial position.

For the discrimination of the calculations outcome, we used Altman's (1968) zones, namely the safe, grey and distress zone. Firms with a score of more than 2.99 are classified as safe, the ones with score between 1,81 and 2,99 are included in the grey zone and those scoring under 1,81 are classified as bankrupt, belonging to the distress zone.

The second accounting-based model evaluated in this study is Zmijewski's (1984) prediction model, as presented previously. We kept the same coefficients and Probit equation to calculate Zmijewski's score, as presented in Table 5. - Variables of the Zmijewski Model, in accordance to author's guidance. Classifications are based on the estimated probabilities, using a 0.5 probability cutoff, that is, firms with probabilities greater than or 0,5 are classified as bankrupt and those with probabilities less than 0,5 as non-bankrupt (Zmijewski, 1984, p. 70).

Both techniques are applied in healthy and bankrupt firms for years $t=0$ and $t=-1$. Although Zmijewski's model does not produce a gray zone outcome to be compared to Altman's, it is interesting to notice the overall classification accuracy of both techniques and their evolution, especially for bankrupt firms, from $t=-1$ to $t=0$.

It is also important to mention that the initial purpose of this study is not to compare its outcome to the outcome of models' creators or other researcher's, as our dataset's characteristics are not always comparable to theirs, but rather to come up to the most accurate technique for the special characteristics of our sample. Of course, this consideration applies not only to accounting-based models but also to the adopted ANN technique, as presented subsequently.

3.2.2 Artificial Neural Networks

The methodology used for the bankruptcy prediction via ANN is based on the Zapranis & Refenes (1999) approach, who came up with a complete backpropagation model that can be used in multiple prediction cases.

The first step for the specification of the neural network is to split the dataset in two samples, a training sample including 70% of the initial dataset and a testing sample including 30% of it. Under this methodology, the training sample is used for the training and mapping of the neural network, while the testing sample for the scheme's effectiveness evaluation (Zapranis, 2005).

This process was applied to the last two years of available financial information for the bankrupt firms and respectively for their non-bankrupt pairs ($t = 0$, $t = -1$), ending up to two training samples for the two investigated years, consisting of 57 firms for the training sample and 24 for the testing sample. The two samples were chosen at random in order to ensure the unbiased function of the scheme.

As described in previous chapter, the neural network consists of an input layer, a hidden layer and the output layer. In this application, the input layer includes the financial ratios used in the accounting based prediction models that have been investigated in this study, namely the Altman's Z-Score and Zmijewski's model variables as seen below:

Table 8 – Input Variables of the ANN Model

	Variable	Description
Input 1	WC/TA	Working Capital / Total Assets
Input 2	RE/TA	Retained Earnings / Total Assets
Input 3	EBIT/TA	Earnings Before Interest Expense and Taxes / Total Assets
Input 4	MVE/BKD	Market Value of Equity / Book Value of Total Debt
Input 5	S/TA	Sales / Total Assets
Input 6	NI/TA	Net Income/ Total Assets
Input 7	TL/TA	Total Liabilities / Total Assets
Input 8	CA/CL	Current Assets/ Current Liabilities

The most crucial parameter for the effective function of a neural network model is the determination of the number of hidden layer's units. At that stage we tried several times to train the network using from 1 up to 10 units, using the *Bpsim* computer application, in order to come up with the most effective model for each one of the investigated periods.

Specifically, for the evaluation of each training case, the outcome variables investigated were *Prediction Risk: E [L]* and *Empirical Loss: Ln*, with best fitting number of hidden layers being the one that minimizes those two variables (Zapranis, 2005). In our case, the optimal number of hidden layers proved to be three ($\lambda=3$) for the year $t=0$, and coincidentally the same for the year $t=-1$.

The outcome of the training or the testing process, specifically the *forecast value*, is defined as a dependent variable that takes two values, 1 in case the firm is forecasted to fail and 0 in case it is classified as healthy. For this assessment, firms with *forecast value* higher than 0.5 are classified as bankrupt and lower than 0.5 as healthy.

For the evaluation of the selected neural network model effectiveness, the testing sample is trained with the same number of hidden layers as the training sample, under the same process, and the results are compared to the ones of the training sample for verification purposes.

4 Empirical Analysis

The empirical analysis of this study is conducted for experimental purposes, following the practice of bankruptcy prediction literature. The analysis wants to assess whether the selected prediction models are accurate, using the specific accounting variables, and to what extend they can be useful to auditors in their going concern opinion assessment.

For the calculation of model's outcome we used *Microsoft Excel*, as there was no need for complicated calculations or a deeper understanding of model's structure. We calculated all requisite financial ratios needed, as presented previously, as well as the final outcome for each model.

This chapter presents the results obtained from this study, starting from Altman's MDA model, following Zmijewski's Probit model and finally ANN's performance. Also, there is a comparison between them, in order to determine which one is more accurate in bankruptcy prediction, as well as drawbacks that have to be mentioned.

4.1 MDA Model's Performance

For the calculation of the Z-Score we divided the dataset in two, the first dataset contained bankrupt firms and the other one the healthy ones, and calculated the score of each one separately.

4.1.1 Bankrupt Firms' MDA Score

The following table present the performance of MDA model in predicting firm's bankruptcy, viability, or unknown status (grey zone), as applied to the dataset of bankrupt firms, numerically and as a percentage:

Table 9 – MDA-Score of Bankrupt Firms (%)

	Z-Score[-1]	Z-Score[0]	Average
Distress Zone	51 (62.96%)	59 (72.84%)	55 (67.90%)
Grey Zone	14 (17.28%)	10 (12.35%)	12 (14.81%)
Safe Zone	16 (19.75%)	12 (14.81%)	14 (17.28%)
Total	81 (100%)	81 (100%)	81 (100%)

One year prior to bankruptcy (*t=-1*), the MDA model predicts effectively the bankruptcy of 63% of firms, while fails to predict accurately the failure of 20% of them. About 17% of them, classified in the grey zone, we consider them not safe but since they are in that alarming zone they are considered to be subject to further examination.

The performance of this model seems to improve in the year that bankruptcy occurred (*t=0*), where its prediction accuracy rises to 73% of the investigated sample, misclassifying just the 15% of them. Furthermore, the percentage of firms classified in the gray zone drops to 12%, which is the smallest population of the dataset, showing that many firms that belong in that zone at *t=-1* have moved to the distress zone.

Summarizing, the predictive accuracy of MDA, when tested on bankrupt firms is considered to be satisfactory, as it effectively predicted the majority of them to fail (68% as an average of two years prior to bankruptcy).

4.1.2 Healthy Firms' MDA Score

The same process was applied to the dataset of healthy firms, so as to test the performance of MDA model in companies that did not face, or maybe overcame, financial distress issues. The following table presents the outcome of our calculations on that sample, numerically and as a percentage:

Table 10 – MDA Score of Healthy Firms (%)

	Z-Score[-1]	Z-Score[0]	Average
Distress Zone	22 (27.16%)	23 (28.40%)	23 (27.78%)
Grey Zone	16 (19.75%)	20 (24.69%)	18 (22.22%)
Safe Zone	43 (53.09%)	38 (46.91%)	41 (50.00%)
Total	81 (100%)	81 (100%)	81 (100%)

For the dataset of healthy firms, the evolution of time is not a factor to be considered, as there is not an event following at *t=0*, except from potential market fluctuations or non-financial issues that may took place at that time and affected them as well as their bankrupt pair. Due to our lack of knowledge on those issues, we are rather interested to comment on the average outcome of both years examined, than on each one separately.

The average predictive accuracy of MDA model, applied on our database of healthy firms, is 50%, as it classified correctly as viable the half of the viable firms included in it. The other important figures to mention is the 20% of them that classified in the grey zone, which in other words were not classified as bankrupt, and the 28% that were misclassified as in the bankrupt zone.

Nevertheless, it is possible that those companies, classified as bankrupt, could have faced issues concerning their ability to continue their operations and overcame them eventually. Meaning that, it is not sure that misclassification is a model's fault, but it could reflect a real financial distress situation of those firms, for the time those financial information were announced. Also, there is a possibility that the accounting information they provided were not reliable, but this conjecture applies to both bankrupt and healthy datasets.

4.2 Probit Model's Performance

The same process followed in the calculation of the MDA Score, was applied to the same dataset for the calculation of the Zmijewski's Probit model's performance. The main differences in the application of the two techniques is the equation used for the calculation of the score and the classification pattern, as in Probit model there is no gray zone but firms are classified either as bankrupt or as healthy. As a consequence, the comparison between the two models is not equitable, but it is required for the purpose of our study

Here, we present the predictive accuracy of Zmijewski's model, when applied in the dataset of bankrupt firms.

4.2.1 Bankrupt Firms' Probit Score

As seen in the following table, the classification is to bankrupt and healthy companies and applies to the year prior to bankruptcy (*t=0*) as well as the year of the bankruptcy event (*t=-1*):

Table 11 – Probit Score of Bankrupt Firms (%)

	Probit-Score[-1]	Probit -Score[0]	Average
Bankrupt	44 (54.32%)	58 (71.60%)	51 (62.96%)
Healthy	37 (45.68%)	23 (28.40%)	30 (37.04%
Total	81 (100%)	81 (100%)	81 (100%)

At *t=-1* the Probit model does not appear to be effective in classifying bankrupt firms, as only the half of them (54%) were classified as bankrupt, and the rest 46% were classified falsely as healthy. However, the model's performance change at *t=0*, where it predicts effectively the bankruptcy of 72% of the bankrupt firms and leaves aside 28% of them.

The percentage of 28% misclassification, is an indicator of potential non-financial issues that provoked the bankruptcy of that companies, but for its understanding it is needed to be compared to the misclassification rate of other prediction models. In example, MDA for the same period, categorized almost the same percentage of firms (28%) as bankrupt or of unknown status (grey zone), a fact that could verify the hypothesis above.

4.2.2 Healthy Firms' Probit Score

As for the dataset of bankrupt firms, the same calculation process applied to the dataset of healthy firms, and the outcome of Zmijewski's model performance on that sample is presented in the following table:

Table 12 - Probit Score of Healthy Firms (%)

	Probit-Score[-1]	Probit -Score[0]	Average
Bankrupt	8 (9.88%)	14 (17.28%)	11 (13.58%)
Healthy	73 (90.12%)	67 (82.72%)	70 (86.42%)
Total	81 (100%)	81 (100%)	81 (100%)

In contrast to the model's outcome, on the dataset of bankrupt firms at *t=-1*, when applied to the dataset of healthy firms its accuracy rises to 90%, leaving aside only 10% classified as bankrupt. However, as mentioned above, for the dataset of healthy firms it is useful to comment the average results of the model, for both years (*t=-1, t=0*).

The average classification rate for the selected period of two years is 86%, while 14% of the total healthy firms were misclassified as bankrupt. Consequently, the predictive accuracy of the Probit model, when applied in a dataset of healthy firms, is very satisfactory, because as a percentage it is the highest compared to all previous cases.

Similarly to the MDA, the 14% of firms that were misclassified may happened due to real financial distress situations that those firms were facing at the time or due to the model's dysfunction on evaluating correctly the requested financial information.

4.3 ANN's Performance

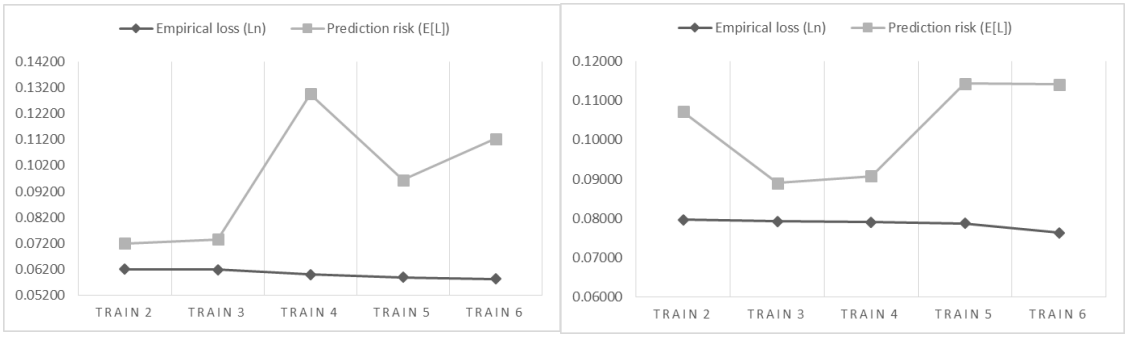
ANN is a relatively new method, compared to the traditional bankruptcy prediction models, able to process accounting data and calculate a probability of a firm to go bankrupt. The specific process of its function was described previously, so here we are presenting the predictive accuracy of this technique.

