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**Z-Altman's model effectiveness
in bank failure prediction -
The case of European banks**

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Abstract

The corporate bankruptcy is a significant problem for economy since it is considered as a limiting factor for economic growth. The financial crisis that broke out in USA on 2007 as a result of miscalculated subprime mortgage strategies turn into a full international banking crisis affecting successively the European banks, especially those of South European countries. Given that the role and the impact of the banks in the national and international economies are significant , it is vital for all interested economy stakeholders to constantly assess and measure the financial health of banks by use of reliable bankruptcy prediction models.

This work includes a literature review of known prediction models for firm bankruptcy which are based on multivariate discriminant analysis. Additionally, it presents the findings of the empirical study implemented by use of Altman's Z-score model specialized for firms from emerging markets. The main tasks carried out were:

- Financial data analysis for “failed” banks located mostly in South European countries (GIIPS group)
- Application of the above analysis outcome to benchmark the financial status of Central European banks that are still active

The aim of this work was to examine the effectiveness and accuracy of Altman's Z-score model for measuring the financial health of banking sector organizations and answer the research question whether Altman's specialized formula, for firms from emerging markets, could be used for banking sector organizations too.

The findings of the empirical study, allows someone to claim that the accuracy and predictability of the tested Altman Z-score model, specialized for firms from emerging markets, is questionable as regards predictions for private firms operating with high leverage.

Keywords: European banks, financial health, prediction models, multivariate discriminant analysis, Z- score model , Altman

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Introduction

The financial crisis that broke out in USA on 2007 as a result of miscalculated subprime mortgage strategies turn into a full international banking crisis affecting successively the banks in Europe as well. Some European banks with high exposure on the American banking system were directly affected and brought to the brink of collapse. However, this was not the only reason for bank collapsing. A plethora of additional reasons contributed in this as well i.e. inefficient fiscal policies of European countries for consecutive years, overloaded public sector that did not correspond to the real country's needs etc. In Greece, a sovereign national debt in conjunction to the impact of the international financial crisis put in troubles many banks.

Several Greek banks were exposed to the threat of a "disorderly bankruptcy" as a bi-effect of the policies of non-cautious lending activity and the over-investment in the past years. The lack of crucial funds for these banks imposed the need of an urgent recapitalization of them. The Greek government was surprised and reacted gradually to this by taking a series of measures (bail-out programme) in order to avoid a collapse of the Greek banking system that could lead to chaotic situation with tremendous economic and social consequences for the country.

Undoubtedly, the role and the impact of banks in the social-economic life of any country are of great significance and this applies for Greece too. Therefore their financial health is matter of great concern for all involved to financial activities and finance researchers as well.

This work aimed to check if it is possible to measure and predict the financial health of banks in an efficient and reliable way.

Inspiration about choosing this research topic was the collapse threat that Greek banks faced when the Eurozone crisis broke out. According to my point of view, if there were effective predicting tools for corporate default which could also be used in the banking sector too, it would be a significant tool for European governments in their decision making. These would be able to immediately react and take appropriate mitigation measures for their economies which in combination with assistance from the European Central Bank and the International Monetary Fund could keep off

upcoming default of European banks and consequently avoid their catastrophic effects on the social-economic life of the European countries affected.

Research objectives and tasks

Based on the fact that the banking sector could be considered as a service sector organisation which plays a crucial role in development of the economy, both on national and international level, it is always challenging and valuable to measure the financial health of banks, especially on economic recession time.

First objective of this work is to present known prediction models for the measurement of firm financial health. Special focus is given on those of multivariate discriminant analysis which are commonly used by many finance researchers and professionals. The second objective, the main one, was to test and evaluate the strength and accuracy of Altman's Z- score model and its suitability to be used for predicting imminent threats of financial distress in banking sector. For that, a data sample of European banks was selected which was divided in two target groups.

In the first group were included banks mainly from countries of South Europe, namely Greece, Italy, Ireland, Portugal, Spain plus Cyprus. Further on, this group will be referred to as GIIPS banks or "failed" group. The second was consisted of banks from countries of Central Europe, namely Germany, France, Belgium, Netherlands and Switzerland which will be called as CE banks or "active" group.

The main tasks of the second objective were:

- Analysis of financial data of failed banks of GIIPS group by use of the Altman's Z-score specialized for firms from emerging markets
- Application of the analysis outcome in benchmarking of the financial status of CE banks

in order to examine the effectiveness and accuracy of Altman's Z-score in measuring the financial health of banking sector organizations and answer the research question whether Altman's specialized formula for emerging markets could be used for banking sector organizations too.

Literature review

Risks faced by financial institutions

According to organisation theory, any organisation is confronted with many different risks during its whole life. Financial institutions are characterized as organizations of the service sector. Their role and impact in the social-economic life of countries is significant and multifarious. They are evolved in different financial activities like lending, asset management, deposit keeping etc. which means that these are exposed to different kind of risks explained below. The financial health of banks reflects to the economy of a country and in some cases of the whole world. The most crucial risks faced by banks are outlined in the below table:

Risk type	Event
Systemic risk	A default by one financial institution may possibly create a “ripple effect” that leads to defaults by other financial institutions and threatens the stability of the financial system. (Hull, 2015, p.326)
Credit risk	The possibility that a bank borrower or counterparty will fail to meet its payment obligations regarding the terms agreed with the bank (GARP, 2014, p. 14).
Market risk	The risk of losses in on and off-balance sheet positions arising from adverse movements in market prices (EBA, 2017).
Operational risk	The risk of loss resulting from inadequate or failed internal processes, people, and systems or from external events. This definition includes legal risk but excludes strategic and reputational risk (BIS, 2011).
Liquidity risk	The possibility that over a specific horizon the bank will become unable to settle obligations. (Drehmann, M. and Nikolaou, 2010, p.1).

Table 2: Crucial risks faced by banks

When a bank cannot repay and meet its economic obligations to its investors, lenders and generally to its stakeholders then reaches a default situation or in other words it becomes in a ‘failed condition’. If corrective measures are not taken or are incorrect then the bank's problematic situation can result to a disorderly bankruptcy with chaotic consequences in every aspect of the social-economic life of the country that the bank is operating.

In order to predict and avoid bank failure situations and their subsequent economic disaster a regulatory framework for banking sector was necessary to be established. Hull (2015) pointed out the importance of regulations in order to avoid bank failing. He justified this need and explained that “...main purpose of bank regulation is to ensure that a bank keeps enough capital for the risks it takes. It is not possible to eliminate altogether the possibility of a bank failing, but governments want to make the probability of default for any given bank very small. By doing this, they want to create a stable economic environment where private individuals and businesses have confidence in the banking system” (Hull, 2015, p. 325).

On 1974, G10 countries represented by their central bank Governors and the monetary authorities of Luxembourg, Switzerland and Spain formed the Committee of Banking Regulations and Supervisory Practices. The main goal of this Committee, which convened in Basel of Switzerland, was to strengthen financial stability worldwide by setting common principles that all financial institutions should follow and be supervised for. Nowadays, the Basel Committee has expanded its membership from the G10 to 45 institutions from 28 jurisdictions. (BIS, 2017; Culp, 2015).

A document entitled “International Convergence of Capital Measurement and Capital Standards” was the main outcome of Basel Committee. This was referred to as “The 1988 BIS Accord” and was the first attempt to set international risk-based standards for capital adequacy (Culp, 2015). Later on it became known as Basel I and paved the way for significant increases in the resources banks devote to measuring, understanding, and managing risks. The key innovation in the 1988 was a measure, for assessing the bank total credit exposure, named Cooke ratio. Hull (2015) clarifies the components of this measure by explaining that “The Cooke ratio considers credit risk exposures that are both on balance-sheet and off balance-sheet. It is based on what is known as the banks total risk-weighted assets.” (p. 327).

Since several issues remained still unsettled, i.e. there was not developed any model of default correlation, two more Accords were published Basel II and Basel III, establishing a series of international standards concerning mostly the capital adequacy.

The Basel II capital requirements applied to “international active” banks. In Europe, all banks were regulated under Basel II but in the United States the regulatory authorities decided that Basel II would not apply to small regional banks (Hull, 2015, pp. 336-337). The Basel II is based on the following three “pillars”:

1. Minimum Capital Requirements
2. Supervisory Review
3. Market Discipline

Following the 2007-2009 credit crisis, the Basel committee realized that improvements on Basel II were necessary. Capital requirements needed to sufficiently cover not only market risk but credit risk as well. Additionally, it was considered that the definition of capital had to be tightened and that regulations were needed to address liquidity risk (BIS, 2017; Hull 2015). The final version of the Basel III regulations was published in December 2010 and settled issues about:

1. Capital Definition and Requirements
2. Capital Conservation Buffer
3. Countercyclical Buffer
4. Leverage Ratio
5. Counterparty Credit Risk

The establishment of a series of international standards for bank regulation contributed not only to enhancement of financial stability by improving the quality of banking supervision worldwide but facilitated also the availability of financial data for research. More specifically, all type of organizations are obliged to prepare and provide on an annual basis, specifically processed information about their operation, which are stored in various databases. This information is considered as credible and

is provided in standard formats which means that someone can easily access and process it. Subsequently, the testing of any model proposed for financial analysis purposes can be easily supplied with credible and homogenous data which was the case for the empirical study of this work too.

Financial Distress and Corporate Bankruptcy

The early prediction of financial distress is essential for investors or lending institutions who wish to protect their financial investments. As a consequence, modeling, prediction and classification of firms to determine whether these are potential candidates for financial distress have become key topics of debate and detailed research. Financial distress is defined as "... a condition where a company cannot meet, or has difficulty paying off its official obligations to its creditors. The chance of financial distress increases when a firm has high fixed costs, illiquid assets or revenues sensitive to economic downturns" (Sofat and Hiro, 2015, p. 406).