Unlike previous models, the dataset required to calculate ANN's predictive ability needs to contain both bankrupt and healthy firms. Consequently, we came up with one dataset for the year prior to bankruptcy ($t=-1$), and another for the year of bankruptcy ($t=0$). However, for purposes of comparison we have separated bankrupt from healthy companies, in order to measure their singular accuracy.

As mentioned before, the multiple training of both samples, at the initial step of determining the appropriate value of hidden layers, concluded to three hidden layers ($\lambda=3$) for both datasets.

The following figure zooms in five of the several attempts we did, training the datasets, in an attempt to minimize Empirical Loss and Prediction Risk, through different values of hidden units (TRAIN 2-6):

Figure 4 – Process of Hidden Layers Determination at t=0 (left) and t=-1 (right)



As seen in the figure above, the number of three hidden units, coincidentally proved to be the optimal solution for both datasets, theoretically able to bring the most accurate forecasting value. As a result, the structure of the neural network we used consists of an input layer with 8 units, a hidden layer of three units and a single output layer, forming an *8-3-1* backpropagation neural network model.

Following the required process, the two datasets separated randomly into four. Two training samples, one for the year prior to bankruptcy and one for the year of failure (*t=-1, t=0*), and two testing samples respectively. As mentioned in the previous chapter of this study, training samples contain 70% of the total firms and are used for the main process of prediction, while testing ones contain 30% of them and their purpose is to confirm the outcome of the training ones. Additionally, the financial ratios used for this model are the eight variables of the two accounting-based models we utilized, combined.

The full list of the examined training datasets and the performance of ANN in predicting the correct value for each firm can be found on Appendix D: ANN Training Sample Performance. The relevant testing datasets and the information related to their performance can be found on Appendix E: ANN Testing Sample Performance.

4.3.1 Training Sample

The results of the training dataset for the year prior to bankruptcy (*t=-1)* are presented in the following table:

Table 13 – ANN Training Sample Score for Bankrupt and Healthy Firms at t=-1

	Classified Correctly	Misclassified	Total
Bankrupt	30 (52.63%)	27 (47.37%)	57 (100%)
Healthy	40 (70.18%)	17 (29.82%)	57 (100%)
Overall	70 (61.40%)	44 (38.60%)	

One year prior to the bankruptcy event, the overall classification of our sample is 61% and the misclassified firms are 39% of the total sample. Specifically, 53% of failed firms were classified correctly, while the classification rate for healthy ones reached 70%. Those results are not that satisfactory for the bankrupt firms, especially if compared to traditional accounting prediction models, although ANN managed to foresee the failure of the narrow majority of those firms. However, it predicted correctly the financial situation of the vast majority of the healthy ones.

Although those information can give a first impression about the capabilities of the ANN model we use, it is more informative to notice its outcome at the last year (*t=0*), as seen in the following table:

Table 14 - ANN Training Sample Score for Bankrupt and Healthy Firms at t=0

	Classified Correctly	Misclassified	Total
Bankrupt	32 (56.14%)	25 (43.86%)	57 (100%)
Healthy	51 (89.47%)	6 (10.53%)	57 (100%)
Overall	83 (72.81%)	31 (27.19%)	

The overall predictive accuracy of ANN at the year of bankruptcy event rise to 72%, in comparison to the previous one of 61%, and the misclassification rate dropped to 27% from 39%. Specifically, bankrupt companies were classified correctly at the percentage of 56% and for healthy ones that percentage reached 73%, so although there is a slightly improved prediction performance for the bankrupt firms, the overall rate has improved due to the accurate classification of healthy firms.

Although the prediction accuracy of ANN is not outstanding at this point, it is useful to examine the performance of the testing sample and the combined performance of the two samples, as it will complete the examined dataset making the outcome comparable to the accounting-based bankruptcy prediction models.

4.3.2 Testing Sample

The following table presents the performance of ANN on the testing sample, one year prior to bankruptcy (t=-1):

Table 15 - ANN Testing Sample Score for Bankrupt and Healthy Firms at t=-1

	Classified Correctly	Misclassified	Total
Bankrupt	21 (87.50%)	3 (12.50%)	24 (100%)
Healthy	23 (95.83%)	1 (4.17%)	24 (100%)
Overall	44 (91.67%)	4 (8.33%)	

In contrast to the training sample, the overall effectiveness of ANN in predicting bankruptcy, when applied to the testing sample, rise from 61% to 92%. In particular, 88% of the bankrupt firms were classified correctly and for the healthy ones that rate reached 96%. Before commenting on the dissimilar outcomes of the two samples, it would be interesting to see the performance of the testing sample at the year that the bankruptcy event occurred, as follows:

Table 16 - ANN Testing Sample Score for Bankrupt and Healthy Firms at t=0

	Classified Correctly	Misclassified	Total
Bankrupt	22 (91.67%)	2 (4.17%)	24 (100%)
Healthy	24 (100.00%)	0 (0.00%)	24 (100%)
Overall	46 (95.83%)	2 (4.17%)	

At the year *t=0,* ANN predicted correctly 92% of bankrupt firms and 100% of healthy firms, misclassifying only 4% of the total testing sample. Although the classification rate of the testing sample for that year is the highest of all in this study, there is an inconsistency compared to the corresponding results of the training sample. The reason for this differentiation may be a technical malfunction of the ANN model due to the large number of data, or the nature of the data included in the training sample.

4.3.3 Combined Sample

For a better understanding of the ANN model's predictive accuracy and in order to come up with an outcome that can be comparable to the outcome of Altman's and Zmijewski's models, we have formed the following table, which contains the classification results of both the training and the testing samples:

Table 17 - ANN Combined Sample Score for Bankrupt and Healthy Firms at t=-1

	Classified Correctly	Misclassified	Total
Bankrupt	51 (62.96%	30 (37.04%)	81 (100%)
Healthy	63 (77.78%)	18 (22.22%)	81 (100%)
Overall	114 (70.37%)	48 (29.63%)	

The sample containing training and testing sample, for the year *t=-1*, presents an overall classification rate of 70%, while the rest 30% of the dataset were not classified correctly. Specifically, 63% of bankrupt companies were forecasted to fail, and for the healthy companies the rate reached 78%. The misclassification of 37% of the bankrupt companies and 22% of the healthy ones may be due to financial distress conditions revealed in accounting information or due to false estimations of the ANN model.

The most notable information deriving from the application of ANN in bankruptcy prediction come from the model's ability to classify bankrupt and healthy firms correctly, at the time of the bankruptcy event. The following table, shows the predicting outcome of the combined training and testing samples, showing the whole picture of the ANN model's performance, able to be compared to the outcome of the other prediction models used in this study:

Table 18 - ANN Combined Sample Score for Bankrupt and Healthy Firms at t=0

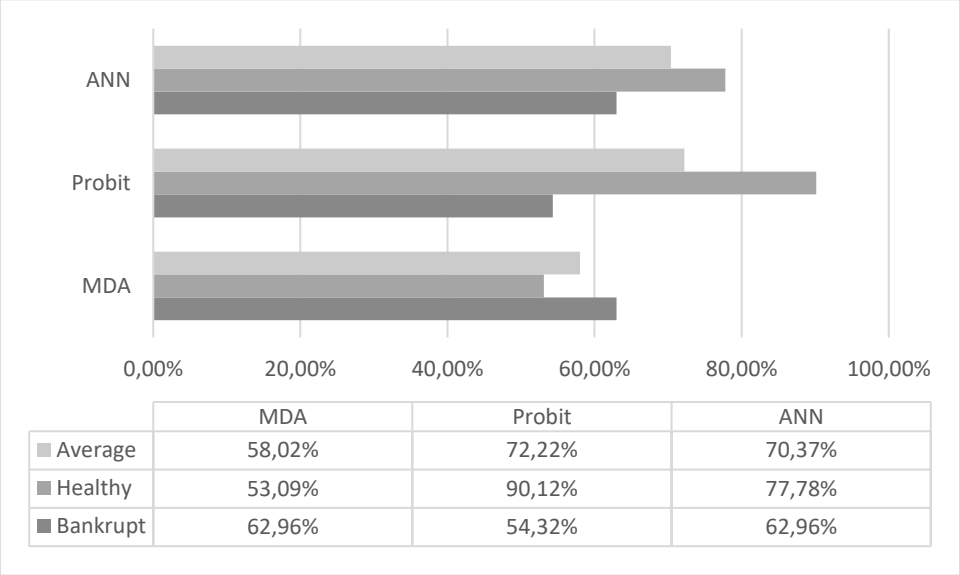
	Classified Correctly	Misclassified	Total
Bankrupt	54 (66.67%)	27 (33.33%)	81 (100%)
Healthy	75 (92.59%)	6 (7.41%)	81 (100%)
Overall	129 (79.63%)	33 (20.37%)	

At the year of the bankruptcy event, the overall prediction accuracy of ANN reached 80%, classifying incorrectly 20% of the total sample. In particular, 67% of the bankrupt companies were foreseen to fail and 93% of the healthy ones were predicted to survive. Both classification rates can be perceived satisfactory, as for bankrupt firms the model predicted effectively the failure of the majority of the firms and for healthy firms the model classified almost all of them as healthy. As said before, the misclassification rate of 33% of the bankrupt firms, and 7% for healthy firms, may have occurred due to financial destress conditions or due to model's false calculations,.

4.4 Comparison of Results

Taking into account the performance of the three bankruptcy prediction models presented and examined in this study, it is considered useful to compare their predictive accuracy. The following figure presents the percentage of accurate predictions for each one of the three models utilized, applied on the year *t=-1*:

Figure 5 – Comparison of the Three Models' Predictive Accuracy (t=-1)



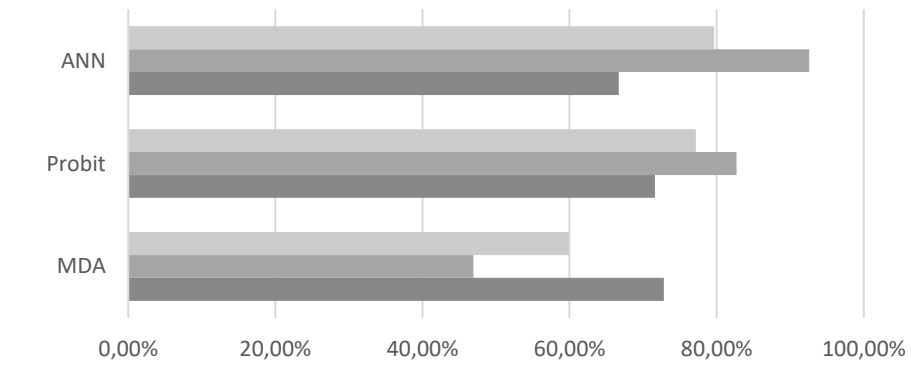
One year prior to bankruptcy, MDA and ANN predict the exactly same percentage of firms as probable to fail (63%), while Probit did not prove to be that effective in this case. However, it predicted with very high accuracy (90%) that healthy firms will survive.

The concurrence of MDA and ANN may be due to actual alarming accounting data that where interpreted in the same way, indicating that a specific number of firms are suffering financial distress issues. If this hypothesis is true, those two models proved that for a large number of firms, they are able to predict effectively their probability to fail, at *t=-1*.

For the same period, Probit and ANN classified correctly healthy firms as viable, with Probit outperforming ANN, while MDA classified only 53% of healthy firms as that. However, it is possible that MDA categorized many of those firms in the grey zone, an outcome not included in the rest of the models, making it unfair to compare it with them when its performance is not satisfactory.

On average, Probit and ANN are able to classify accurately, 72% and 70% respectively, of all firms included in our dataset, one year prior to the failure of the bankrupt ones. The predictive accuracy rates of the tested models, at the year of the bankruptcy event, are presented in the same form, as follows:

Figure 6 - Comparison of the Three Models' Predictive Accuracy (t=0)



	MDA	Probit	ANN
Average	59,88%	77,16%	79,63%
Healthy	46,91%	82,72%	92,59%
Bankrupt	72,84%	71,60%	66,67%

The most accurate tool to estimate the prediction of failure, among the ones we used in this study, proved to be MDA, as it predicted accurately the bankruptcy of 73% bankrupt firms. Probit is also very effective with its estimations, predicting 72% of the failure events, while ANN predicted the majority of failures with a lower rate of 67%.

Besides, ANN proved to outperform MDA and Probit in estimating effectively the vast majority (93%) of healthy companies' ability to continue their operations, along with Probit that corroborated the 83% of healthy firms' ability to survive. MDA did not

manage to compete with ANN and Probit, although MDA's grey zone is an issue that makes it incompetent for comparison in the cases its predictive accuracy is not satisfying

On average, ANN outperformed MDA and Probit in estimating accurately the financial situation of a firm, mainly due to its high rate on healthy firms, with an average rate of 80%. Similarly, Probit proved able to estimate financial distress and soundness with an average rate of 77%, while MDA achieved accurate predictions for an average of 60% of all firms included in our dataset.

4.5 Drawbacks

The area of bankruptcy prediction is still a major field of scientific research for finance, applying to many other areas, such as auditing. However, there are certain drawbacks of the existing models, which need to be mentioned for the better understanding of the empirical outcome of this study.

4.5.1 Industry and Time Period Limitations

A major limitation of bankruptcy prediction models lies to the fact that they are sensitive to time periods. In other words, the performance of a model may decline when applied to different time periods than those used at the time of their development (Grice & Dugan, 2001). That is because during different periods, the financial reporting rules and restrictions are not the same, a fact that affects accounting figures as well as their quality. Furthermore, market fluctuations and non-financial issues, for example political issues, are able to affect all companies of an economy at a certain period, in a positive or negative way, with impact to the objectivity of corporate financial information.

Another important factor, to be considered, is the sectoral structure of the tested firms dataset, as between different sectors financial figures are not always consistent and as a consequence bankruptcy prediction models developed under a specific dataset consistency can bring different results, than the initial, when tested on another dataset.

Knowing that there cannot be a single prediction model that fits all tested datasets and time periods, in order for someone to understand empirical misclassification rates, he has to compare the performance of additional models and take into consideration any other influencing factors that are not included in the evaluation process of the tested prediction models.

4.5.2 Dataset Limitations

4.5.2.1 Data Bias

While ending up to the final form of the dataset, one of the selection criteria was the complete financial figures for the testes periods, both for bankrupt and healthy companies. Although this is a necessary restriction for the formation of a dataset, according to Zmijewski (1984), firms with incomplete data are more probable to fail than those with complete data. Under that hypothesis, the dataset of this study is biased towards understating bankruptcy probability, due to this selection criterion. However, even if this drawback exists, the prediction accuracy doesn't seem to suffer (Zmijewski, 1984, p. 80).

4.5.2.2 Accounting Data Manipulation

Corporate scandals involving audit companies, occurred during the las decades, along with a number of cases associated to creative accounting and accounting data manipulation, indicate the danger of non-reliable accounting information.

Creative accounting is a well-known term used for the manipulation of accounting data, usually within the operating regulatory framework. According to Ghosh (2009), creative accounting manipulates data through premature or fictitious revenue calculation, aggressive capitalization and extended amortization policies, misreported assets and liabilities, and problems with cash-flow reporting.

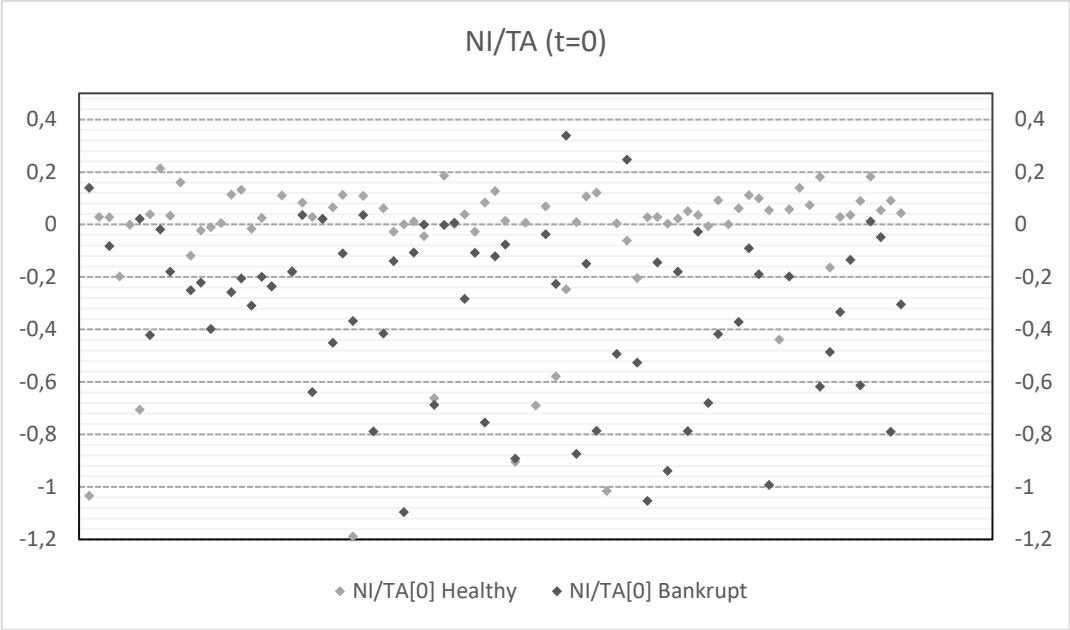
The financial figures mentioned above, such as revenues and assets, are utilized by the prediction models we used in this study and highly affect their outcome. Consequently, although auditor's responsibility to discover such cases during their control reassures for the opposite, the suspicion of fraudulent reporting is present for any dataset.

4.5.3 Quasi-Complete Separation

The quasi-complete or complete separation problem, occurs when an explanatory variable predicts, almost by itself, the outcome of the independent variable. Consequently, a specific indicator is able to separate dataset's firms into a group of bankrupt and healthy (Boyle, 1996). In the case of complete separation, a variable can sharply classify firms into bankrupt and healthy, while in quasi-complete separation this variable can classify only the majority of each group.

The current study, used Zmijewski's Probit regression prediction model, which among its variable indicators includes NI/TA ratio. As seen in the following figure, the value of this ration is negative for the most of bankrupt companies and positive for the most of the healthy ones, while a zero value seems to separate those groups effectively.

Figure 7 – Quasi-Complete Separation of NI/TA Variable



Following those observations, it seems that this variable results to a quasi-complete separation. The issue is that the maximum likelihood estimate doesn't exist for variables exhibiting this statistical phenomenon (Allison, et al., 2004, p. 221). Also, such a biased variable could be able to predict bankruptcy for the whole dataset, depending on its positive or negative value.

There are many ways to solve this problem, although it is not an objective of this study to further deepen on the development of the Probit model, but to indicate specific weaknesses and drawbacks that may contribute to potential biased results.

5 Concluding Remarks

This study concludes with certain findings, answering the basic questions raised in the introduction of this paper. Specifically, the predictive accuracy of the tested bankruptcy prediction models and their capability on assisting auditors with their evaluation on an entity's ability to continue as a going concern.

5.1 Summary

In this study, MDA, Probit and ANN models, were tested to evaluate their accuracy in predicting corporate failure, using financial data from 81 bankrupt and 81 healthy US firms. For bankrupt firms we used the last available reports *(t=0)* and reports from the period prior to it *(t=-1)*. The outcome of our calculations, assume that the prediction accuracy of the tested models varies greatly between different types and time periods.

Time period *t=-1*, has been examined as capable to provide a potential warning signal of high financial distress, while *t=0* represents the basic period of investigation as it is strongly related to auditors going concern assessment right before the bankruptcy event.

The results are encouraging in that the selected prediction models have the potential to provide with insightful information on the financial situation of an investigated firm. At the period *t=-1*, MDA and ANN classified the same percentage of bankrupt firms correctly with 63%, while Probit did not prove to be that accurate. On the contrary, at t=0, Z-Score model outperformed the two others, by predicting accurately the future of 73% of bankrupt firms, followed by Probit and ANN with 72% and 67% respectively. Under a wide perspective, MDA and ANN seem to be the most accurate bankruptcy prediction techniques, while Probit did not prove to be that effective.

Commenting on the findings of the healthy firms' dataset is crucial for the evaluation of the utilized prediction models, although it is not that important distinct between the two time periods, as there is not an event following *t=0*. However, specific market or non-financial conditions, occurred at that time, may have affected firms' financial soundness and in any case the examination of both periods separately can validate models' performance. As for this dataset, at *t=-1*, Probit outperformed ANN and MDA by reassuring the financial soundness of 90% of the healthy firms, while the other models were accurate for 78% and 53% of them respectively. At t=0, ANN managed to predict accurately the financial position of 93% of healthy firms, along with Probit that evaluated 83% of them as able to continue their operations.

MDA's performance was not satisfactory, despite the fact that its *grey zone* makes it hard for comparison to other models, as the classification characteristics of this model include this outcome, which is not included to any of the other models examined in this study. Consequently, with respect to that distinctive feature of MDA, considering firms that classified to the *grey zone* as healthy, we assume that all of the tested models are able to

evaluate accurately more than ¾ of the overall healthy firms' dataset, with ANN and Probit performing significant outcomes, each one during different time periods.

Our analysis shows that bankruptcy prediction models were more effective in classifying healthy firms correctly than bankrupt ones. A potential interpretation of that outcome could mean that bankruptcies do not occur only due to financial reasons but also due to non-financial risk factors. That assumption is confirmed by the behavior of MDA and Logit, at *t=0* tested in the bankrupt firms' dataset, where misclassification was almost the same, including *grey zone* in MDA.

As a result, although we cannot suggest one of these models as appropriate for all cases, we show that bankruptcy prediction models are able to evaluate the financial robustness or distress of US firms and even predict bankruptcy events. In other words, management, auditors and users of financial statements can extract significant information from financial figures, through bankruptcy prediction models.

Creditors, for example, have a vested interest to identify negative developments of their borrowers, such as stockholders that hold similar monetary concerns. Subsequently, regulation has given the responsibility of evaluating the financial position of a firm to auditors, so as to determine the ability of a firm to operate and potential dangers associated to this ability (Altman, 1982).

Except from creditors, investors are also interested in relying on reassuring companies' ability to operate, or be informed with an early warning on the opposite. Auditors, are called to play a significant role to this process, by providing their opinion on the assessment of an entity's ability to continue as a going concern. As creditors and investors are highly interested in foreseeing an entity's probability to fail, auditor's opinion is a legitimate and reliable statement, intended to inform them on that matter. Specifically, auditor's opinion is of high value for financial statement users, who find it useful as a warning signal for bankruptcy (Hopwood, et al., 1989).

In order, for an auditor, to provide a going concern opinion, there are specific guidelines and procedures that have to be followed. Auditor's assessment, on that matter, is not associated only to financial figures, but also to non-financial information about an entity's ability to continue its operations. However, bankruptcy prediction literature, as well as the findings of this study, show that there are significant information that can be extracted from annual statements. Specifically, auditors could benefit from bankruptcy prediction

models by using them as an assisting tools to identify or confirm potential substantial doubts on a firm's ability to continue as a going concern.

Although this study cannot propose one of the tested models as effective for all cases, it is clear that since substantial doubt is associated to financial distress, auditors could include bankruptcy prediction models in their evaluation procedures, in order to seal their judgement and form a more accurate going concern opinion. That way, public's expectations gap of the audit profession could be decreased, while public's confidence on information provided by auditors would be increased.

5.2 Suggestions for Further Research

This study has shown that bankruptcy prediction models can extract significant information on an entity's financial robustness or distress, which can benefit auditors with their going concern assessment. Nevertheless, future researchers could improve the outcome of this study or even develop further aspects associated with its objectives.

An initial attempt to improve this study could be the elimination of drawbacks and limitations related to the prediction models we used. Dataset biased factors along with quasi-complete separation indicator are two limitations further researches can overcome, in order to form a more reliable prediction method. Further models can also be tested, using the same data sample, which could potentially bring a more accurate outcome.

For example, a supplementary research could include market-based models and SVMs, or even develop a new model that could be proven to predict bankruptcy more accurately. Auditors, as well as management, could use specific models for particular sectors, depending on relevant important indicators, or a unique model that can be applied to all of them, except from financial, insurance and real estate sectors.

Another example of financial distress estimation, relies on the scientific method of linguistic analysis, under which auditor's opinion text or news articles associated to firm's operations can be analyzed in order to evaluate their sentiment and provide knowledge with an alternative way, a firm's ability to continue as a going concern. Especially for news articles, auditors could benefit from the information they contain, as they are associated to factors that could raise substantial doubts.

Furthermore, it would be interesting to examine auditor's opinion on companies that filed for bankruptcy and compare their ability to predict failure in comparison to bankruptcy prediction models.

6 References

Adnan Aziz, M. & Dar, H. A., 2006. Predicting corporate bankruptcy: where we stand?. *Corporate Governance: The international journal of business in society,* 6(1), pp. 18-33.

Agarwal, V. & Taffler, R., 2008. Comparing the performance of market-based and accounting-based bankruptcy prediction models. *Journal of Banking & Finance,* 32(8), pp. 1541-1551.

Aharony, J., Jones, C. P. & Swary, I., 1980. An analysis of risk and return characteristics of corporate bankruptcy using capital market data. *The Journal of Finance* , 35(4), pp. 1001-1016.