One of the major concerns in the specific research area is the lack of consensus on the definition of the corporate failure and the financial distress. Several scientists are using the term bankruptcy instead of the previous two. Moreover Muller et al. (2012) denote that there are also researchers which define financial distress as mergers, absorptions, delisting or liquidations or major structural changes to the company.

For this study purposes, financial distress is regarded as a prior step before bankruptcy therefore a timely prediction of financial status might actuate the assessed firm to react and take corrective measures and potentially avoid its oncoming bankruptcy. However, a financially unhealthy firm may not mandatory be bankrupt but to be merged with others, acquired by another etc. In these cases, the firm could be considered as a failed one.

From 1930, several theories, models and techniques were proposed by researchers aiming to predict whether a firm is about to face bankruptcy (Bellovary et al. 2007). Each of them proposed his/her own formula but in several occasions these are using similar financial data and ratios in order to calculate indicators and results. Nowadays, there exist a plethora of methods and models available for measuring and assessing the financial distress or bankruptcy of firms.

Historically, corporate bankruptcy was first modeled, classified and predicted by Beaver in 1966. He defined financial distress as bankruptcy, insolvency, liquidation for the benefit of a creditor, firms which defaulted on loan obligations or firms that missed preferred dividend payments. In his research compared the mean values of 30 ratios of 79 failed and 79 non-failed firms in 38 industries but also tested the individual ratios' predictive abilities in classifying bankrupt and non-bankrupt firms. Actually he tested separately ratios of a) Net Income to Total Debt b) Net Income to Sales c) Net Income to Net Worth d) Cash Flow to Total Debt and e) Cash Flow to Total Assets with high accuracy results for all ratios. He came to conclusion that cash flow to debt ratio was the single best indicator of bankruptcy (Beaver, 1966a; Muller et al., 2012) and suggested that if multiple ratios considered simultaneously, in future research, might have higher predictive ability than single ratios (Bellovary et al., 2007).

More specifically, Beaver (1966b) developed the first parametric model for corporate bankruptcy and his kind of analysis was characterized as univariate (Fitzpatrick, 1932; Horrigan, 1965). Prediction models that came up afterwards were categorized either as parametric or non-parametric. Accordingly, the evolution of the next generation of bankruptcy prediction models was based on the concept of firm classification in failed non-failed respectively.

Recently Cybinski (2001) claimed that there is no clear distinction between "failed" and "non-failed" firms and all of them are rather laying on a common continuum of failed and non-failed. She argued that in reality there is not an obvious cut-off point between "failed" and "non-failed" firms but rather an overlap or grey area between these two classification groups. According Cybinski, it is quite difficult to accomplish predictions of financial distress for firms belonging to this grey area (Cybinski, 2001; Muller et al., 2012).

Besides univariate models another kind of prediction models, the so called multivariate models, came in use a few years later. A multivariate model can be characterized as discriminant analysis or multi discriminant analysis (MDA) (Altman, 1968; Altman 1993, Altman, 2000). The evolution of MDA models came with probability models like Probit and Logit or Ohlson's model (1980).

An interesting overview of bankruptcy predictions from 1930 to 2002 is provided by Bellovary, Giacomino, and Akers (2007).

MDA analysis

Discriminant analysis is a statistical technique for distinguishing between two or more groups on the basis of their observed and measured characteristics. For example, an analyst might take multiple factors into account, such as different financial ratios, when choosing between stocks in order to design an efficient portfolio.

Fischer (1936) used the term discriminant analysis in the article "The Use of Multiple Measurement in Taxonomic Problems". The method was applied for exploration of the relationship between a group of independent characters (discriminators) and one qualitative dependent variable-output. This output could be in simple cases 0 or 1 allowing the classification of the analysed objects either to first or the second class.

The classes are known to be clearly distinguishable and each object clearly belongs to one of them. The task can also be identification of features that contribute to the identification process. The purpose is to find a prediction model classifying new objects (for example firms, financial institutions, banks etc) into classes. New objects are classified into classes based on their high degree of similarity.

According to the numbers of variations of qualitative variable one might distinguish:

- discriminant analysis for two groups,
- discriminant analysis for more groups.

Discriminant analysis method is applied in classification problems of many research fields. For example in financing area, a bank can monitor in the sample used its client's way of repaying their loans and some other indicators. Subsequently on this basis, the bank may evaluate potential clients (based on same characteristics with those of the sample) as more or less credible for a loan.

The main task of discriminant analysis is to find the optimal attributing rules that will minimize the likelihood of erroneous classification of elements, i.e. it will minimize the median of erroneous decision (it may happen that an element actually comes from a particular group but it is classified into different group by obtained discriminant analysis). Each element is characterized by several features which reflect its

properties. This means that the examined elements (units) are realizations of the random vector $X = (X_1, X_2, \dots, X_n)$. Random variables X_i , where $i = 1, 2, \dots, m$, corresponding to measured characteristics (Kočiřová & Miřanková, 2014).

Altman's prediction models

The corporate bankruptcy is considered as an especially important problem for economy since it is considered as a limiting factor for the economic growth. The first research work on multivariate analysis of corporate bankruptcy prediction began in 1968 with the famous model of Altman and is going on until now with a variety of models both statistical and theoretical. The first attempt to build a model that predicts the likelihood of bankruptcy of a firm was made by Edward Altman.

In 1968, Altman (1968) developed and presented the Z-score formula in order to provide a more effective financial assessment tool to assist risk analysts and lenders in their estimations. His work was based on the notion that univariate prediction models served in most cases as indicators and not as predictors of bankruptcy. For that reason, these models were not good enough for the actual needs of the financial analysts. He used instead, multi discriminant analysis since this allowed the use of a model which could treat binary variables as depended in order to explain the behaviour of two different groups.

The method of multiple distinct analysis (MDA) was initially used to classify or to make predictions in problems where the dependent variable is displayed in high quality formats such as male or female, bankruptcy and non-bankruptcy etc. The main advantage of the method is the simultaneous analysis of financial indicators that have been chosen while as a downside is highlighted from the literature the violation of normality and independence of variables.

By that time multi-discriminant analysis was used merely by behavioural and biological sciences (Altman, 1968).

Altman introduced two types of errors for testing of final results which are presented in the below table.

Error Type	Occurrence
I.	Error occurs when a bankrupt firm has a z-score that classifies it as non-bankrupt .
II.	The exact opposite, namely when a non-bankrupt firm's Z-score is beneath 1.81 .

Table 3: Error types for Altman's model

The results of Altman's model test indicated that bankruptcy could be predicted with an accuracy of 95% one year before it happened, 72% two years before, 48% three years before, 29% four years before and 36% five years before it happens (Altman, 1993).

Later Altman revised his model to incorporate a "four variable Z-Score" prediction model (Altman, 1993). The new one improved further the predictive ability of his original model. Altman (2000, 2002) came repeatedly forward with several revisions of this model seeking to make it available to different economic life conditions and to advance its prediction accuracy figures.

The Altman's model from its publication since now has been of great concern to the scientific community. Many variants of it have been proposed trying either improvements or adjustments/modifications for use in specialized cases. Variant models are considered the linear Probability Model and the Quadratic Discriminant Analysis. An outline of the most known variants comes on the following pages.

Nevertheless the worldwide acceptance of Altman's model, there exist researchers that have expressed their concern regarding the effectiveness of the discriminant analysis in financial predictions. Eisenbeis (1977), Ohlson (1980), Jones (1987) were critics of MDA and they argued that the results could be biased and did not have sufficient information value. The lack of qualitative variables and the inability for integration of modern analysis techniques were also pointed out as undermining elements of the method efficiency (Zopounidis, 1995).

Despite of criticizing arguments, financial analysts and scientists are still considering Altman's Z-Score as an effective and suitable indicator of a firm's ability to avoid

bankruptcy. All over the world, financial and credit professionals are constantly using Altman's models in order to mitigate risk in debt portfolios. It is quite popular because it uses multiple variables to measure the financial health and credit worthiness of anyone (person or firm). Since Z-score is an open system, the variables employed in the formula can easily be understood by its users.

As aforementioned, the Z-score model was initially developed for publicly held manufacturing firms with assets of more than \$1 million. Over the years, Altman revised its model in order to be applicable to privately held firms (the Altman Z'-Score) and non-manufacturing firms (the Altman Z"-Score). Altman's Z-score formulas are used in a variety of contexts and countries.

Z-score formula

The formula uses a statistical technique known as multiple discriminant analysis (MDA), by which Altman attempted to predict defaults by use of the following five accounting ratios (Hayes et al., 2010; Hull, 2015, p. 400):

X1: Working Capital/Total Assets

X2: Retained Earnings/Total Assets

X3: Earnings before interest and taxes/Total Assets

X4: Market value of equity/Book Value of Total Liabilities

X5: Sales/Total Assets

Depending on the nature of the enterprises assessed the Z-score formula varies (Altman, 1968; Altman, 1977; Altman, 1993; Altman, 2000). In case of publicly traded manufacturing companies (general formula) the original Z-score is:

$$Z=1.2*X1+1.4*X2+3.3*X3+0.6*X4+0.999*X5 \quad (1)$$

While, in the predictions for non-manufacturing firms (not applicable for banks & finance companies), the calculation formula uses only four variables and becomes (Altman, 1977, p. 22; Chotalia, 2014):

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

Respectively, for companies from emerging markets (banks) the calculation formula takes the following form:

$$Z=6.56*X1+3.26*X2+6.72*X3+1.05*X4+3.26 \quad (3)$$

Variable name	Ratio of	Result to be achieved
X1	Working Capital / Total Assets (WC/TA)	This ratio measures the net working capital relative to the size of the assets used in the business. It is used as a measure of liquidity standardized by the size of the firm.
X2	Retained Earnings / Total Assets (RE/TA)	This variable relates the total retained earnings of the firm to the total assets employed. It is able to capture the cumulative profitability of the firm since inception. Also, since young firms tend to have low RE/TA ratios, this variable may capture the age of the firm as well.
X3	Earnings Before Interest and Taxes / Total Assets (EBIT/TA)	The operating profitability in relation to total assets measures the productivity of the assets or the earning power.
X4	Market Value Equity / Book Value of Total Liabilities (MVE/TL)	This ratio measures the extent to which total assets can decline in value before total liabilities exceed book value of equity. In other words, this indicates the asset cushion of the firm. ¹

¹ X4*, Book Value Equity / Book Value of Total Liabilities (BE/TL)

This alternative ratio for X4 variable is appropriate for a firm that is not publicly traded, and hence the Z-model with this variable definition is called the Z'-model or the private firm model.