AICPA, 1981. *SAS No. 34 "The Auditor's Considerations When a Question Arises About and Entity's Continued Existence".* New York: American Institute of Certified Public Accountants (AICPA).

AICPA, 1988. *SAS No. 59 "The Auditor's Consideration of an Entity's Ability to Continue as a Going Concern", AU section 341.* New York: American Institute of Certified Public Accountants (AICPA).

AICPA, 2012. *SAS No. 126 "The Auditor's Consideration of an Entity's Ability to Continue as a Going Concern (Redrafted)", AU-C section 570.* New York: American Institute of Certified Public Accountants (AICPA).

AICPA, 2016. *AICPA Mission and History.* [Online]
Available at:
http://www.aicpa.org/ABOUT/MISSIONANDHISTORY/Pages/MissionHistory.aspx
[Accessed 17 10 2016].

Al-Shayea, Q. K., El-Refae, G. A. & El-Itter, S. F., 2010. Neural Networks in Bank Insolvency Prediction. *International Journal of Computer Science and Network Security,* 10(5), pp. 240-245.

Altman, E., 1968. Financial ratios, discriminant analysis and the prediction of corporate bankruptcy. *The Journal of Finance,* 23(4), pp. 589-609.

Altman, E. I., 1982. Accounting implications of failure prediction models. *Journal of Accounting, Auditing and Finance,* 6(1), pp. 4-19.

Altman, E. I., Haldeman, R. G. & Narayanan, P., 1977. ZETATM Analysis A New Model to Identify Bankruptcy Risk of Corporations. *Journal of banking & finance,* 1(1), pp. 29-54.

Altman, E. I. & McGough, T. P., 1974. Evaluation of a company as a going concern. *Journal of Accountancy,* 138(6), pp. 50-57.

Altman, E. I. & McGough, T. P., 1974. Evaluation of a company as a going concern. *Journal of Accountancy,* 138(6), pp. 50-57.

Asare, S. K., 1990. The auditor’s going concern decision: A review and implications for future research. *Journal of Accounting Literature,* 9(1), pp. 39-64.

Bauer, J. & Agarwal, V., 2014. Are hazard models superior to traditional bankruptcy prediction approaches? A comprehensive test. *Journal of Banking & Finance,* Volume 40, pp. 432-442.

Beaver, W. H., 1966. Financial Ratios As Predictors of Failure. *Journal of Accounting Research,* pp. 71-111.

Black, F. & Scholes, M., 1973. The pricing of options and corporate liabilities. *The journal of political economy,* 81(3), pp. 637-654.

Blum, M., 1974. Failing company discriminant analysis. *Journal of accounting research,* 12(1), pp. 1-25.

Bolten, S. E. & Crockett Jr., J. H., 1979. How Independent Are the Independent Auditors?. *Financial Analysts Journal,* 35(6), pp. 76-78.

Boritz, J. E. & Kennedy, D. B., 1995. Effectiveness of neural network types for prediction of business failure. *Expert Systems with Applications,* 9(4), pp. 503-512.

Boyacioglu, M. A., Kara, Y. & Baykan, Ö. K., 2009. Predicting bank financial failures using neural networks, support vector machines and multivariate statistical methods: A comparative analysis in the sample of savings deposit insurance fund (SDIF) transferred banks in Turkey. *Expert Systems with Applications,* 36(2), pp. 3355-3366.

Boyle, M. J., 1996. *Quasicomplete Seperation in Logistic Regression: A Medical Example.* Charlotte: Sesug, SAS Users Group Annual Meeting, pp. 375-380.

Carcello, J. V., Hermanson, D. R. & Huss, H. F., 1995. Temporal changes in bankruptcy-related reporting. *Auditing ,* 14(2), p. 133.

Carcello, J. V. & Neal, T. L., 2000. Audit committee composition and auditor reporting. *The Accounting Review,* 75(4), pp. 453-467.

Chava, S. & Jarrow, R. A., 2004. Bankruptcy prediction with industry effects.. *Review of Finance,* 8(4), pp. 537-569.

Chen, K. C. W. & Church, B. K., 1996. Going Concern Opinions and the Market's Reaction to Bankruptcy Filings. *The Accounting Review,* 71(1), pp. 117-128.

Chen, K. C. W. & Wei, K. C. J., 1993. Creditors' decisions to waive violations of accounting-based debt covenants. *The Accounting Review,* 68(2), pp. 218-232.

Chi, L.-C. & Tang, T.-C., 2006 . Bankruptcy Prediction: Application of Logit Analysis in Export Credit Risks. *Australian Journal of Management,* 31(1), pp. 17-27.

Chudson, W. A., 1945. *The Pattern of Corporate Financial Structure: A Cross-Section View of Manufacturing, Mining, Trade, and Construction.* New York: National Bureau of Economic Research.

Coates, J. C., 2007. The goals and promise of the Sarbanes–Oxley Act. *The Journal of Economic Perspectives,* 21(1), pp. 91-116.

Cormier, D., Magnan, M. & Morard, B., 1995. The auditor's consideration of the going concern assumption: A diagnostic model. *Journal of Accounting, Auditing & Finance,* 10(2), pp. 201-222.

Cristianini, N. & Shawe-Taylor, J., 2000. *An introduction to support vector machines and other kernel-based learning methods.* Cambridge: Cambridge university press.

Dambolena, I. G. & Khoury, S. J., 1980. Ratio stability and corporate failure. *The Journal of Finance,* 35(4), pp. 1017-1026.

Deakin, E. B., 1972. A Discriminant Analysis of Predictors of Business Failure. *Journal of Accounting Research,* 10(1), p. 167.

DeAngelo, L. E., 1981. Auditor size and audit quality. *Journal of accounting and economics,* 3(3), pp. 183-199.

DeFond, M. L. & Subramanyam, K. R., 1998. Auditor changes and discretionary accruals. *Journal of accounting and Economics,* 25(1), pp. 35-67.

Dichev, I. D., 1998. Is the risk of bankruptcy a systematic risk?. *The Journal of Finance,* 53(3), p. 1131–1147 .

Fargher, N. L. & Jiang, L., 2008. Changes in the audit environment and auditors' propensity to issue going-concern opinions. *Auditing: A Journal of Practice & Theory,* 27(2), pp. 55-77.

FASB, 2013. *Accounting Standards Update No. 2013-07: Presentation of Financial Statements,* Norwalk, CT: Financial Accounting Foundation.

FASB, 2014. *Accounting Standards Update No. 2014-15: Disclosure of uncertainties about an Entity's Ability to Continue as a Going Concern,* Norwalk, CT: Financial Accounting Foundation.

Feldmann, D. A. & Read, W. J., 2010. Auditor conservatism after Enron. *Auditing: A Journal of Practice & Theory,* 29(1), pp. 267-278.

FitzPatrick, P. J., 1932. A comparison of ratios of successful industrial enterprises with those of failed companies. *Journal of Accounting Research,* Issue (In three issues: October, 1932, p. 598-605; November, 1932, p. 656-662; December, 1932, p. 727-731).

Geiger, M. A., Raghunandan, K. & Rama, D. V., 1998. Going-concern audit report recipients before and after SAS No. 59. *The National Public Accountant,* 43(8), p. 24.

Geiger, M. A., Raghunandan, K. & Rama, D. V., 2005. Recent changes in the association between bankruptcies and prior audit opinions. *Auditing: A Journal of Practice & Theory,* 24(1), pp. 21-35.

Gerantonis, N., Vergos, K. & Christopoulos, A. G., 2009. Can Altman Z-score Models Predict Business Failures in Greece?. *Research Journal of International Studies,* 12(10), pp. 21-28.

Ghahramani, Z., 2004. Unsupervised learning. In: *Advanced lectures on machine learning* . Berlin, Heidelberg: Springer, pp. 72-112.

Gloubos, G. & Grammatikos, T., 1988. The success of bankruptcy prediction models in Greece. *Studies in Banking and Finance,* 7(1), pp. 37-46.

Goldstein, F. R., 1989. Documenting Compliance With SAS 59. *The CPA Journal,* 59(7), p. 50.

Grice, J. S. & Dugan, M. T., 2001. The limitations of bankruptcy prediction models: Some cautions for the researcher. *Review of Quantitative Finance and Accounting,* 17(2), pp. 151-166.

Grice, J. S. & Dugan, M. T., 2003. Re-estimations of the Zmijewski and Ohlson bankruptcy prediction models. *Advances in Accounting,* Volume 20, pp. 77-93.

Grice, J. S. & Ingram, R. W., 2001. Tests of the generalizability of Altman's bankruptcy prediction model. *Journal of Business Research,* 54(1), pp. 53-61.

Guy, D. M. & Sullivan, J. D., 1988. The expectation gap auditing standards. *Journal of Accountancy,* 165(4), p. 36.

Hillegeist, S. A., Keating, E. K., Cram, D. P. & Lundstedt, K. G., 2004. Assessing the probability of bankruptcy. *Review of accounting studies,* 9(1), pp. 5-34.

Hopwood, W., McKeown, J. & Mutchler, J., 1989. A test of the incremental explanatory power of opinions qualified for consistency and uncertainty. *Accounting Review* , 61(1), pp. 28-48.

Jackendoff, N., 1962. *A study of published industry financial and operating ratios.* Philadelphia: Temple University. Bureau of Economic and Business Research.

Jo, H., Han, I. & Lee, H., 1997. Bankruptcy prediction using case-based reasoning, neural networks, and discriminant analysis. *Expert Systems with Applications,* 13(2), pp. 97-108.

Johnsen, T. & Melicher, R. W., 1994. Predicting corporate bankruptcy and financial distress: Information value added by multinomial logit models. *Journal of Economics and Business,* 46(4), p. 269–286.

Jouzbarkand, M. et al., 2013. Creation Bankruptcy Prediction Model with Using Ohlson and Shirata Models. *Journal of Basic and Scientific Research,* 3(1), pp. 89-93.

Jr., J. S. G. & Dugan, M. T., 2003. Re-estimations of the Zmijewski and Ohlson bankruptcy prediction models. *Advances in Accounting,* Volume 20, pp. 77-93.

Kim, K.-j., 2003. Financial time series forecasting using support vector machines. *Neurocomputing,* 55(1), pp. 307-319.

Kogan, S. et al., 2009. *Predicting Risk from Financial Reports with Regression.* Boulder, Colorado, USA, Association for Computational Linguistics, pp. 272-280.

Koh, H. C. & Killough, L. N., 1990. The use of multiple discriminant analysis in the assessment of the going-concern status of an audit client. *Journal of Business Finance & Accounting,* 17(2), pp. 179-192.

Koh, H. C. & Tan, S. S., 1999. A neural network approach to the prediction of going concern status. *Accounting and Business Research,* 29(3), pp. 211-216.

Kohonen, T., 1982. Self-organized formation of topologically correct feature maps. *Biological cybernetics,* 43(1), pp. 59-69.

Lacerda, A. I. & Moro, R. A., 2008. Analysis of the predictors of default for portuguese firms. *Estados e Documentos de Traballio, Working Paper.*

Laitinen, E. K., 1991. Financial ratios and different failure processes. *Journal of Business Finance & Accounting,* 18(5), pp. 649-673.

Lau, A. H.-L., 1987. A five-state financial distress prediction model. *Journal of Accounting Research,* 25(1), pp. 127-138.

Law, J. & Smullen, J., 2008. *A Dictionary of Finance and Banking.* s.l.:Oxford: Oxford University Press.

Lee, K., Booth, D. & Alam, P., 2005. A comparison of supervised and unsupervised neural networks in predicting bankruptcy of Korean firms. *Expert Systems with Applications,* 29(1), pp. 1-16.

Lenard, M. J., Alam, P. & Madey, G. R., 1995. he application of neural networks and a qualitative response model to the auditor's going concern uncertainty decision. *Decision Sciences,* 62(2), pp. 209-227.

Levitan, A. S. & Knoblett, J. A., 1985. Indicators of exceptions to the going concern assumption. *Auditing - A Journal of Practice & Theory,* 5(1), pp. 26-39.

Lin, F., Yeh, C. C. & Lee, M. Y., 2013. A hybrid business failure prediction model using locally linear embedding and support vector machines. *Romanian Journal of Economic Forecasting,* 16(1), pp. 82-97.

Low, S.-W., Nor, F. M. & Yatim, P., 2001. Predicting corporate financial distress using logit model: The case of Malaysia. *Asian Academy of Management Journal,* 6(1), pp. 49-62.

Martens, D. et al., 2008. Predicting going concern opinion with data mining. *Decision Support Systems,* 45(4), pp. 765-777.

Martin, D., 1977. Early warning of bank failure: A logit regression approach. *Journal of Banking and Finance,* 1(3), p. 249–276.

McCulloch, W. S. & Pitts, W., 1943. A logical calculus of the ideas immanent in nervous activity.. *he bulletin of mathematical biophysics,* 5(4), pp. 115-133.

Menon, K. & Schwartz, K. B., 1987. An empirical investigation of audit qualification decisions in the presence of going concern uncertainties. *Contemporary Accounting Research,* 3(2), pp. 302-315.

Menon, K. & Schwartz, K. B., 1987. An empirical investigation of audit qualification decisions in the presence of going concern uncertainties. *Contemporary Accounting Research,* 3(2), pp. 302-315.

Metron, R. C., 1974. On the pricing of corporate debt: The risk structure of interest rates*. *The Journal of Finance,* 29(2), pp. 449-470.

Min, J. H. & Lee, Y.-C., 2005. Bankruptcy prediction using support vector machine with optimal choice of kernel function parameters. *Expert systems with applications,* 28(4), pp. 603-614.

Min, S.-H., Lee, J. & Han, I., 2006. Hybrid genetic algorithms and support vector machines for bankruptcy prediction. *Expert systems with applications,* 31(3), pp. 652-660.

Mohri, M., Rostamizadeh, A. & Talwalkar, A., 2012. *Foundations of machine learning.* s.l.:MIT press.

Muller, G. H., Steyn-Bruwer, B. & Hamman, W., 2009. Predicting financial distress of companies listed on the JSE-a comparison of techniques. *South African Journal of Business Management,* 40(1), pp. 21-32.

Mutchler, J. F., 1985. A multivariate analysis of the auditor's going-concern opinion decision. *Journal of Accounting Research,* 23(2), pp. 668-682.

Odom, M. D. & Sharda, R., 1990. A neural network model for bankruptcy prediction. *990 IJCNN International Joint Conference on neural networks.,* Volume 2, pp. 163-168.

Ohlson, J. A., 1980. Financial ratios and the probabilistic prediction of bankruptcy. *Journal of accounting research,* 18(1), pp. 109-131.

Piesse, J. & Wood, D., 1992. Issues in assessing MDA models of corporate failure: A research note. *The British Accounting Review,* 24(1), pp. 33-42.

Raghunandan, K. & Rama, D. V., 1995. Audit reports for companies in financial distress: Before and after SAS No. 59. *Auditing ,* 14(1), p. 50.

Rama, D. V. & Read, W. J., 2006. Resignations by the Big 4 and the market for audit services. *Accounting Horizons,* 20(2), pp. 97-109.

Ripley, B. D., 1994. Neural networks and related methods for classification. *Journal of the Royal Statistical Society. Series B (Methodological),* pp. 409-456.

Ryu, T. G., Uliss, B. & Roh, C.-Y., 2009. The effect of the Sarbanes-Oxley Act on auditors' audit performance. *Journal of Finance and Accountancy,* Volume 1, pp. 1-7.

Santomero, A. M. & Vinso, J. D., 1977. Estimating the probability of failure for commercial banks and the banking system. *Journal of Banking and Finance,* Volume 1, p. 185–215.

Shin, K.-S., Lee, T. S. & Kim, H.-j., 2005. An application of support vector machines in bankruptcy prediction model. *Expert Systems with Applications,* 28(1), pp. 127-135.

Shirata, C. Y., 1995. Read the Sign of Business Failure. *Journal of Risk and Management,* Volume 23, pp. 117-138.

Shumway, T., 2001. Forecasting bankruptcy more accurately: A simple hazard model. *The Journal of Business,* 74(1), pp. 101-124.

Singh, Y. & Chauhan, A. S., 2009. Neural networks in data mining. *Journal of Theoretical and Applied Information Technology,* 5(6), pp. 36-42.

Smith, R. F. & Winakor, A. H., 1935. Changes in the financial structure of unsuccessful industrial corporations. In: B. o. B. Research, ed. *Bulletin No. 51.* Urbana, Illinois: University of Illinois.

Tay, F. E. & Cao, L., 2001. Application of support vector machines in financial time series forecasting. *Omega,* 29(4), pp. 309-317.

Tinoco, M. H. & Wilson, N., 2013. Financial distress and bankruptcy prediction among listed companies using accounting, market and macroeconomic variables. *International Review of Financial Analysis,* Volume 30, pp. 394-419.

Tseng, F.-M. & Lin, L., 2005. A quadratic interval logit model for forecasting bankruptcy. *Omega,* 33(1), p. 85–91.

Tsukuda, J. & Baba, S.-i., 1994. Predicting Japanese corporate bankruptcy in terms of financial data using neural network. *Computers & Industrial Engineering,* 27(1), pp. 445-448.

Uang, J.-Y., Citron, D. B., Sudarsanam, S. & Taffler, R. J., 2006. Management Going-concern Disclosures: Impact of Corporate Governance and Auditor Reputation. *European Financial Management,* 12(5), pp. 789-816.

Udo, G., 1993. Neural network performance on the bankruptcy classification problem.. *Computers & Industrial Engineering,* 25(1-4), pp. 377-380.

Vapnik, V. N., 1995. *The Nature of Statistical Learning Theory.* New York: Springer Heidelberg.

Vassalou, M. & Xing, Y., 2004. Default risk in equity returns. *The Journal of Finance,* 59(2), pp. 831-868.

Warner, B. & Misra, M., 1996. Understanding neural networks as statistical tools. *The american statistician,* 50(4), pp. 284-293.

Weiss, L. A., 1996. *Corporate bankruptcy: economic and legal perspectives.* s.l.:Cambridge University Press.

Wilson, R. L. & Sharda, R., 1994. Bankruptcy prediction using neural networks. *Decision support systems,* 11(5), pp. 545-527.

Wu, Y., Gaunt, C. & Gray, S., 2010. A comparison of alternative bankruptcy prediction models. *Journal of Contemporary Accounting & Economics,* 6(1), pp. 34-35.

Zapranis, A., 2005. *Financial and neural systems.* Athens: Klidarithmos.

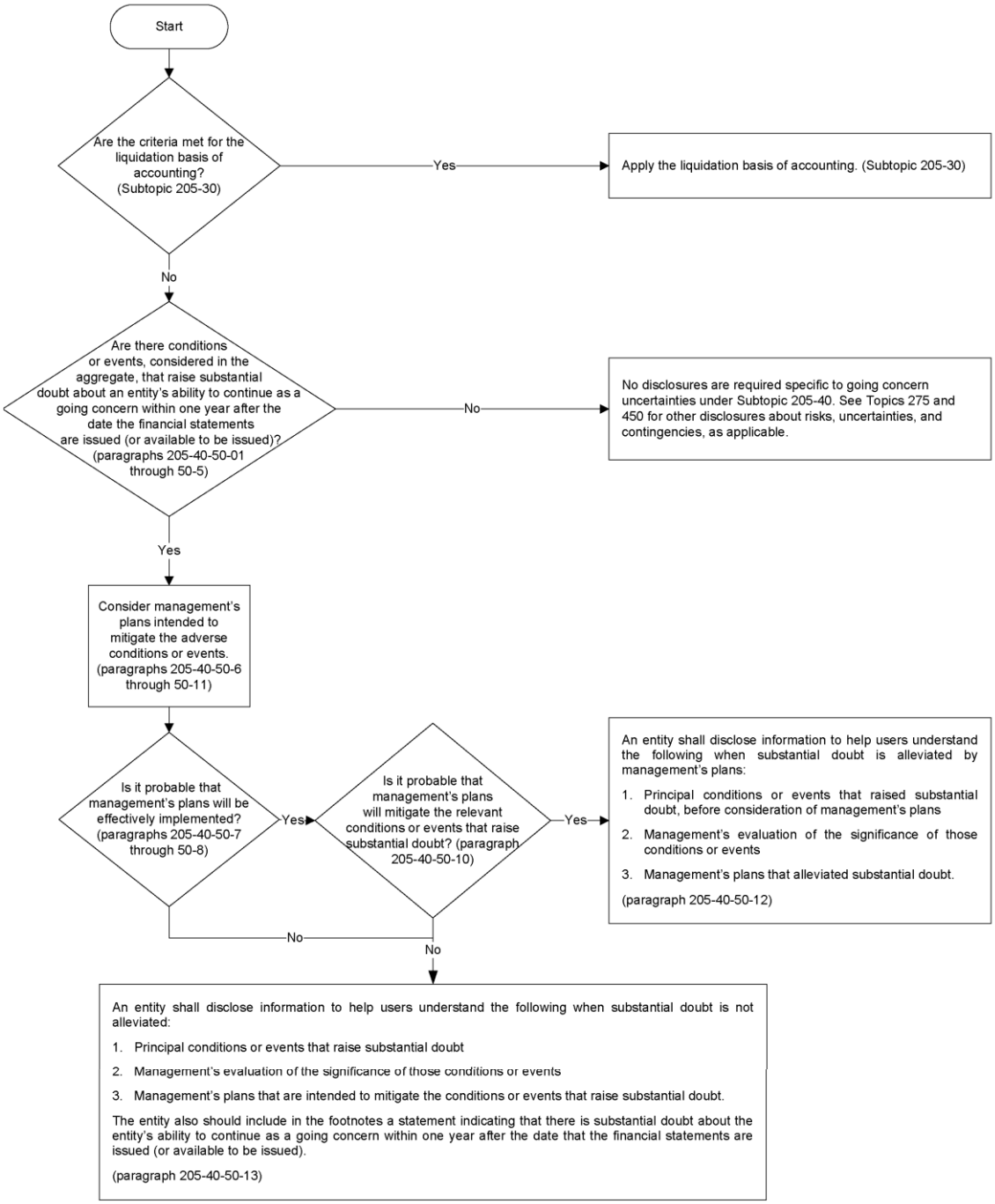
Zapranis, A. & Refenes, A. P. N., 1999. *Principles of Neural Model Identification, Selection and Adequacy: With Applications to Financial Econometrics..* London: Springer Science & Business Media.

Zhang, G., Hu, M. Y., Patuwo, B. E. & Indro, D. C., 1999. Artificial neural networks in bankruptcy prediction: General framework and cross-validation analysis. *European journal of operational research,* 116(1), pp. 16-32.

Zmijewski, M. E., 1984. Methodological Issues Related to the Estimation of Financial Distress Prediction Models. *Journal of Accounting Research,* 22(1), pp. 59-82.

Appendix A: Decision flowchart on going concern evaluation by management

The following flowchart describes the decision process management has to follow, under the new Update ASU No. 2014-15 "Disclosure of uncertainties about an Entity's Ability to Continue as a Going Concern" as issued by FASB (2014), in order to evaluate whether there is a substantial doubt about an entity's ability to continue as a going concern and defining related disclosure requirements[21]



[21] Reproduced from Accounting Standards Codification (ASC) 205-40-55-1.