X5	Sales / Total Assets (S/TA)	<p>This asset turnover ratio is intended to capture the sales generating ability of the assets.</p> <p>Altman found this to be industry sensitive and least discriminating between the bankrupt and non-bankrupt companies. As a result, Altman proposed a variant of the Z'-model called the Z''-model which excludes S/TA.</p>
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Table 4: Variables and ratios used in Altman's Z-score models

In the table below is presented a classification of Z-score cutoffs proposed from Altman for his models. There exist three zones (or credit ratings) that a firm might be classified depending on the Z-score achieved after its assessment. These zones are safe, gray and distress and their low and upper limits vary depending on the model version used.

Model	Zone		
	Safe	Gray	Distress
Z (original model)	>2.99	2.99-1.80	<1.80
Z (emerging markets model)	>2.60	2.60-1.10	<1.10

Table 5: A classification of Z-score cutoffs

Grover's model

Grover model is a model that is generated by performing redesign and reassessment of the Altman Z-Score model. Grover Model does categorize bankruptcy with a G-score of less than or equal to -0.02 ($G \leq -0.02$) while the state does not go bankrupt more than or equal to 0.01 ($G \geq 0.01$) (Grover, 2003).

Grover's formula

where:

CAR: Capital Adequacy Ratio

X1: working capital/ total assets

X3: earnings before interest and taxes/ total assets

ROA: net income/ total assets

$$CAR = \alpha + \beta_1 * X1 + \beta_2 * X3 + \beta_3 * ROA + \epsilon$$

Springate's model

Springate model follows procedures developed by Altman. In 1978, Springate used step-wise multiple discriminant analysis to select four out of 19 popular financial ratios that best distinguished sound firms from those that failed (Vickers, 2006, p. 67).

Actually, the applied formula classifies a firm with S-score > 0,862 as a company that is healthy and there is no potential to be bankrupt, and vice versa. In simple words, the lower score is the greater probability for default becomes. The specific model examines insufficient liquidity, excess debt, insufficient sales and lack of profit (Sands et al. 1983; Sadgrove, 2006, p. 178).

Springate's formula

where:

CAR: Capital Adequacy Ratio

A: Working Capital/ Total Assets

B: Net profit before interest and Taxes/ Total Assets

C: Net profit before taxes/ Current Liabilities

D: Sales / Total Assets

$$CAR = \alpha + \beta_1 * A + \beta_2 * B + \beta_3 * C + \beta_4 * D + \epsilon$$

Ohlson's model

Ohlson proposed the O-score as a more effective statistical bankruptcy indicator generated from a set of nine independent balance sheet ratios (Ohlson, 1980). He applied Logit model which was based on the same assumptions as MDA. Financial data of over 2000 companies were processed to feed the model scaling factors applied to its nine variables with the aim of increasing its accuracy. Its main difference/advantage from Altman's model is the sample size since its assessment process is based on a much larger sample of corporate successes and failures in order to inform the model.

Ohlson's formula

$$\begin{aligned} \text{CAR} = & \alpha + \beta_1 \text{SIZE} + \beta_2 \text{TLTA} + \beta_3 \text{WCTA} \\ & + \beta_4 \text{CLCA} + \beta_5 \text{OENEG} + \beta_6 \text{NITA} + \\ & \beta_7 \text{FUTL} + \beta_8 \text{INTWO} + \beta_9 \text{CHIN} + \varepsilon \end{aligned}$$

where:

CAR: Capital Adequacy Ratio

SIZE: log (total assets)

TLTA: total liabilities / total assets

WCTA: working capital / total assets

CLCA: current liabilities / current assets

OENEG: is a dummy variable, 1 if total liabilities exceed total assets, and 0 if otherwise

NITA: net income / total assets

FUTL: funds provided by operations / total liabilities

INTWO: is a dummy variable, it would be worth 1 if negative net income for at least two years in a row, and 0 if not

CHIN: $(\text{NIt} - (\text{NIt} - 1)) / (|\text{NIt}| + |\text{NIt} - 1|)$, where NIt is the net income for all periods.

Zmijewski's Model

Zmijewski model (1984) used ratio analysis that measures the performance, leverage and liquidity of a firm for the model predictions in order to predict a firm's bankruptcy in two years (X-score). The analysis applied by Zmijewski used 40 firms that have gone bankrupt and 800 firms that were still on business at that time. Zmijewski model assessment criteria is the greater the value of X (exceeding 0), the more likely the firm could be bankrupt. On the contrary, if a firm gets a score of less than zero then the firm will not potentially bankrupt (Zmijewski, 1984).

Zmijewski's formula

$$CAR = \alpha + \beta_1 * X_1 + \beta_2 * X_2 + \beta_3 * X_3 + \epsilon$$

where:

CAR: Capital Adequacy Ratio

X1: ROA (Return on Assets)

X2: Leverage (Debt Ratio)

X3: Liquidity (Current Ratio)

Empirical Study

In this section, the sample, data, methodology and results of the empirical study are presented.

As aforementioned, Altman's Z-Score is considered by many scientists and finance professionals as an effective and suitable tool for predicting corporate failures. In 2013, Altman, Danovi and Falini (2013) applied Z-score model to predict the corporate failure of Italian firms subject to extraordinary administration. The results of their Z-score application shown a high prediction failure rate (ca. 95%) for the firms measured.

As every model, Altman's Z-score has pros and cons. The main advantages are (Altman et al., 1995; Altman et al., 2013):

- ✦ High rate of prediction accuracy from its appearance time until now (82%-94%)
- ✦ User friendliness. Anyone with finance knowledge and statistical skills can easily use it.
- ✦ Multi-dimensional use. It is proposed for bankruptcy predictions of every firm type (private, publicly listed, non-manufacturing)
- ✦ Availability of strong credit scoring. The Altman Z-score offers a strong credit scoring based on the financial data analysis of a sample of firms which might be used as a benchmark basis.

On the other side, its main setbacks are (Eisenbeis, 1977; Ohlson, 1980; Jones 1987; Zopounidis, 1995):

- ✦ Inability for modern analysis techniques integration. The Altman Z-score initially developed for industrial firms. Its modified versions have to be cautiously used in prediction cases for other firm types.
- ✦ Biased results due to data manipulation easiness. There exists possibility of manipulation of the accounting statements from the firms in order to show good figures. This may lead to wrong conclusions, something that cannot be substantiated by Altman Z-score model.

The use of Z-score model to predict bank failure has a relatively recent appearance. In previous research works, aiming to measure the financial status of banks by use of Z-score, the specialized Altman's formula for firms from emerging markets was preferred (Chieng, 2013; Chotalia, 2014; Samarakoon and Hasan; 2003). In some cases, in the formula used for emerging markets was also included a specific constant proposed by Altman et al. (1995), so that the scores equal or less than zero would be equivalent to the default situation. The latter is the case for this empirical study too.

Sample and data

The data sample consisted of 42 banks which were classified into two groups of 21 unmatched and randomly categorized banks for each group. In the first one were included all "failed" banks and the second contained the "non-failed" or still active banks, according to Altman's model specifications.

In the so-called "failed" group are included of banks from Greece, Italy, Ireland Portugal, Spain and Cyprus. Further on, in this work, these countries will be called as GIIPS countries and respectively the banks as GIIPS banks. The "non-failed" group is consisted of still active banks from several Central European countries, namely Germany, France, Belgium, Netherlands and Switzerland. The last one is not a European Union member but it is an associated country to EU and their banks are following the rules of Basel (BIS, 2017). For this work purposes, these countries will be referred to as CE countries and their banks as CE banks.

The selection of the banks examined, in this work, is based on specific characteristics for each target group. More specifically, for the group of GIIPS "failed" banks is their status after failure which might be:

- merged
- acquired from another bank
- defaulted

It is worthy to mention that in the European Union does not exist any authorized association to keep certified, valid and accessible records of the "failed" European banks (merged, defaulted, acquired). On the contrary, in United States there exists an

authority named Federal Deposit Insurance Corporation (FDIC) which is monitoring, collecting and providing such information.

For the above reason, the selection and grouping of failed banks was a difficult and time-consuming task which was accomplished with personal search and processing of raw data from financial statements, documents etc. One of the set criteria was that the failure event had to be occurred during the years of the financial crisis (2006-2016). Another one was that these banks would have their headquarters to someone of the so-called GIIPS countries.