Appendix B: US Firms Included in the Dataset

DATASET OF BANKRUPT FIRMS		
R/N	Company Name	Inactive Company Date
1	ABLE LABORATORIES INC	Apr06
2	ALLEGRO BIODIESEL CORP	Dec10
3	ALLIED DEFENSE GROUP INC	Sep11
4	AMERICA ONLINE LTN AMR	Jun06
5	ARMSTRONG HOLDINGS INC	Dec07
6	ASTROPOWER INC	Dec04
7	AUSPEX SYSTEMS INC	Mar06
8	BEARINGPOINT INC	Dec09
9	BETHLEHEM STEEL CORP	Jan04
10	BIOPURE CORP	Jul11
11	BMC INDUSTRIES INC	Feb06
12	BOMBAY CO INC	Sep08
13	BUILDING MATERIALS HLDG CP	Jan10
14	CAGLE'S INC	Nov12
15	CARAUSTAR INDUSTRIES INC	Aug09
16	CENTRAL EUROPEAN DIST CORP	Jun13
17	CHAMPION ENTERPRISES INC	May11
18	COLD METAL PRODUCTS INC	Jul05
19	COLDWATER CREEK INC	Oct14
20	COMMERCE ONE INC	Oct05
21	CONCORD CAMERA CORP	May10
22	CONE MILLS CORP	Feb04
23	CYGNUS INC	Apr06
24	DATATEC SYSTEMS INC	Mar05
25	DURA AUTOMOTIVE SYS	Jun08
26	EDEN BIOSCIENCE CORP	Jun09
27	ELECTROGLAS INC	May11
28	ELSINORE CORP	Mar04
29	ENERGY CONVERSION DEV	Sep12
30	ENESCO GROUP INC	Jul08
31	EPRESENCE INC	Dec07
32	EVERGREEN SOLAR INC	Jul12
33	EXIDE TECHNOLOGIES	May15
34	FAIRCHILD CORP	Nov11
35	FEDDERS CORP	Sep08
36	FLEETWOOD ENTERPRISES INC	Aug10
37	FLEMING COMPANIES INC	Aug04
38	FLYI INC	May07
39	FOAMEX INTERNATIONAL INC	Jun09
40	FRONTLINE CAPITAL GROUP	Sep08
41	FROZEN FOOD EXPRESS INDS	Aug13
42	FURNITURE BRANDS INTL INC	Aug14
43	GADZOOKS INC	May06
44	GENAERA CORP	Jul09
45	GENERAL MAGIC INC	Sep02
46	GOTTSCHALKS INC	Mar11
47	GREAT ATLANTIC & PAC TEA CO	Mar12
48	HAYES LEMMERZ INTL INC	Dec09
49	IBIS TECHNOLOGY CORP	May12
50	INTERSTATE BAKERIES CORP	Feb09
51	JACKSON HEWITT TAX SERVICE	Aug11
52	LARGE SCALE BIOLOGY CORP	Aug09
53	LODGENET INTERACTIVE CORP	Apr13
54	MAXYGEN INC	Aug13
55	MEDICAL STAFFNG NTWRK HLDGS	Jul11
56	MIDWAY GAMES INC	Jun10
57	MILACRON INC	Feb13
58	MOVIE GALLERY INC	Oct11
59	NATIONAL RV HOLDINGS INC	Aug10
60	NEOSE TECHNOLOGIES INC	Jun10
61	NEXCEN BRANDS INC	Sep10
62	NORTHFIELD LABORATORIES INC	Oct09
63	NUCENTRIX BROADBAND NETWORKS	Jun04
64	OILSANDS QUEST INC	Aug14
65	OSCIENT PHARMACEUTICALS CORP	Jul10
66	PENN TRAFFIC CO	Oct11
67	PRICE COMMUNICATIONS CORP	Aug07
68	SAVIENT PHARMACEUTICALS INC	Jun14
69	SHEFFIELD PHARMACEUTICALS	Jun03
70	SOAPSTONE NETWORKS INC	Dec12
71	SPATIALIGHT INC	Feb08
72	TENERA INC	Jan04
73	THQ INC	Aug13
74	THREE-FIVE SYSTEMS INC	Feb10
75	TL ADMINISTRATION CORP	Sep05
76	TRICO MARINE SERVICES INC	Feb12
77	TROPICAL SPORTSWEAR INTL CP	Apr05
78	TXCO RESOURCES INC	Feb10
79	ULTIMATE ELECTRONICS INC	Feb06
80	VERSO TECHNOLOGIES INC	Mar13
81	VIA NET WORKS INC	Oct12

DATASET OF HEALTHY FIRMS	
R/N	Company Name
1	EMISPHERE TECHNOLOGIES INC
2	QUAKER CHEMICAL CORP
3	JARDEN CORP
4	SIMON WORLDWIDE INC
5	AK STEEL HOLDING CORP
6	STEMCELLS INC
7	BALL CORP
8	FASTENAL CO
9	HAVERTY FURNITURE
10	SANDERSON FARMS INC
11	INSTEEL INDUSTRIES
12	WAUSAU PAPER CORP
13	CULP INC
14	UNIVERSAL FOREST PRODS INC
15	CHICOS FAS INC
16	MERIDIAN BIOSCIENCE INC
17	PDF SOLUTIONS INC
18	PHOTRONICS INC
19	ALLIANCE ONE INTL INC
20	SEMTECH CORP
21	BROADVISION INC
22	STANDARD MOTOR PRODS
23	FRP HOLDINGS INC
24	OXFORD INDUSTRIES INC
25	LA-Z-BOY INC
26	WINNEBAGO INDUSTRIES
27	DISCOVERY LABORATORIES INC
28	SYSCO CORP
29	HAWAIIAN HOLDINGS INC
30	WHOLE FOODS MARKET INC
31	AMERICAN AXLE & MFG HOLDINGS
32	TREDEGAR CORP
33	CARRIAGE SERVICES INC
34	DESTINATION XL GROUP INC
35	SMITH MICRO SOFTWARE INC
36	SPECTRUM PHARMACEUTICALS INC
37	BON TON STORES INC
38	KFORCE INC
39	ULTIMATE SOFTWARE GROUP INC
40	CONTANGO OIL & GAS CO
41	INTEVAC INC
42	LUMINEX CORP
43	PEREGRINE PHARMACEUTICALS INC
44	ENTEGRIS INC
45	GERON CORP
46	ACI WORLDWIDE INC
47	CERUS CORP
48	ABRAXAS PETROLEUM CORP/NV
49	CABLEVISION SYSTEMS CORP
50	PTC INC
51	UNITED GUARDIAN INC
52	RESEARCH FRONTIERS INC
53	VERSAR INC
54	EMCORE CORP
55	AKORN INC
56	PERRY ELLIS INTERNATIONAL INC
57	TRANS WORLD ENTERTAINMENT CORP
58	AWARE INC
59	ALBANY MOLECULAR RESEARCH INC
60	ARC DOCUMENT SOLUTIONS INC
61	FALCONSTOR SOFTWARE INC
62	AXT INC
63	BALLANTYNE STRONG INC
64	CAMBREX CORP
65	CEVA INC
66	DONALDSON CO INC
67	FLOWERS FOODS INC
68	HEALTHSTREAM INC
69	INSITE VISION INC
70	KIRBY CORP
71	MONARCH CASINO & RESORT INC
72	NETFLIX INC
73	NIC INC
74	PENDRELL CORP
75	SILICON GRAPHICS INTL CORP
76	STANDEX INTERNATIONAL CORP
77	TOWERS WATSON & CO
78	TRAVELZOO INC
79	VILLAGE SUPER MARKET
80	DREW INDUSTRIES INC
81	WORLD FUEL SERVICES CORP

Appendix C: MDA and Probit Performance

1. Equation: Z-Score = 1,2*x1 + 1,4*x2 + 3,3*x4 + 0,6*x5 + 1,0* x6

2. Equation: Prob-Score = -4.336 -4.513*x1 + 5.679*x2 - 0.004*x3

1. Bankrupt Companies

	Z-Score[-1]	Z-Score[0]	Average
Distress Zone	51	59	55
Grey Zone	14	10	12
Safe Zone	16	12	14

	Z-Score[-1]	Z-Score[0]	Average
Distress Zone	62.96%	72.84%	67.90%
Grey Zone	17.28%	12.35%	14.81%
Safe Zone	19.75%	14.81%	17.28%

2. Healthy Companies

	Z-Score[-1]	Z-Score[0]	Average
Distress Zone	22	23	23
Grey Zone	16	20	18
Safe Zone	43	38	41

	Z-Score[-1]	Z-Score[0]	Average
Distress Zone	27.16%	28.40%	27.78%
Grey Zone	19.75%	24.69%	22.22%
Safe Zone	53.09%	46.91%	50.00%

1. Bankrupt Companies

	P-Score[-1]	P-Score[0]	Average
Bankrupt	44	58	51
Healthy	37	23	30

	P-Score[-1]	P-Score[0]	Average
Bankrupt	54.32%	71.60%	####
Healthty	45.68%	28.40%	####

2. Healthy Companies

	P-Score[-1]	P-Score[0]	Average
Bankrupt	8	14	11
Healthy	73	67	70

	P-Score[-1]	P-Score[0]	Average
Bankrupt	9.88%	17.28%	13.58%
Healthy	90.12%	82.72%	86.42%

Index: Bankrupt Zone | Grey Zone | Safe Zone

Z-Score[-1]	Z-Score[0]
3.844	4.571
-40.783	-532.428
1.976	1.612
-25.678	-43.118
0.828	18.451
4.883	3.630
-0.897	0.442
-0.731	0.417
-0.567	-1.227
-59.714	-86.625
1.867	1.765
2.938	1.959
3.517	2.003
4.941	4.505
1.879	0.100
0.707	-1.873
2.796	1.404
2.333	0.365
1.570	2.993
-33.391	-188.041
-0.107	-0.820
2.068	2.148
-9.515	-452.903
7.765	4.279
0.459	-0.324
-29.314	-32.932
-1.199	2.314
0.874	1.500
-0.638	-1.654
4.377	4.173
0.370	0.835
0.082	-3.989
1.837	0.386
0.879	0.656
-351.542	-0.707
5.694	3.268
5.211	5.620
3.331	0.314
1.910	1.791
-6.149	-11.544
2.835	3.067
2.406	2.454
3.905	1.081
-18.130	-53.366
-14.098	-32.668
3.402	2.525
2.079	2.076
1.756	-0.364
-6.022	-14.107
1.548	2.135
1.348	-0.839
-12.933	-22.760
-0.992	-3.182
0.241	0.617
3.894	-2.116
1.993	-7.202
0.382	0.409
1.688	-1.066
4.354	3.042
-12.237	-12.071
-33.346	-38.255
-6.152	-11.384
-0.496	-2.744
-1.187	-12.323
-2.650	-5.654
5.281	3.944
1.480	1.544
-15.254	-8.991
-89.501	-116.746
-0.063	-5.521
-30.927	-38.204
1.861	-4.142
1.167	-1.632
0.937	-0.224
-0.359	-3.270
0.987	0.951
3.112	2.485
1.686	0.031
3.445	2.699
-2.330	-21.918
-4.569	-5.618

Z-Score[-1]	Z-Score[0]
-4.855	-19.369
3.301	3.265
2.650	2.838
-11.231	-16.410
1.399	1.223
-5.694	-6.434
4.730	4.913
8.386	7.653
3.460	3.603
5.691	5.137
2.035	1.877
3.399	3.915
2.835	3.036
4.429	4.422
4.106	4.724
5.255	5.974
2.302	1.706
1.365	1.698
2.129	2.576
3.373	4.054
-5.279	2.512
3.908	4.482
2.043	2.257
3.477	2.596
4.026	4.276
7.619	7.678
-4.493	-10.857
10.236	10.481
-81.993	-75.355
4.213	4.572
2.415	0.210
3.630	3.036
0.473	0.669
2.395	3.462
0.398	-1.599
3.410	2.364
3.178	2.472
4.432	4.574
8.647	4.796
3.115	2.821
5.257	3.720
3.074	3.369
-4.858	-7.966
2.431	2.019
-7.087	-11.941
3.437	3.461
-1.597	-4.324
1.435	2.565
-3.735	-1.208
2.262	2.537
4.984	4.281
-11.233	-13.189
3.002	2.865
-0.021	-1.131
1.207	0.607
2.671	2.837
2.561	2.960
2.008	1.689
2.257	2.499
3.681	2.615
5.993	5.077
0.217	-0.531
3.407	4.180
2.307	2.222
2.094	2.736
5.343	5.536
4.725	4.732
0.623	0.419
-5.445	-7.760
3.138	2.751
3.127	5.954
22.959	5.471
10.169	10.951
-4.734	-5.547
4.773	3.127
3.608	3.532
3.347	3.175
7.710	13.390
5.338	5.095
4.035	4.825
11.542	10.753

Index: Bankrupt | Healthy

P-Score[-1]	P-Score[0]
-4.244	-4.575
12.085	67.808
-0.095	0.186
23.039	32.967
2.818	-215.020
-3.850	-3.728
4.409	-0.812
3.509	3.300
5.647	7.204
9.179	7.119
-0.353	1.100
-1.012	0.330
1.244	2.666
-1.084	27.435
0.142	2.626
3.715	2.807
-0.470	1.971
0.786	2.461
0.826	1.796
16.343	8.415
-1.580	-0.584
0.357	-0.490
-5.611	4.220
0.615	0.283
6.106	8.316
-3.405	-3.738
1.283	2.477
0.080	-2.039
1.856	4.521
-0.814	0.906
-2.336	-3.189
0.055	7.094
1.404	1.875
0.523	-0.135
2.112	8.089
1.235	0.562
0.787	0.535
-1.753	1.213
5.227	5.758
21.172	23.236
0.720	0.589
0.431	1.176
-2.541	3.441
-0.186	4.883
2.248	7.199
-0.722	-0.413
3.533	4.494
-0.006	0.987
-3.860	-0.007
3.486	4.752
-1.079	5.299
1.805	3.297
2.055	7.441
-5.832	-5.368
4.296	6.501
2.668	11.080
1.797	2.454
2.604	12.905
-0.622	0.636
2.423	1.918
13.941	4.178
-1.338	-0.725
-0.907	0.045
-2.753	5.003
2.420	5.671
0.557	0.688
-2.079	-0.866
3.896	12.397
20.833.516	25.729.752
-6.198	-3.375
8.500	24.117
-0.496	8.960
0.613	4.592
-1.529	0.184
3.618	3.493
0.987	1.356
-1.344	3.500
-1.475	-0.529
-2.857	-1.811
3.103	5.300
-1.160	1.180