“Failed” group (GIIPS banks)	Year of “failure”
1. Proton Bank S.A. (Greece)	2011
2. Marfin Egnatia Bank S.A. (Greece)	2011
3. Geniki Bank S.A. (Greece)	2014
4. Millenium Bank (Greece)	2013
5. Banca di Credito Cooperativo di Sagna S.C.(Italy)	2010
6. Valore Italia Holding di Partecipazioni S.p.A.(Italy)	2015
7. Cassa Rurale ed Artigiana di Treviso Credito Cooperativo (Italy)	2015
8. Banca Agricola di Mantovana S.p.A.(Italy)	2007
9. Banca Antonoveta (Italy)	2007
10. Bancaperta S.p.A. (Italy)	2008
11. Banco di Sicilia S.p.A (Italy)	2006
12. Credito Artigiano S.p.A (Italy)	2012
13. Irish Bank Resolution Corporation Limited(Ireland)	2013
14. Banco BIC Portugues S.A. (Portugal)	2010
15. Cyprus Popular Bank Public Co Ltd	2012
16. Caixa d Estalvis de Catalunya Tarragona I Manresa (Spain)	2012
17. Banca Civica S.A. (Spain)	2012
18. Banco de Andalucia S.A. (Spain)	2009
19. Banco de Valencia S.A. (Spain)	2013
20. Banco Espanol de Credito S.A. (Spain)	2013

21. Banco Pastor S.A. (Spain)	2011
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Table 6: “Failed” group members (GIIPS banks)

Respectively, for the banks comprising the non-failed group of CE banks, the characteristics applied were the following:

- still active
- large in terms of assets (ranking list www.relbanks.com)
- located in countries of Central Europe which were not severely affected by the recent economic crisis of Eurozone.

On the basis of the above criteria, there were selected 3-6 large banks from each country of the CE group.

“Non-failed” group (CE active banks)
1. AXA Bank Belgium N.V.
2. Belfius Banque S.A. (Belgium)
3. ING Belgium S.A.
4. BNP Paribas S.A. (ENXTPA:BNP) (France)
5. BPCE S.A. (France)
6. Credit Agricole S.A. (France)
7. Bayerische Landesbank (Germany)
8. Commerzbank AG (Germany)
9. Deutsche Bank Aktiengesellschaft (DB:DBK) (Germany)
10. Kfw (ASX:KFWHZ) (Germany)
11. Landesbank Baden-Wuerttemberg (Germany)
12. de Volksbank N.V. (Netherlands)
13. Achmea B.V. (Netherlands)
14. ABN Amro Bank N.V. (Netherlands)
15. NIBC bank N.V. (Netherlands)
16. ING Bank N.V. (Netherlands)
17. Credit Suisse AG (Switzerland)
18. Banque Cantonale Vaudoise (SWX:BCVN) (Switzerland)
19. UBS AG (Switzerland)

20. Raiffeisen Schweiz Genossenschaft (Switzerland)

21. Zurcher Kantonalbank (Switzerland)
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Table 7: “Non-failed” group members (CE banks)

Methodology

The financial health assessment of the banks examined was performed by use of the statistical Altman’s specialized model for firms from emerging markets. More specifically, the following Z- score formula was applied to the data analysis performed (Altman et al., 1995):

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

Where:

Z = the score

X = the independent variables (ratios of)

X1: Working Capital/Total Assets

X2: Retained Earnings/Total Assets

X3: EBIT/Total Assets

X4: Book Value Equity/Total liabilities

All financial data to calculate the needed ratios for the formula application were extracted from balance sheets and income statements of the sample banks. These were accessed and retrieved via the S&P Capital IQ platform or directly from their websites. The date of all financial documents used in this process was the 31st December for each year of reference.

For testing the accuracy and predictability of the model used, the Z-scores for the “failed” group members were estimated two years before the known “event” per each case. For example, if a bank was merged on 2012, the Z-score was calculated for years 2010 and 2011. Thus, the financial status of this bank was based on the average of the estimated Z-score for these two years.

On the contrary, for the “non-failed” group members (still active CE banks) their Z-score was explicitly estimated for years 2015 and 2016. Consequently, their financial soundness was characterized on the basis of the calculated average of Z-score.

Actually, the financial status of the banks examined was characterized depending on which of the following zones was laying their calculated Z-score average, namely if it was:

- above 2.6 – The bank was sorted in the “Safe” zone
- between 1.1 to 2.6 – The bank was sorted in the “Grey zone”
- less than 1.1 or had a negative number – The bank was sorted in the “Distress zone”

Financial data analysis and results

The following table displays the outcome of the Z-score analysis implemented for the “failed” group (GIIPS banks). The final Z-score result (second column) is the average of the Z-scores of the last two years before the “failed” event (which varies depending on each bank case).

“Failed” group Banks of GIIPS countries	Z-score Result (Average of two years before the “failed” event)	Estimated status (zone)
1. Proton Bank S.A. (Greece)	-0.21	Distress
2. Marfin Egnatia Bank S.A. (Greece)	-1.06	Distress
3. Geniki Bank S.A. (Greece)	-2.01	Distress
4. Millenium Bank (Greece)	-3.92	Distress
5. Banca di Credito Cooperativo di Sagna S.C.(Italy)	2.34	Grey
6. Valore Italia Holding di Partecipazioni S.p.A.(Italy)	-2.36	Distress
7. Cassa Rurale ed Artigiana di Treviso Credito Cooperativo (Italy)	-0.18	Distress
8. Banca Agricola di Mantovana S.p.A.(Italy)	0.05	Distress
9. Banca Antonoveta (Italy)	1.37	Grey
10. Bancaperta S.p.A. (Italy)	4.51	Safe

11. Banco di Sicilia S.p.A (Italy)	0.16	Distress
12. Credito Artigiano S.p.A (Italy)	-0.63	Distress
13. Irish Bank Resolution Corporation Limited (Ireland)	-4.38	Distress
14. Banco BIC Portugues S.A. (Portugal)	0.73	Distress
15. Cyprus Popular Bank Public Co Ltd	-0.46	Distress
16. Caixa d Estalvis de Catalunya Tarragona I Manresa (Spain)	-0.80	Distress
17. Banca Civica S.A. (Spain)	-0.32	Distress
18. Banco de Andalucia S.A. (Spain)	-1.44	Distress
19. Banco de Valencia S.A. (Spain)	-1.29	Distress
20. Banco Espanol de Credito S.A. (Spain)	0.03	Distress
21. Banco Pastor S.A. (Spain)	-0.26	Distress

Table 8: Characterization of failed banks after Z-score analysis

In the first subgroup of GIIPS banks, the Z-score outcome of all Greek banks examined (Proton Bank, Marfin Bank, Egnatia Bank, Geniki Bank, Millenium Bank) was negative. This could be interpreted as that these specific banks were in difficult financial situation and their calculated Z-scores correctly predicted the upcoming “financial distress” that they were confronted with in the next years.

More specifically, Proton Bank was liquidated and merged on 2001, Egnatia Bank was acquired on 2011, Geniki Bank acquired on 2014, and Millenium Bank with a significant negative Z-score (-3.92).

A significant factor determining their final Z-score was the large negative liquidity ratio X1 (Working Capital /Total Assets) based on the fact that Current Liabilities over-exceed the Current Assets for calculating Working Capital. For further details see appendixes I and II.

Italian banks composed the second subgroup. This was consisted of 8 banks which on the basis of their calculated Z-score were sorted as follows: five in the “Distress zone”, two in Grey zone and the last one in “Safe zone”. Again Z-score proved its high precision and effectiveness acting as distress indicator Banca di Credito Cooperativo (2.34) was acquired on 2010, Valore Italia Holding (-2.36) acquired on 2015, Cassa Rurale ed Artigiana (-0.18) acquired on 2015, Banca Agricola (0.05) was acquired on 2007, Banka Antonoveta (1.37) was acquired on 2007, Banco di Sicilia (0.16) merged on 2006, and Credito Artigiano (-0.63) acquired on 2012. The Bancaperta Spa with 4.51 final Z-score (Safe Zone) was a positive exception that merged with another bank by acquiring it.

The third subgroup of banks was from Spain. It was consisted from 6 small banks. The whole sample from Spain was classified to the “Distress zone” due to the negative Z-scores achieved. In this case too, the significant factor of a very high negative liquidity ratio due to over-exceeding current liabilities to current assets determined the final outcome. Caixa d Estalvis de Catalunya (-0.8) acquired on 2012, Banca Civica (-0.32) acquired on 2012, Banco de Andalucia (-1.44) acquired on 2009, Banco de Valencia (-1.29) acquired-merged on 2013, Banco Espanol de Credito (0.033) acquired on 2013, and Banco Pastor (-0.26) acquired-merged.

The last subgroup is a multinational one since it incorporates three banks from three different European Countries, namely Ireland, Portugal and Cyprus. The Irish Bank Resolution had a negative Z-score (-4.38) which was also the highest of the whole sample. The result indicated that the bank was in a very bad financial situation which later was actually confirmed by the bank’s liquidation on 2013. In this specific case, Z-score was significantly affected from the negative Working Capital, the negative Retained Earnings and consequently by EBIT. The Portuguese Banco Bic had also a low Z-score by which it was classified to the distress zone. Finally, in the case of the Cyprus Popular bank, that was defaulted on 2012, the achieved Z-score was a strong indication for immerse financial danger.

“Non-failed” group Active CE banks	Z-score Result (Average of the Z-score for 2015 and 2016)	Estimated status (zone)
1. AXA Bank Belgium N.V.	-0.68	Distress
2. Belfius Banque S.A. (Belgium)	0.65	Distress
3. ING Belgium S.A.	-0.84	Distress
4. BNP Paribas S.A. (ENXTPA:BNP) (France)	1.60	Grey
5. BPCE S.A. (France)	1.08	Distress
6. Credit Agricole S.A. (France)	2.02	Grey
7. Bayerische Landesbank (Germany)	0.73	Distress
8. Commerzbank AG (Germany)	0.91	Distress
9. Deutsche Bank Aktiengesellschaft (DB:DBK) (Germany)	2.23	Grey
10. Kfw (ASX:KFWHZ) (Germany)	3.42	Safe
11. Landesbank Baden-Württemberg (Germany)	1.43	Grey
12. de Volksbank N.V. (Netherlands)	-1.38	Distress
13. Achmea B.V. (Netherlands)	2.53	Grey
14. ABN Amro Bank N.V. (Netherlands)	-0.72	Distress
15. NIBC bank N.V. (Netherlands)	2.50	Grey
16. ING Bank N.V. (Netherlands)	-0.91	Distress
17. Credit Suisse AG (Switzerland)	2.88	Safe
18. Banque Cantonale Vaudoise (SWX:BCVN) (Switzerland)	0.12	Distress

19. UBS AG (Switzerland)	2.13	Grey
20. Raiffeisen Schweiz Genossenschaft (Switzerland)	-0.21	Distress
21. Zurcher Kantonalbank (Switzerland)	1.08	Distress

Table 9: Financial status estimation of the non-failed banks

The analysis of the final Z-scores for the “non-failed” or still active banks showed that 57% of the active Central European banks were sorted in the “Distress” zone, 33% of the rest testing sample was placed to the “Grey zone” and only 10% of banks examined could be classified to the “Safe zone”.

By applying the specialized Z-score formula on the largest banks of Belgium, France, Germany, Netherlands and Switzerland and analyzing cautiously the findings, a significant limitation of this model was exposed. The specific formula has not a proper and accurate performance and respectively predictability in cases of firms (here banks) having high leverage (debt). As it was the case with the Z-scores of the “failed” banks, it was evidently confirmed here too that the highest was the liquidity ratio (with negative value at the same time) due to over-exceed of the current liabilities to current assets, the smallest became the estimate of the Z-score.

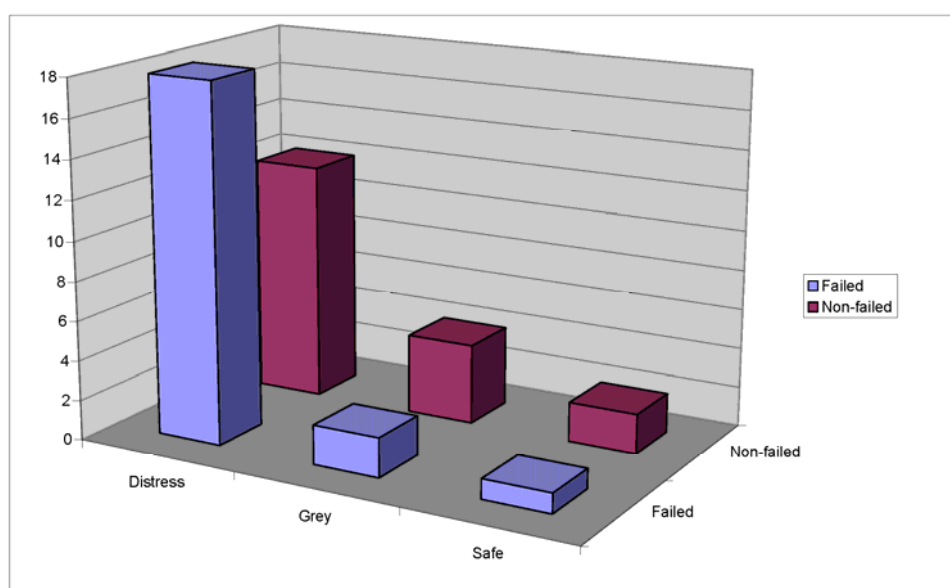


Figure 1: Z-score estimations per group and zone

Limitations of the empirical study

The biggest challenge of this work was the model itself and its applicability to banking sector organisations. The Z-Altman score was initially developed for predicting bankruptcy for industrial firms almost 50 years ago in USA. It is an old model which is generally accepted as appropriate for bankruptcy prediction by finance experts and researchers. Despite that during all these years, it has undergone a lot of improvements and modifications/adjustments in order to be expanded its application to all types of firms, it is still presenting some malfunctions.

The problem lies on the fact that the banks/financial institutions are usually operating under conditions of high current liabilities. Consequence of that is the appearance of a great negative impact on the first variable X1 (Working Capital/Total Assets) which actually affects and reduces the calculated total Z-score of banks under examination.

In most cases, the current liabilities of banks are exceeding their current assets. Therefore, the outcome of Working Capital (Current Assets minus Current Liabilities) is always negative for the banks/financial institutions. This liquidity ratio is very important for the calculation of Z-score because is helping to screening of serious financial problems that a firm could face in the future (Altman, 1995).

However, a negative Working Capital might be an ambiguous indicator as well. In some case, this can be interpreted as a sign of a firm's managerial efficiency for example a firm with low accounts receivable might also mean that it is operates effectively on a cash basis (Damodaran, 2012, p. 268; Stockopedia, 2017).

Another significant limitation for prediction models like Altman's Z-score is that their applicability is principally based on historical information. Eisenbeis (1977) pointed out the insufficient value information used in prediction models like Altman's where the prediction of a firm's future financial status is only based on analysis of past data. Economy as life is changing dynamically. According to Grice (2001) "the models' accuracies may significantly decline when using samples from time periods, industries, and financial distress situations other than those used to originally develop the models"

Finally, the access to LINC room, where the Bloomberg platform is installed, was not possible during the summer time. Therefore, the sole source to retrieve the necessary

financial data was S&P Capital Iq platform where balance sheets for a few “failed” banks were not available. In these cases, the necessary information was retrieved from financial statements and documents uploaded on the bank websites.

Therefore, a cross-checking of the retrieved financial data for these banks was not possible.

Conclusions

In this work was attempted a testing and evaluation of the strength and the effectiveness of Altman's Z-score model in predicting financial distress in the European banking sector. Following the specifications of the Altman's Z-score model, the testing sample was consisted of two groups. The first included "failed" banks from countries that faced huge economic problems in the period of financial crisis (2006-2016). The second was comprised of large banks from Central Europe which are still active.

The estimated results of the "failed" group were 100% confirmed which is indicating that Altman's Z-score model might be an effective indicator of financial distress 2 years prior to a known "failure" event. However, some drawbacks of the specialized model for firms from emerging markets were revealed too. Actually, the results achieved from the financial data processing of the "non-failed" group (still active CE banks) made discernible a significant limitation. More specifically, the calculated Z-scores of this group were low and indicated that 12 banks might possibly be threatened by direct financial distress in the next years, 7 banks are placed in the grey zone signaling concerns about their financial situation and only two were in the "safe" zone. The problem is caused form the fact that liquidity ratio (X1 model's variable), in most cases, was negative something that affected directly the final outcome of Z-score and respectively the characterization of the financial health of the banks examined. It seems that the accuracy and predictability of the tested Altman model, specialized for emerging markets, is questionable as regards predictions for private firms with high leverage.

Shumway (1999) proved that the Z-score model is dead and totally not trustworthy anymore about use on predicting corporate bankruptcy. He claimed that half of Altman variables have poor predictive strength. Therefore, he proposed a model with market-driven variables and two accounting ratios. According to Shumway (1999) this was considered as more accurate in out-of-sample tests than Altman's Z-score model. Chava & Jarrow (2004) validated the superiority of Shumway's model against Altman's Z-score model by confirming the crucial element of introducing industry effects in the hazard rate models.

Based on the findings of this work, one may claim that Altman's Z-score model, specialized for firms from emerging markets, is somehow outdated and has to be handled in a very cautious way, especially in predictions concerning banking sector organisations. Further improvement of the Altman's Z-score model is needed in order to be a trustworthy prediction tool for private firms (banks) operating with high leverage. Perhaps, Altman will soon provide us with one more Z-score formula which will be more appropriate for use with banks/financial institutions. This will be a new research challenge for finance researchers.

References

- Altman, Edward I. (1968). Financial Ratios, discriminant analysis and the Prediction of Corporate Bankruptcy. *Journal of Finance*, pp. 189–209. doi:10.1111/j.1540-6261.1968.tb00843.x
- Altman, Edward I. (1977). *The Z-Score Bankruptcy Model: Past, Present, and Future in Financial crises: institutions and markets in a fragile environment.* - New York [u.a.] : John Wiley & Sons, ISBN 0471026859. - 1977, pp. 89-108.
- Altman, Edward I. (1993). *Corporate Financial Distress and Bankruptcy: A Complete Guide to Predicting and Avoiding Distress and Profiting from Bankruptcy*, 2nd Edn. New York: John Wiley and Sons.
- Altman E.I. Hartzell J. Peck M. (1995). *Emerging Markets Corporate Bonds: A Scoring System.* Salomon Brothers Inc. New York, and in Levich, R. and Mei, J.P. *The Future of Emerging Market Flaws.* Kluwer and revisited in Altman, E.I. and Hotchkiss, E. (2006) *Corporate Financial Distress & Bankruptcy.* J. Wiley & Sons.
- Altman, Edward I. (2000). Predicting Financial Distress of Companies: Revisiting the Z-score and Zeta Models. [pdf] Available at: <http://pages.stern.nyu.edu/~ealtman/PredFnclDistr.pdf> [Accessed on 06-07-2017]
- Altman E.I. (2002). Revisiting Credit Scoring Models in a Basel 2 Environment. *Salomon Center for the Study of Financial Institutions*, 2(1): pp.2-37.
- Altman, E.I, Danovi, A. and Falini, A. (2013). Z-Score Models'Application to Italian Companies Subject to Extraordinary Administration. *Journal of Applied Finance*, 23(1), pp. 128-137.
- Beaver, W. H. (1966a). Financial ratios as predictors of failure. *Empirical Research in Accounting: Selected Studies*, 71-111.
- Beaver, W. H. (1966b). Market prices, financial ratios, and the prediction of failure. *Journal of Accounting Research*, 6(2), pp. 179-182.
- Bellovary, J., Giacomino, D. and Akers M. (2007). A Review of Bankruptcy Prediction Studies: 1930 to Present, *Journal of Financial Education*, Vol. 33 (Winter), 1-42.
- Chava, Sudheer and Jarrow, Robert A., (2004). Bankruptcy Prediction with Industry Effects, *Review of Finance*, Kluwer Academic Publishers, Vol. 8, pp. 537–569.
- Cybinski, Patti, (2001). "Description, explanation, prediction – the evolution of bankruptcy studies?", *Managerial Finance*, Vol. 27 Issue: 4, pp.29-44.
- Damodaran Aswath (2012). *Investment Valuation: Tools and Techniques for Determining the Value of any Asset*, University Edition, Wiley Finance, John Wiley & Sons, ISBN: 9781118206591.