P-Score[-1]	P-Score[0]
2.404	7.762
-0.760	-0.710
-0.360	-0.628
-3.515	-3.568
0.214	0.782
-0.486	1.496
0.270	0.483
-4.518	-4.625
-2.236	-2.359
-3.098	-3.750
-0.494	0.445
-0.796	-0.222
-1.015	-1.117
-2.015	-2.506
-3.133	-3.107
-1.492	-1.961
8.073	-3.560
-2.826	-2.668
-0.387	1.750
-11.547	-3.717
3.559	1.928
-2.018	-2.266
-2.377	-2.389
-1.743	-1.302
-2.964	-2.844
-2.418	-2.409
0.690	4.811
-1.159	-1.385
510.206	135.253
-1.902	-2.322
-0.457	2.564
-2.424	-2.224
-0.988	0.291
0.033	-0.226
-2.352	0.454
-3.272	-2.754
0.408	0.336
-0.914	-2.624
-2.331	-0.506
-2.989	-2.660
-3.670	-4.137
-3.331	-3.844
0.306	1.215
-3.699	-3.376
-1.164	-0.443
-1.279	-1.686
-3.450	-0.407
-3.466	2.142
0.438	1.061
-0.961	-1.479
-4.608	-4.425
0.336	0.653
-0.185	-0.903
0.985	-0.676
0.879	1.247
-0.543	-0.593
-1.180	-1.563
-4.148	-4.100
-3.522	-3.695
-1.071	-1.143
-2.900	-3.154
-2.994	-3.060
-2.835	-2.311
-0.304	0.086
-4.019	-4.099
-1.868	-1.879
-1.773	-2.169
-2.807	-2.860
5.912	9.120
-1.731	-1.576
-1.422	-2.449
-1.081	-0.185
-1.941	-2.572
-4.997	-3.435
-2.864	-3.208
-0.993	-1.246
-2.329	-2.051
-4.151	-4.289
-2.256	-1.969
-3.109	-3.589
-1.002	-0.868

Appendix D: ANN Training Sample Performance

R/N	Company Name	Actual	Score	Forecast	Evaluation
1	ABLE LABORATORIES INC	1	0.294	0	FALSE
2	ALLEGRO BIODIESEL CORP	1	0.938	1	TRUE
3	ALLIED DEFENSE GROUP INC	1	0.442	0	FALSE
4	AMERICA ONLINE LTN AMR	1	0.977	1	TRUE
5	ARMSTRONG HOLDINGS INC	1	0.576	1	TRUE
6	ASTROPOWER INC	1	0.287	0	FALSE
7	AUSPEX SYSTEMS INC	1	0.324	0	FALSE
8	BEARINGPOINT INC	1	0.512	1	TRUE
9	BETHLEHEM STEEL CORP	1	0.362	0	FALSE
10	BIOPURE CORP	1	0.944	1	TRUE
11	BMC INDUSTRIES INC	1	0.350	0	FALSE
12	BOMBAY CO INC	1	0.730	1	TRUE
13	BUILDING MATERIALS HLDG	1	0.736	1	TRUE
14	CAGLE'S INC	1	0.947	1	TRUE
15	CARAUSTAR INDUSTRIES INC	1	0.803	1	TRUE
16	CENTRAL EUROPEAN DIST CO	1	0.466	0	FALSE
17	CHAMPION ENTERPRISES IN	1	0.562	1	TRUE
18	COLD METAL PRODUCTS INC	1	0.699	1	TRUE
19	COLDWATER CREEK INC	1	0.753	1	TRUE
20	COMMERCE ONE INC	1	0.909	1	TRUE
21	CONCORD CAMERA CORP	1	0.374	0	FALSE
22	CONE MILLS CORP	1	0.449	0	FALSE
23	CYGNUS INC	1	0.277	0	FALSE
24	DATATEC SYSTEMS INC	1	0.562	1	TRUE
25	DURA AUTOMOTIVE SYS	1	0.526	1	TRUE
26	EDEN BIOSCIENCE CORP	1	0.277	0	FALSE
27	ELECTROGLAS INC	1	0.338	0	FALSE
28	ELSINORE CORP	1	0.464	0	FALSE
29	ENERGY CONVERSION DEV	1	0.300	0	FALSE
30	ENESCO GROUP INC	1	0.675	1	TRUE
31	EPRESENCE INC	1	0.281	0	FALSE
32	EVERGREEN SOLAR INC	1	0.320	0	FALSE
33	EXIDE TECHNOLOGIES	1	0.404	0	FALSE
34	FAIRCHILD CORP	1	0.388	0	FALSE
35	FEDDERS CORP	1	0.578	1	TRUE
36	FLEETWOOD ENTERPRISES IN	1	0.754	1	TRUE
37	FLEMING COMPANIES INC	1	0.964	1	TRUE
38	FLYI INC	1	0.375	0	FALSE
39	FOAMEX INTERNATIONAL IN	1	0.579	1	TRUE
40	FRONTLINE CAPITAL GROUP	1	0.986	1	TRUE
41	FROZEN FOOD EXPRESS INDS	1	0.909	1	TRUE
42	FURNITURE BRANDS INTL IN	1	0.420	0	FALSE
43	GADZOOKS INC	1	0.981	1	TRUE
44	GENAERA CORP	1	0.743	1	TRUE
45	GENERAL MAGIC INC	1	0.902	1	TRUE
46	GOTTSCHALKS INC	1	0.476	0	FALSE
47	GREAT ATLANTIC & PAC TEA	1	0.828	1	TRUE
48	HAYES LEMMERZ INTL INC	1	0.739	1	TRUE
49	IBIS TECHNOLOGY CORP	1	0.313	0	FALSE
50	INTERSTATE BAKERIES CORP	1	0.889	1	TRUE
51	JACKSON HEWITT TAX SERVI	1	0.344	0	FALSE
52	LARGE SCALE BIOLOGY CORP	1	0.827	1	TRUE
53	LODGENET INTERACTIVE CO	1	0.946	1	TRUE
54	MAXYGEN INC	1	0.277	0	FALSE
55	MEDICAL STAFFNG NTWRK H	1	0.983	1	TRUE
56	MIDWAY GAMES INC	1	0.966	1	TRUE
57	MILACRON INC	1	0.367	0	FALSE
1	EMISPHERE TECHNOLOGIES I	0	0.382	0	TRUE
2	QUAKER CHEMICAL CORP	0	0.372	0	TRUE
3	JARDEN CORP	0	0.330	0	TRUE
4	SIMON WORLDWIDE INC	0	0.278	0	TRUE
5	AK STEEL HOLDING CORP	0	0.355	0	TRUE
6	STEMCELLS INC	0	0.298	0	TRUE
7	BALL CORP	0	0.355	0	TRUE
8	FASTENAL CO	0	0.308	0	TRUE
9	HAVERTY FURNITURE	0	0.484	0	TRUE
10	SANDERSON FARMS INC	0	0.472	0	TRUE
11	INSTEEL INDUSTRIES	0	0.409	0	TRUE
12	WAUSAU PAPER CORP	0	0.460	0	TRUE
13	CULP INC	0	0.361	0	TRUE
14	UNIVERSAL FOREST PRODS I	0	0.717	1	FALSE
15	CHICOS FAS INC	0	0.400	0	TRUE
16	MERIDIAN BIOSCIENCE INC	0	0.320	0	TRUE
17	PDF SOLUTIONS INC	0	0.301	0	TRUE
18	PHOTRONICS INC	0	0.306	0	TRUE
19	ALLIANCE ONE INTL INC	0	0.338	0	TRUE
20	SEMTECH CORP	0	0.297	0	TRUE
21	BROADVISION INC	0	0.328	0	TRUE
22	STANDARD MOTOR PRODS	0	0.359	0	TRUE
23	FRP HOLDINGS INC	0	0.324	0	TRUE
24	OXFORD INDUSTRIES INC	0	0.354	0	TRUE
25	LA-Z-BOY INC	0	0.376	0	TRUE
26	WINNEBAGO INDUSTRIES	0	0.459	0	TRUE
27	DISCOVERY LABORATORIES I	0	0.499	0	TRUE
28	SYSCO CORP	0	0.933	1	FALSE
29	HAWAIIAN HOLDINGS INC	0	0.308	0	TRUE
30	WHOLE FOODS MARKET INC	0	0.623	1	FALSE
31	AMERICAN AXLE & MFG HOL	0	0.367	0	TRUE
32	TREDEGAR CORP	0	0.365	0	TRUE
33	CARRIAGE SERVICES INC	0	0.309	0	TRUE
34	DESTINATION XL GROUP INC	0	0.424	0	TRUE
35	SMITH MICRO SOFTWARE IN	0	0.558	1	FALSE
36	SPECTRUM PHARMACEUTICA	0	0.294	0	TRUE
37	BON TON STORES INC	0	0.424	0	TRUE
38	KFORCE INC	0	0.740	1	FALSE
39	ULTIMATE SOFTWARE GROU	0	0.441	0	TRUE
40	CONTANGO OIL & GAS CO	0	0.301	0	TRUE
41	INTEVAC INC	0	0.290	0	TRUE
42	LUMINEX CORP	0	0.286	0	TRUE
43	PEREGRINE PHARMACEUTICA	0	0.385	0	TRUE
44	ENTEGRIS INC	0	0.309	0	TRUE
45	GERON CORP	0	0.297	0	TRUE
46	ACI WORLDWIDE INC	0	0.315	0	TRUE
47	CERUS CORP	0	0.294	0	TRUE
48	ABRAXAS PETROLEUM CORP	0	0.454	0	TRUE
49	CABLEVISION SYSTEMS CORP	0	0.326	0	TRUE
50	PTC INC	0	0.341	0	TRUE
51	UNITED GUARDIAN INC	0	0.282	0	TRUE
52	RESEARCH FRONTIERS INC	0	0.330	0	TRUE
53	VERSAR INC	0	0.434	0	TRUE
54	EMCORE CORP	0	0.316	0	TRUE
55	AKORN INC	0	0.546	1	FALSE
56	PERRY ELLIS INTERNATIONAL	0	0.310	0	TRUE
57	TRANS WORLD ENTERTAINM	0	0.403	0	TRUE