Drehmann, M. and Nikolaou, K. (2010). BIS Working Papers No 316, [pdf] Available at: <http://www.bis.org/publ/work316.pdf> [Accessed 20 June 2017]

Fisher, R. A. (1936). *The Use of Multiple Measurements in Taxonomic Problems*, Annals of Eugenics, London.

Fitzpatrick, J.P. (1932), *A Comparison of the Ratios of Successful Industrial Enterprises with those of Failed Companies*, Accountants Publishing Company.

GARP (Global Association of Risk Professionals) (2014). *Foundations of Banking Risk: An Overview of Banking, Banking Risks, and Risk-Based Banking Regulation*, John Wiley & Sons.

Grice, J. S., (2001). *The Limitations of Bankruptcy Prediction Models: Some Cautions for the Researcher*, *Review of Quantitative Finance and Accounting*, Kluwer Academic Publishers, vol. 17, pp. 151–166.

Grover, J. (2003). *Validation of a cash flow model: A non-bankruptcy approach*. Ph.D. dissertation, Nova Southeastern University.

Hayes, S.K., Hodge, K. A. and Hughes L. W. (2010). *A Study of the Efficacy of Altman's Z To Predict Bankruptcy of Specialty Retail Firms Doing Business in Contemporary Times*, *Economics & Business Journal: Inquiries & Perspectives*, Vol. 3 Number 1.

Horrigan, J. O. (1966). *The Determination of long-term credit standing with financial ratios*, *Empirical Research in Accounting: Select Studies*, Supplement to Vol.4, *Journal of Accounting Research*, pp. 44-62.

Hull, John C. (2015). *Risk Management and Financial Institutions*, John Wiley & Sons Inc., 4th edn., Hoboken, New Jersey.

Jones, F. L. (1987). *Current techniques in bankruptcy prediction*. *Journal of Accounting Literature*, 6, pp. 131–164.

Kočíšová K., Mišanková M. (2014). *Discriminant analysis as a tool for forecasting company's financial health in Contemporary Issues in Business, Management and Education 2013*, *Procedia - Social and Behavioral Sciences* 110, pp. 1148 – 1157. Available Online: http://ac.els-cdn.com/S1877042813056012/1-s2.0-S1877042813056012-main.pdf?_tid=5dd7fcea-7cf5-11e7-a85a-00000aab0f6b&acdnat=1502278074_59db3c744935fbff9cb2a9d63cf2cb0c

Ohlson, J. A. (1980). *Financial ratios and the probabilistic prediction of bankruptcy*. *Journal of Accounting Research*, New York: 18(1), pp. 109–131, ISSN 1475-679X.

Sadgrove, Kit. (2015). *The Complete Guide to Business Risk Management*, Hardcover, Gower Pub Co; 2nd edn.

Samarakoon, Lalith P. and Hasan, Tanweer. (2003). Altman's Z-Score Models of Predicting Corporate Distress: Evidence from the Emerging Sri Lankan Stock Market. *Journal of the Academy of Finance*, vol. 1, pp. 119-125. Available Online: SSRN: <https://ssrn.com/abstract=1395229> [Accessed on 06-07-2017]

Sands, E. G., Springate G. L. V. and Turgut V. (1983). Predicting Business Failures. *CGA Magazine*, 24-27. ISSN 0318-742X.

Shumway, Tyler (2001). Forecasting Bankruptcy More Accurately: A Simple Hazard Model, *The Journal of Business*, Vol. 74, No. 1, pp. 101-124.

Sofat, Rajni, Hiro, Preeti (2015). *Strategic Financial Management*, Second Edition, Phi Learning Pvt. Ltd., 2nd edn., ISBN: 9788120351608.

Vickers, Frank. (2006) *Recession Proofing Your Business*, Lulu.com, ISBN: 9780615135779

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

Zopounidis C. (1995). *Evaluation du Risque de Défaillance de l' Entreprise: Méthodes et Cas d'Application.*, Collection: Techniques de Gestion, Economica, Paris.

Digital references

BIS (Bank for International Settlements), (2011). Principles for the Sound Management of Operational Risk, Available Online: <http://www.bis.org/publ/bcbs195.pdf> [Accessed 19 June 2017]

BIS (Bank for International Settlements), (2017). History of the Basel Committee, Available Online: <http://www.bis.org/bcbs/history.htm> [Accessed 20 June 2017]

Chieng, J. R. (2013). Verifying the validity of Altman's Z" Score as a predictor of bank failures in the case of the Eurozone. Unpublished, Masters Thesis, [pdf] Available Online: [http:// trap.ncirl.ie/865/1/jasminechieng.pdf](http://trap.ncirl.ie/865/1/jasminechieng.pdf) [Accessed 21 June 2017]

Chotalia, Parul. (2014), Evaluation of Financial Health of Sampled Private Sector Banks with Altman Z-score Model *International Journal of Research in Management, Science & Technology* (E-ISSN: 2321-3264) Vol. 2, No. 3, Available Online: <http://www.ijrmst.org/download/vol2no3/parul-chotalia.pdf> [Accessed 21 June 2017]

Culp, Christopher L. (2015). *Risk-Based Capital Regulations on Financial Institutions in Structured Finance and Insurance: The Art of Managing Capital and Risk*, Wiley Online Library, pp. 788-793, Available Online: <http://onlinelibrary.wiley.com/doi/10.1002/9781119201243.app2/pdf> [Accessed 20 June 2017]

EBA (European Banking Authority), (2017). Available Online: <https://www.eba.europa.eu/regulation-and-policy/market-risk> [Accessed 28 June 2017]

Eisenbeis, R. (1977). Pitfalls in the application of discriminant analysis in business, finance and economics. *Journal of Finance*, 32, pp. 875–900. <http://dx.doi.org/10.1111/j.1540-6261.1977.tb01995.x>

Muller, G.H., Steyn-Bruwer, B.W. and Hamman W.D. (2012). What is the best way to predict financial distress of companies, Available Online: <http://www.usb.ac.za/thoughtprint/Pages/What-is-the-best-way-to-predict-financial-distress-of-companies.aspx> [Accessed 01 July 2017]

Stockopedia. (2017). I don't agree with the Altman Z-Score for company X?, Available Online: <http://ideas.stockopedia.com/knowledgebase/articles/132951-i-don-t-agree-with-the-altman-z-score-for-company> [Accessed 30 June 2017]

Appendix I Processed data and ratios of failed banks

Greece																
Name	Year	CA	CL	TA	X1	RE	TA	X2	EBIT	TA	X3	MC	TL	X4	Z"	Status
<u>Proton Bank S.A.</u>	2010	1,298.34	3,912.14	4,225.29	-0.6186084	-47.998	4225.29	-0.01136	-8.851	4225.29	-0.0020948	195.81	3979.37	0.0492063	-0.8075141	liquidated and merged on 2011
	2009	452.4	1,763.35	2,904.40	-0.4513669	-38.245	2904.4	-0.013168	12.632	2904.4	0.0043493	236.37	2587.92	0.0913359	0.37123541	
-0.2181394																
Martin Egnatia Bank S.A.																
Name	Year	CA	CL	TA	X1	RE	TA	X2	EBIT	TA	X3	MC	TL	X4	Z"	Status
<u>Martin Egnatia Bank S.A.</u>	2010	1,501.60	16,618.20	22,130.9	-0.688054	186.2	22,130	0.0084139	-16.1	22,130.9	-0.0007275	1,000.60	21,176.10	0.0472514	-1.1586797	acquired on 2011
	2009	2,332.90	17,614.80	23,187.60	-0.6590548	215.3	23,187.60	0.0092851	29.3	23,187.6	0.0012636	1,119.40	17,614.80	0.0635488	-0.9679125	
-1.0652961																
Geniki Bank S.A.																
Name	Year	CA	CL	TA	X1	RE	TA	X2	EBIT	TA	X3	MC	TL	X4	Z"	Status
<u>Geniki Bank S.A.</u>	2013	677.7	2,310.70	2,675.60	-0.6103304	-798.7	2,675.60	-0.298512	-3.2	2,675.60	-0.001196	350.8	2,320.80	0.1511548	-1.5762426	acquired on 2014
	2012	448.3	2,275.30	2,650.10	-0.6894079	-795.7	2,650.10	-0.300253	-143.4	2650.1	-0.0541112	356	2,294.10	0.1551807	-2.4520276	
-2.0141351																
Millenium Bank																
Name	Year	CA	CL	TA	X1	RE	TA	X2	EBIT	TA	X3	MC	TL	X4	Z"	Status
<u>Millenium Bank</u>	2012	334.641	4,314.68	4,822.37	-0.8253291	-514.748	4,822.37	-0.106742	-324.069	4,822.37	-0.0672012	187.075	4,635.21	0.0403596	-2.921352	acquired on 2013
	2011	1,273.84	5,713.60	6,212.96	-0.7145966	-237.763	6,212.96	-0.038269	-168.967	6,212.96	-0.0271959	323.909	5,888.99	0.0550025	-4.9375139	
-3.929433																
Italy																
Name	Year	CA	CL	TA	X1	RE	TA	X2	EBIT	TA	X3	MC	TL	X4	Z"	Status
<u>Banca di Credito Cooperativo di Sagna S.C.</u>	2009	127.148	266.767	606.204	-0.2303169	45.462	606.204	0.0749946	1.769	606.204	0.0029182	61.421	544.762	0.1127483	2.12159944	acquired on 2010
	2008	130.188	222.779	521.224	-0.1776415	46.026	521.224	0.0883037	5.118	521.224	0.0098192	56.152	465.072	0.1207383	2.56550214	
2.34345079																
Valore Italia Holding di Partecipazioni S.p.A.																
Name	Year	CA	CL	TA	X1	RE	TA	X2	EBIT	TA	X3	MC	TL	X4	Z"	Status
<u>Valore Italia Holding di Partecipazioni S.p.A.</u>	2014	2.759	1.785	5.611	0.1735876	-9.008	5.611	-1.605418	-2.719	5.611	-0.4845839	0.01	5.601	0.0017854	-4.0994566	acquired on 2015
	2013	1.676	2.52	4.143	-0.2037171	-6.292	4.143	-0.001519	-1.738	4.143	-0.4195028	0.857	3.286	0.2608034	-0.6365503	
-2.3680035																
Cassa Rurale ed Artigiana di Treviso Credito Cooperativo																
Name	Year	CA	CL	TA	X1	RE	TA	X2	EBIT	TA	X3	MC	TL	X4	Z"	Status
<u>Cassa Rurale ed Artigiana di Treviso Credito Cooperativo</u>	2013	8.125	220.629	364.748	-0.582605	36.348	364.748	0.0996524	-4	364.748	-0.103578	38.561	326.188	0.1182171	-0.1824986	acquired/merged on 2015