R/N	Company Name	Actual	Score	Forecast	Evaluation
1	ABLE LABORATORIES INC	1	0.483	0	FALSE
2	ALLEGRO BIODIESEL CORP	1	0.550	1	TRUE
3	ALLIED DEFENSE GROUP INC	1	0.499	0	FALSE
4	AMERICA ONLINE LTN AMR	1	0.513	1	TRUE
5	ARMSTRONG HOLDINGS INC	1	0.495	0	FALSE
6	ASTROPOWER INC	1	0.481	0	FALSE
7	AUSPEX SYSTEMS INC	1	0.509	1	TRUE
8	BEARINGPOINT INC	1	0.501	1	TRUE
9	BETHLEHEM STEEL CORP	1	0.496	0	FALSE
10	BIOPURE CORP	1	0.538	1	TRUE
11	BMC INDUSTRIES INC	1	0.498	0	FALSE
12	BOMBAY CO INC	1	0.495	0	FALSE
13	BUILDING MATERIALS HLDG CP	1	0.495	0	FALSE
14	CAGLE'S INC	1	0.499	0	FALSE
15	CARAUSTAR INDUSTRIES INC	1	0.503	1	TRUE
16	CENTRAL EUROPEAN DIST CORP	1	0.503	1	TRUE
17	CHAMPION ENTERPRISES INC	1	0.505	1	TRUE
18	COLD METAL PRODUCTS INC	1	0.496	0	FALSE
19	COLDWATER CREEK INC	1	0.504	1	TRUE
20	COMMERCE ONE INC	1	0.524	1	TRUE
21	CONCORD CAMERA CORP	1	0.492	0	FALSE
22	CONE MILLS CORP	1	0.501	1	TRUE
23	CYGNUS INC	1	0.496	0	FALSE
24	DATATEC SYSTEMS INC	1	0.516	1	TRUE
25	DURA AUTOMOTIVE SYS	1	0.502	1	TRUE
26	EDEN BIOSCIENCE CORP	1	0.485	0	FALSE
27	ELECTROGLAS INC	1	0.492	0	FALSE
28	ELSINORE CORP	1	0.505	1	TRUE
29	ENERGY CONVERSION DEV	1	0.491	0	FALSE
30	ENESCO GROUP INC	1	0.492	0	FALSE
31	EPRESENCE INC	1	0.482	0	FALSE
32	EVERGREEN SOLAR INC	1	0.498	0	FALSE
33	EXIDE TECHNOLOGIES	1	0.501	1	TRUE
34	FAIRCHILD CORP	1	0.498	0	FALSE
35	FEDDERS CORP	1	0.459	0	FALSE
36	FLEETWOOD ENTERPRISES INC	1	0.501	1	TRUE
37	FLEMING COMPANIES INC	1	0.502	1	TRUE
38	FLYI INC	1	0.492	0	FALSE
39	FOAMEX INTERNATIONAL INC	1	0.502	1	TRUE
40	FRONTLINE CAPITAL GROUP	1	0.572	1	TRUE
41	FROZEN FOOD EXPRESS INDS	1	0.506	1	TRUE
42	FURNITURE BRANDS INTL INC	1	0.493	0	FALSE
43	GADZOOKS INC	1	0.492	0	FALSE
44	GENAERA CORP	1	0.488	0	FALSE
45	GENERAL MAGIC INC	1	0.502	1	TRUE
46	GOTTSCHALKS INC	1	0.494	0	FALSE
47	GREAT ATLANTIC & PAC TEA CO	1	0.504	1	TRUE
48	HAYES LEMMERZ INTL INC	1	0.503	1	TRUE
49	IBIS TECHNOLOGY CORP	1	0.489	0	FALSE
50	INTERSTATE BAKERIES CORP	1	0.522	1	TRUE
51	JACKSON HEWITT TAX SERVICE	1	0.509	1	TRUE
52	LARGE SCALE BIOLOGY CORP	1	0.505	1	TRUE
53	LODGENET INTERACTIVE CORP	1	0.507	1	TRUE
54	MAXYGEN INC	1	0.514	1	TRUE
55	MEDICAL STAFFNG NTWRK HLDGS	1	0.501	1	TRUE
56	MIDWAY GAMES INC	1	0.500	1	TRUE
57	MILACRON INC	1	0.498	0	FALSE
1	EMISPHERE TECHNOLOGIES INC	0	0.489	0	TRUE
2	QUAKER CHEMICAL CORP	0	0.496	0	TRUE
3	JARDEN CORP	0	0.498	0	TRUE
4	SIMON WORLDWIDE INC	0	0.480	0	TRUE
5	AK STEEL HOLDING CORP	0	0.502	1	FALSE
6	STEMCELLS INC	0	0.487	0	TRUE
7	BALL CORP	0	0.503	1	FALSE
8	FASTENAL CO	0	0.481	0	TRUE
9	HAVERTY FURNITURE	0	0.499	0	TRUE
10	SANDERSON FARMS INC	0	0.495	0	TRUE
11	INSTEEL INDUSTRIES	0	0.500	1	FALSE
12	WAUSAU PAPER CORP	0	0.501	1	FALSE
13	CULP INC	0	0.492	0	TRUE
14	UNIVERSAL FOREST PRODS INC	0	0.493	0	TRUE
15	CHICOS FAS INC	0	0.499	0	TRUE
16	MERIDIAN BIOSCIENCE INC	0	0.496	0	TRUE
17	PDF SOLUTIONS INC	0	0.493	0	TRUE
18	PHOTRONICS INC	0	0.502	1	FALSE
19	ALLIANCE ONE INTL INC	0	0.494	0	TRUE
20	SEMTECH CORP	0	0.494	0	TRUE
21	BROADVISION INC	0	0.510	1	FALSE
22	STANDARD MOTOR PRODS	0	0.494	0	TRUE
23	FRP HOLDINGS INC	0	0.503	1	FALSE
24	OXFORD INDUSTRIES INC	0	0.498	0	TRUE
25	LA-Z-BOY INC	0	0.488	0	TRUE
26	WINNEBAGO INDUSTRIES	0	0.488	0	TRUE
27	DISCOVERY LABORATORIES INC	0	0.488	0	TRUE
28	SYSCO CORP	0	0.500	0	TRUE
29	HAWAIIAN HOLDINGS INC	0	0.574	1	FALSE
30	WHOLE FOODS MARKET INC	0	0.503	1	FALSE
31	AMERICAN AXLE & MFG HOLDINGS	0	0.500	1	FALSE
32	TREDEGAR CORP	0	0.499	0	TRUE
33	CARRIAGE SERVICES INC	0	0.506	1	FALSE
34	DESTINATION XL GROUP INC	0	0.499	0	TRUE
35	SMITH MICRO SOFTWARE INC	0	0.488	0	TRUE
36	SPECTRUM PHARMACEUTICALS IN	0	0.488	0	TRUE
37	BON TON STORES INC	0	0.499	0	TRUE
38	KFORCE INC	0	0.500	0	TRUE
39	ULTIMATE SOFTWARE GROUP INC	0	0.503	1	FALSE
40	CONTANGO OIL & GAS CO	0	0.502	1	FALSE
41	INTEVAC INC	0	0.485	0	TRUE
42	LUMINEX CORP	0	0.495	0	TRUE
43	PEREGRINE PHARMACEUTICALS IN	0	0.494	0	TRUE
44	ENTEGRIS INC	0	0.490	0	TRUE
45	GERON CORP	0	0.485	0	TRUE
46	ACI WORLDWIDE INC	0	0.505	1	FALSE
47	CERUS CORP	0	0.481	0	TRUE
48	ABRAXAS PETROLEUM CORP/NV	0	0.504	1	FALSE
49	CABLEVISION SYSTEMS CORP	0	0.507	1	FALSE
50	PTC INC	0	0.497	0	TRUE
51	UNITED GUARDIAN INC	0	0.477	0	TRUE
52	RESEARCH FRONTIERS INC	0	0.487	0	TRUE
53	VERSAR INC	0	0.494	0	TRUE
54	EMCORE CORP	0	0.498	0	TRUE
55	AKORN INC	0	0.521	1	FALSE
56	PERRY ELLIS INTERNATIONAL INC	0	0.490	0	TRUE
57	TRANS WORLD ENTERTAINMENT C	0	0.497	0	TRUE

Appendix E: ANN Testing Sample Performance

ANN Evaluation for Testing Set **t=0**

R/N	Company Name	Actual	Score	Forecast	Evaluation
58	MOVIE GALLERY INC	1	1081728.000	1	TRUE
59	NATIONAL RV HOLDINGS IN	1	0.857	1	TRUE
60	NEOSE TECHNOLOGIES INC	1	1049115.000	1	TRUE
61	NEXCEN BRANDS INC	1	0.932	1	TRUE
62	NORTHFIELD LABORATORIES	1	0.960	1	TRUE
63	NUCENTRIX BROADBAND NE	1	1042862.000	1	TRUE
64	OILSANDS QUEST INC	1	1113382.000	1	TRUE
65	OSCIENT PHARMACEUTICALS	1	1066796.000	1	TRUE
66	PENN TRAFFIC CO	1	0.717	1	TRUE
67	PRICE COMMUNICATIONS C	1	0.250	0	FALSE
68	SAVIENT PHARMACEUTICALS	1	1074983.000	1	TRUE
69	SHEFFIELD PHARMACEUTICA	1	1088941.000	1	TRUE
70	SOAPSTONE NETWORKS INC	1	0.403	0	FALSE
71	SPATIALIGHT INC	1	1121191.000	1	TRUE
72	TENERA INC	1	1112442.000	1	TRUE
73	THQ INC	1	1047877.000	1	TRUE
74	THREE-FIVE SYSTEMS INC	1	0.868	1	TRUE
75	TL ADMINISTRATION CORP	1	0.906	1	TRUE
76	TRICO MARINE SERVICES INC	1	0.712	1	TRUE
77	TROPICAL SPORTSWEAR INT	1	0.518	1	TRUE
78	TXCO RESOURCES INC	1	0.923	1	TRUE
79	ULTIMATE ELECTRONICS INC	1	0.566	1	TRUE
80	VERSO TECHNOLOGIES INC	1	1118492.000	1	TRUE
81	VIA NET WORKS INC	1	1017209.000	1	TRUE
58	AWARE INC	0	0.052	0	TRUE
59	ALBANY MOLECULAR RESEAR	0	0.093	0	TRUE
60	ARC DOCUMENT SOLUTIONS	0	0.276	0	TRUE
61	FALCONSTOR SOFTWARE IN	0	-0.040	0	TRUE
62	AXT INC	0	0.282	0	TRUE
63	BALLANTYNE STRONG INC	0	0.073	0	TRUE
64	CAMBREX CORP	0	0.188	0	TRUE
65	CEVA INC	0	-0.022	0	TRUE
66	DONALDSON CO INC	0	0.001	0	TRUE
67	FLOWERS FOODS INC	0	0.081	0	TRUE
68	HEALTHSTREAM INC	0	0.488	0	TRUE
69	INSITE VISION INC	0	0.233	0	TRUE
70	KIRBY CORP	0	0.213	0	TRUE
71	MONARCH CASINO & RESOR	0	-0.015	0	TRUE
72	NETFLIX INC	0	-0.010	0	TRUE
73	NIC INC	0	-0.052	0	TRUE
74	PENDRELL CORP	0	0.247	0	TRUE
75	SILICON GRAPHICS INTL COR	0	0.014	0	TRUE
76	STANDEX INTERNATIONAL C	0	0.334	0	TRUE
77	TOWERS WATSON & CO	0	0.173	0	TRUE
78	TRAVELZOO INC	0	-0.054	0	TRUE
79	VILLAGE SUPER MARKET	0	0.311	0	TRUE
80	DREW INDUSTRIES INC	0	0.050	0	TRUE
81	WORLD FUEL SERVICES CORP	0	0.176	0	TRUE

ANN Evaluation for Testing Set **t=-1**

R/N	Company Name	Actual	Score	Forecast	Evaluation
1	ABLE LABORATORIES INC	1	0.760	1	TRUE
2	ALLEGRO BIODIESEL CORP	1	0.784	1	TRUE
3	ALLIED DEFENSE GROUP INC	1	1113711.000	1	TRUE
4	AMERICA ONLINE LTN AMR	1	1113734.000	1	TRUE
5	ARMSTRONG HOLDINGS INC	1	0.870	1	TRUE
6	ASTROPOWER INC	1	0.995	1	TRUE
7	AUSPEX SYSTEMS INC	1	0.688	1	TRUE
8	BEARINGPOINT INC	1	0.989	1	TRUE
9	BETHLEHEM STEEL CORP	1	0.634	1	TRUE
10	BIOPURE CORP	1	0.610	1	TRUE
11	BMC INDUSTRIES INC	1	1080304.000	1	TRUE
12	BOMBAY CO INC	1	1115981.000	1	TRUE
13	BUILDING MATERIALS HLDG CP	1	0.216	0	FALSE
14	CAGLE'S INC	1	1116065.000	1	TRUE
15	CARAUSTAR INDUSTRIES INC	1	1048213.000	1	TRUE
16	CENTRAL EUROPEAN DIST CORP	1	0.766	1	TRUE
17	CHAMPION ENTERPRISES INC	1	0.716	1	TRUE
18	COLD METAL PRODUCTS INC	1	0.875	1	TRUE
19	COLDWATER CREEK INC	1	0.716	1	TRUE
20	COMMERCE ONE INC	1	0.289	0	FALSE
21	CONCORD CAMERA CORP	1	0.603	1	TRUE
22	CONE MILLS CORP	1	0.456	0	FALSE
23	CYGNUS INC	1	0.794	1	TRUE
24	DATATEC SYSTEMS INC	1	1038133.000	1	TRUE
25	DURA AUTOMOTIVE SYS	0	0.081	0	TRUE
26	EDEN BIOSCIENCE CORP	0	0.197	0	TRUE
27	ELECTROGLAS INC	0	0.190	0	TRUE
28	ELSINORE CORP	0	-0.001	0	TRUE
29	ENERGY CONVERSION DEV	0	0.454	0	TRUE
30	ENESCO GROUP INC	0	0.313	0	TRUE
31	EPRESENCE INC	0	0.483	0	TRUE
32	EVERGREEN SOLAR INC	0	0.141	0	TRUE
33	EXIDE TECHNOLOGIES	0	0.066	0	TRUE
34	FAIRCHILD CORP	0	0.163	0	TRUE
35	FEDDERS CORP	0	0.695	1	FALSE
36	FLEETWOOD ENTERPRISES INC	0	0.497	0	TRUE
37	FLEMING COMPANIES INC	0	0.260	0	TRUE
38	FLYI INC	0	0.330	0	TRUE
39	FOAMEX INTERNATIONAL INC	0	-0.097	0	TRUE
40	FRONTLINE CAPITAL GROUP	0	-0.081	0	TRUE
41	FROZEN FOOD EXPRESS INDS	0	-0.099	0	TRUE
42	FURNITURE BRANDS INTL INC	0	0.137	0	TRUE
43	GADZOOKS INC	0	0.321	0	TRUE
44	GENAERA CORP	0	0.249	0	TRUE
45	GENERAL MAGIC INC	0	-0.006	0	TRUE
46	GOTTSCHALKS INC	0	0.305	0	TRUE
47	GREAT ATLANTIC & PAC TEA CO	0	0.169	0	TRUE
48	HAYES LEMMERZ INTL INC	0	0.219	0	TRUE