(no balance sheet provided for 2014)

Name	Year	CA	CL	TA	X1	RE	TA	X2	EBIT	TA	X3	MC	TL	X4	Z"	Status
Banca Agricola di Mantovana S.p.A.	2006	1.416.10	7.923.20	12.322.50	-0.5280665	125.7	12.322.50	0.0102009	357.1	12322.5	0.0289795	899.7	11,435.80	0.078674	0.10648823	acquired on 2007
	2005	1.314.20	6.918.20	10,551.20	-0.5311244	114.7	10,551.00	0.010871	171.3	10551.2	0.0162351	885.2	10,551	0.0838973	0.00845541	Distress zone
Banca Antonoveta	2006	6.400	24.379	48.608	-0.3698774	189.8	48.608	0.0039047	777.8	48608	0.0160015	3.515	45,051	0.0780227	1.03578746	acquired on 2007
	2005	5.499	26.493	45.638	-0.4600114	-224.8	26.493	-0.008485	345.5	45638	0.0075726	3,097	42,233	0.0733333	0.34254927	Grey zone
Bancaperta S.p.A.	2007	2.844.60	2.267.30	3.263.57	0.1768919	28.887	3.263.57	0.0088514	16.91	3,263.59	0.0051814	124.75	3,138.82	0.0397442	4.52581697	merged on 2008 (acquire another company)
	2006	2.952.16	2.293.71	3,732.71	0.1764	25.357	3,732.71	0.0067932	15.53	3,263.59	0.0047586	121.809	3,732.71	0.0326329	4.50557176	Safe zone
Banco di Sicilia S.p.A.	2005	1.786.50	16.178.50	24.033.50	-0.5988308	242.6	24.033.50	0.0100942	360.1	24033.5	0.0149833	1,349.60	22,683.90	0.0594959	-0.4722646	merged on 2006
	2004	1,007.70	10,600.20	24,033.50	-0.3991304	206.7	24,033.50	0.0086005	233	24033.5	0.0096948	1,624.90	22,683.90	0.0716323	0.8101059	Distress zone
Credito Artigiano S.p.A.	2011	654.8	6.660.80	9,547.80	-0.6290454	139.6	9,547.80	0.0146212	39.8	9,547.80	0.0041685	385.9	9,547.80	0.0404177	-0.7484221	acquired on 2012
	2010	897.3	6,157.80	8,829.60	-0.5957801	143.4	8,829.60	0.0162408	33.9	8,829.60	0.0038394	388.7	8,070	0.048156	-0.5189975	Distress zone
Ireland																
Irish Bank Resolution Corporation Limited	2011	2.204	49.888	55.141	-0.8647649	-27.806	55.141	-0.504271	-0.772	55.141	-0.0140005	3.238	52.303	0.0619085	-4.0858599	liquidated on 2013
	2010	5.115	60.314	72.183	-0.7647091	-26.916	72.183	-0.372886	-18.944	72.183	-0.2624441	3.534	68.648	0.05148	-4.3837645	Distress zone

Portugal

Name	Year	CA	CL	TA	X1	RE	TA	X2	EBIT	TA	X3	MC	TL	X4	Z"	Status
Banco BIC portugues S.A.	2009	519.4	3,208.60	7,510.60	-0.358054	-216.6	7,510.60	-0.028839	-171.3	7510.6	-0.0228078	2,013	9,524	0.2113608	0.88581079	acquired on 2010
	2008	487.5	3,208.60	8,188.00	-0.3323278	-575.2	8,188.00	-0.070249	-540.7	8188	-0.0660357	1,624	9,812	0.1655116	0.58094499	
															0.73337789	Distress zone

Cyprus

Name	Year	CA	CL	TA	X1	RE	TA	X2	EBIT	TA	X3	MC	TL	X4	Z"	Status
Cyprus Popular Bank Public Co Ltd	2011	2.107	20.517	33.761	-0.543088	-3.007	33.761	-0.089067	-3.291	33.761	-0.0974793	0.327	33.161	0.009861	-1.252259	bankrupted on 2012
	2010	5.673	25.6	42.58	-0.4679897	0.789	42.58	0.018598	0.1004	42.58	0.0023579	3.641	68.648	0.0530387	0.32193083	
															-0.4651641	Distress zone

Spain

Name	Year	CA	CL	TA	X1	RE	TA	X2	EBIT	TA	X3	MC	TL	X4	Z"	Status
Caixa d Estalvis de Catalunya Tarragona I Manresa	2011	9.047	52.858	76.379	-0.5736092	1.24	76.379	0.0016248	-3.291	76.379	-0.0430878	2.2	74.177	0.0002903	-0.7868247	acquired on 2012
	2010	7.989	55.612	76.584	-0.6218401	1.8	76.584	0.0002963	53.5	76.584	0.0005986	1.9	74.478	0.0002488	-0.8135447	
															-0.8001847	Distress zone

Banca Civica S.A.

Name	Year	CA	CL	TA	X1	RE	TA	X2	EBIT	TA	X3	MC	TL	X4	Z"	Status
Banca Civica S.A.	2011	6.543	48.948	71.827	-0.5903769	0.165	71.827	0.0002972	0.179	71.827	0.00024921	2.873	68.951	0.0416673	-0.544886	acquired on 2012
	2010	5.787	43.819	72.643	-0.5235467	0.467	72.643	0.0064287	0.145	72.643	0.0019961	2.417	70.198	0.0344812	-0.1039422	
															-0.3244141	Distress zone

Banco de Andalucia S.A.

Name	Year	CA	CL	TA	X1	RE	TA	X2	EBIT	TA	X3	MC	TL	X4	Z"	Status
Banco de Andalucia S.A.	2008	1.784	11.5	13.682	-0.7101301	0.119	13.682	0.0086976	0.199	13.682	0.0145447	1.195	12.486	0.0957072	-1.1718668	acquired on 2009
	2007	0.764	11.127	12.366	-0.8380236	1.009	12.366	0.0815947	0.274	12.366	0.0221575	1.108	11.528	0.0961138	-1.7216181	
															-1.4467424	Distress zone

Banco de Valencia S.A.

Name	Year	CA	CL	TA	X1	RE	TA	X2	EBIT	TA	X3	MC	TL	X4	Z"	Status
Banco de Valencia S.A.	2012	654.8	13.657	21.500	-0.6047535	-1.912	21.500	-0.088893	-3.103	21.500	-0.1443256	2,232	19,300	0.1156477	-1.8455338	merged on 2013
	2011	1.321	15.039	22.647	-0.6640081	97.554	42,580	0.0022911	1,093	22,647	0.0482625	306	22,099	0.0138314	-0.7495449	
															-1.2975391	Distress zone

Banco Espanol de Credito S.A.

Name	Year	CA	CL	TA	X1	RE	TA	X2	EBIT	TA	X3	MC	TL	X4	Z"	Status
Banco Espanol de Credito S.A.	2012	28.579	80.382	102.420	-0.5057899	-22.825	102.420	-0.000223	-1,640	102.420	-0.0160125	2,458	33,161	0.0741232	-0.0884828	acquired on 2013
	2011	26.210	78.717	108.848	-0.4823883	788.6	106,848	0.007245	-40,518	108,848	-0.0003722	2,579	68,648	0.0375685	0.15609685	
															0.03380704	Distress zone

Banco Pastor S.A.

Name	Year	CA	CL	TA	X1	RE	TA	X2	EBIT	TA	X3	MC	TL	X4	Z"	Status
Banco Pastor S.A.	2010	3.354.70	22.296.70	31.134	-0.6084024	55	31,134	0.0017666	-9.6	31,134	-0.0003083	1453.7	29,528.70	0.0492301	-0.6757412	acquired merged 2011
	2009	6.241	21.984.70	32.252	-0.4881465	85.5	32,252	0.002651	135.7	32,252	0.0042075	1,494	30,715	0.048631	0.14573825	
															-0.2650015	Distress zone

Appendix II Processed data and ratios of non-failed banks

Belgium		Year	CA	CL	TA	X1	RE	TA	X2	EBIT	TA	X3	MC	TL	X4	Z"	Status
Name																	
AXA Bank Belgium N.V.		2016	20,631.20	3,812	27,994.50	-0.6008037	95.3	27,994.50	0.0034042	85.2	27,994.5	0.0030435	1,181.80	26,812.70	0.0440761	-0.6034427	
		2015	23,364.80	4,125.30	30,909.00	-0.6224562	27.2	30,908.70	0.00088	99.4	30909	0.0032159	1,173.70	29,736	0.0394707	-0.7573892	Distress zone
Name																	
Belfius Banque S.A.		2016	41,456.30	115,041	176,720	-0.4163915	209.2	176,720	0.0011838	748	176,720	0.0042327	9,011	167,709	0.05373	0.6171913	
		2015	42,502.40	114,084	176,962	-0.4045027	209.2	176,962	0.0011822	634.9	176,962	0.0035878	8,658	168,302	0.0514432	0.6884417	Distress zone
Name																	
ING Belgium S.A.		2016	24,209	127,369	150,418	-0.6858222	7,259	150,418	0.0482589	1,463.70	150,418	0.0097309	10,286	140,129	0.0734038	-0.9392041	
		2015	27,795	127,107	151,989	-0.6534157	6,700	151,989	0.0440821	1,389.40	151,989	0.0091415	9,771	142,197	0.0687145	-0.7491185	Distress zone
Name																	
France																	
Name																	
BNP Paribas S.A. (ENXTPA:BNP)		2016	915,606	1,498,00	2,076,00	-0.2805366	59,118	2,076,00	0.0284769	10,743	2076	0.0051749	100,655	1,971,74	0.0510488	1.6008908	
		2015	884,256	1,425,44	1,994,19	-0.2713784	54,781	1,994,193	0.0274703	10,876	1994,193	0.0054538	96,269	18,694.12	0.0051497	1.6113674	Grey zone
Name																	
BPCE S.A.		2016	382,01	829,49	1,253,24	-0.3570585	36,56	1,253,24	0.0291724	6,334	1253,24	0.0050541	61,142	1,161,10	0.0526587	1.1020534	
		2015	350,38	773,54	1,166,53	-0.3627511	33,01	1,166,53	0.0282976	5,682	1166,53	0.0048709	57,632	1,101.34	0.0523239	1.0602808	Distress zone
Name																	
Credit Agricole S.A.		2016	648,608	938,35	1,524,23	-0.1900907	3,54	1,524,23	0.0023225	3,52	1524,23	0.0023094	58,276	1,460,29	0.0399071	2.0779975	
		2015	675,05	990,09	1,529,29	-0.2060041	3,516	1,529,29	0.0022991	3,587	1529,29	0.0023455	53,813	1,469,85	0.0366112	1.970312	Grey zone

Germany																
Name	Year	CA	CL	TA	x1	RE	TA	x2	EBIT	TA	x3	MC	TL	x4	Z'	Status
Bayerische Landesbank	2016	21.421	104.579	201.904	-0.411869	4.064	201.904	0.0201284	0.708	201.904	0.0035066	11.041	201.94	0.0546747	0.7047307	
	2015	22.937	105.335	204.644	-0.4026407	3.66	204.644	0.0178847	0.674	204.644	0.0032935	11.055	204.64	0.0540217	0.7558366	Distress zone
0.7302836																
Commerzbank AG	2016	193.766	381.146	480.45	-0.3900094	11.184	480.45	0.0232782	1.821	480.45	0.0037902	28.613	450.81	0.0634702	0.8695392	
	2015	226.539	425.622	532.5	-0.3738648	11.438	532.5	0.0215174	2.255	532.5	0.0042347	29.121	502.57	0.0579442	0.9668925	Distress zone
0.9182158																
Deutsche Bank Aktiengesellschaft	2016	1.053.91	1.318.32	1.590.04	-0.1662893	18.897	1.590.04	0.0118846	3.562	1590.042	0.0022402	64.502	1,525.72	0.0422764	2.2673302	
	2015	1,034.34	1,322.78	1,629.13	-0.1770516	21.182	1,629.13	0.013002	5.605	1629.13	0.0034405	67.354	1,561.50	0.0431342	2.2093394	Grey zone
2.2383348																
KfW (ASX:KFWHZ)	2016	72.671	75.054	507.013	-0.0047001	14.692	507.013	0.0289776	1.917	507.013	0.003781	27.054	479.959	0.0563673	3.4082281	
	2015	69.492	68.492	502.973	0.0019882	12.691	502.973	0.025232	2.196	502.973	0.004366	25.2	477.77	0.052745	3.4400208	Safe zone
3.4241244																
Landesbank Baden-Wuerttemberg	2016	84.853	160.337	243.62	-0.3098432	8.24	243.62	0.0338232	0.598	243.62	0.0024546	13.081	230.501	0.0567503	1.4137752	
	2015	80.701	152.134	234.015	-0.3052497	8.24	234.015	0.0352114	0.624	234.015	0.0026665	13.624	220.372	0.0618227	1.4551842	Grey zone
1.4344797																
Netherlands																
de Volksbank N.V.	2016	7.604	51.341	61.561	-0.710466	0.329	61.561	0.0053443	0.464	61.561	0.0075372	3.451	58.02	0.0594795	-1.2701311	
	2015	3.389	50.044	62.69	-0.7442176	0.348	62.69	0.0055511	0.479	62.69	0.0076408	3.302	59.388	0.0556005	-1.4942442	Distress zone
-1.3821877																
Achmea B.V.	2016	15.325	26.254	93.015	-0.1174972	-3.201	93.015	-0.0344138	-0.145	93.015	-0.0015589	9.774	83.233	0.1174294	2.4898546	
	2015	15.769	25.973	93.439	-0.1092049	-2.617	93.439	-0.0280076	0.108	93.439	0.0011558	10.263	83.159	0.1234142	2.5896663	Grey zone
2.5397588																
ABN Amro Bank N.V.	2016	56.713	305.203	394.48	-0.6299179	1.8	394.48	0.004563	2.792	394.48	0.0070777	18.932	375.545	0.0504121	-0.7568913	
	2015	64.167	316.759	407.373	-0.6200509	1.91	407.373	0.0046886	2.802	407.373	0.0068782	17.568	389.788	0.0450707	-0.6987034	Distress zone
-0.7277974																

Name	Year	CA	CL	TA	x1	RE	TA	x2	EBIT	TA	x3	MC	TL	x4	Z''	Status	
NIBC bank N.V.	2016	10.181	14.351	1.495	23.58	-0.1768448	1.495	23.58	0.0634012	0.118	23.58	0.0050042	1.969	21.611	0.091111	2.4358811	
	2015	11.48	15.057	1.508	23.229	-0.1539885	1.508	23.229	0.0649189	0.102	23.229	0.0043911	1.886	21.343	0.0883662	2.583763	
																2.5098221	Grey zone

Name	Year	CA	CL	TA	x1	RE	TA	x2	EBIT	TA	x3	MC	TL	x4	Z''	Status	
ING Bank N.V.	2016	152.941	697.032	20.638	843.919	-0.6447195	20.638	843.919	0.024455	7.229	843.919	0.008566	43.54	799.773	0.0544404	-0.7749106	
	2015	175.021	855.239	18.006	1,001.99	-0.6788657	18.006	1,001.99	0.0179702	6.7	1001.992	0.0066867	40.857	960.497	0.0425374	-1.0451774	
																-0.910044	Distress zone

Switzerland

Name	Year	CA	CL	TA	x1	RE	TA	x2	EBIT	TA	x3	MC	TL	x4	Z''	Status	
Credit Suisse AG	2016	476.509	582.557	8.833	802.332	-0.1321747	8.833	802.332	0.0110092	-2.258	802.332	-0.0028143	40.682	582.557	0.0698335	2.4832369	
	2015	485.229	499.956	12.427	803.931	-0.0183187	12.427	803.931	0.0154578	1.185	803.931	0.001474	43.406	499.956	0.0868196	3.2912874	
																2.8872622	Safe zone

Name	Year	CA	CL	TA	x1	RE	TA	x2	EBIT	TA	x3	MC	TL	x4	Z''	Status	
Banque Cantonale Vaudoise (SWX)	2016	9.764	34.411	3.148	44.085	-0.5590791	3.148	44.085	0.0714075	0.386	44.085	0.0087558	3.42	40.565	0.0841018	-0.0276241	
	2015	9.593	31.844	3.039	43.418	-0.5124833	3.039	43.418	0.069994	0.398	43.418	0.0091667	3.397	40.021	0.0848804	0.2770147	
																0.1246953	Distress zone

Name	Year	CA	CL	TA	x1	RE	TA	x2	EBIT	TA	x3	MC	TL	x4	Z''	Status	
UBS AG	2016	504.331	785.652	28.265	935.353	-0.3007645	28.265	935.353	0.0302185	5.643	935.353	0.006033	54.304	881.009	0.0616384	1.7907594	
	2015	529.337	715.962	29.433	943.256	-0.1978519	29.433	943.256	0.0312036	6.764	943.256	0.0071709	57.203	886.012	0.0645623	2.4797942	
																2.1352768	Grey zone

Name	Year	CA	CL	TA	x1	RE	TA	x2	EBIT	TA	x3	MC	TL	x4	Z''	Status	
Raiffeisen Schweiz Genossenschaft	2016	40.325	178.983	12.79	218.589	-0.634332	12.79	218.589	0.0585116	0.911	218.589	0.0041676	14.385	204.199	0.070446	-0.3084952	
	2015	34.043	158.521	12.069	205.748	-0.6050022	12.069	205.748	0.0586591	0.943	205.748	0.0045833	13.318	192.422	0.0692125	-0.1141132	
																-0.2113042	Distress zone

Name	Year	CA	CL	TA	x1	RE	TA	x2	EBIT	TA	x3	MC	TL	x4	Z''	Status	
Zurcher Kantonalbank	2016	52.583	128.863	8.377	157.895	-0.4831059	8.377	157.895	0.0530542	0.752	157.895	0.0047627	10.739	147.192	0.0729591	0.3723945	
	2015	51.995	92.762	8.012	154.41	-0.2640179	8.012	154.41	0.0518878	0.663	154.41	0.0042938	10.42	143.981	0.0723707	1.8020404	
																1.0872174	Distress zone