Verifying the Validity of Altman's Z" Score as a Predictor of Bank Failures in the Case of the Eurozone

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Abstract

In light of recent events that have taken place in the Eurozone, the importance of knowing the financial position of banks is imperative to stakeholders. There is a major dearth of literature that examines the applicability of Altman's *Z*" Score model to forecasting banking failures. The focus of this study is to confirm the validity of Altman's *Z*" Score model as a predictor of Eurozone bank failures. This requires two data sets: failed and non-failed banks. Four distressed banks were benchmarked to four comparable control banks. Ratio analysis was carried out on the failed bank's financial statements for five years prior to their bankruptcy or nationalisation as the *Z*" Score model has predictive power of up to five years pre-bankruptcy. The empirical findings verified the predictive ability of the *Z*" Score model to the euro area banks.

Declaration

I declare that this thesis, which I submit to NCI for examination in consideration of the award of a higher degree MSc. Management is my own personal effort. Where any of the content presented is the result of input or data from a related collaborative research programme this is duly acknowledged in the text such that it is possible to ascertain how much of the work is my own. I have not already obtained a degree in NCI or elsewhere on the basis of this work. Furthermore, I took reasonable care to ensure that the work is original, and, to the best of my knowledge, does not breach copyright law, and has not been taken from other sources except where such work has been cited and acknowledged within the text.

Signed ____

Student Number ____

Date ____

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Contents

I. Introduction

The current financial crisis is the biggest cataclysm since the 1929 great depression in the US although extensive research carried out post-depression fixated only on corporate failures. Considering the depression was itself caused by undiversifiable risk due to the collapsed banking system and not by the corporations themselves, there has been a major dearth of accounting and finance literature related to banking failure prediction models. The studies would have been more effective and relevant if they were focused on the fragility of the banking structure. The global financial system has been under astronomical stress the past six years; this has affected the credit market directly by fostering downgraded consumer confidence and hence diminishing growth in economic activity, particularly for the Eurozone.

The reason why Eurozone banks will be the focus of this study is due to the unprecedented events that have occurred over the past six years. The most significant occurring in April 2010; the downgrading of Greek government debt to junk bond status sent alarms throughout the global financial markets. This contagion from Greece threatened the fate of the Euro-area and the common currency. It highlighted large fault lines in the Eurozone as the collapse of a banking system in one European country could easily trigger the demise of other euro banks. The IMF had no option but to inject a €110 billion bailout. While Greece is 'temporarily patched up' the focus has shifted to the other Eurozone countries Ireland, Spain, Italy and Portugal. The ECB is keeping very tight surveillance of its monetary policy, with very low inflation levels amid the euro area recovery. Meanwhile, the Bank of England and Federal Reserve are 'routinely' injecting heavy doses of quantitative easing into their economies. The US are deliberately weakening the dollar in order to increase economic growth. This is exposing a host of problems to the Euro as it is making the euro currency stronger and less competitive. Contagion from Greece still threatens the euro. (Merk, 2012) This pattern was also evident from the great depression as the countries holding on to the gold standard had stronger currencies but endured painful fiscal and political consequences which can be seen in the euro zone today.

Business failures are a natural phenomena in our economic system with firms entering and exiting as a function of overall business activity and expectations (Altman & Loris, 1976, p.1). Corporate failure is the sequential conclusion due to systematic and non-systematic factors. Financial and accounting literature has over and over again renewed the confidence in ratio analysis as a proficient predictor of corporate failure. Nevertheless, more attention should be focused on the prediction of banking failures. While ratio analysis forecasts potential corporate failures using Altman's Z test (1968), Beaver's (1966) univarite test and so forth, the significant limitation of these models are the fact they can only be applied to manufacturing firms.

The focus of my study is to apply an evolved model of Altman's Z Score namely the 'Z" Score model' (Altman, Hartzell and Peck, 1995) to failed Eurozone banks. This model overcomes the manufacturing limitation of Altman's pioneering model and can be used on financial institutions. The main objective is to verify if the Z" Score is a true indicator of financial failure for a Eurozone financial institution. The recent global crisis has demonstrated the importance of banks both at national and international levels. In particular, the Eurozone has been greatly affected by widespread contagion which has drastically diminished the credibility of the single currency euro.

The remaining part of this study shall be outlined as follows: in section II, an up-to date review of the literature in relation to failure prediction models will be carried out with particular focus on the evolution of Altman's Z Score model which will be later on utilised in the research. In section III, there will be an explanation of the data collected and used, applicable to the statistical model that will answer the objectives of this study. Section IV will contain the empirical results of the analysis. Section V will be the discussion of these Z"

Score results. The limitations associated with the methodology used will be discussed in section VI and, finally, the conclusion of this study will be discussed in section VII.

On Franklin National

"People who can read a balance sheet were out of there long ago."

—Harry Keefe

II. Literature Review

The emergence of the financial crisis in 2008, brought with it a tide of corporate failures rooted in the American subprime mortgage crisis. A January 2011 report put forward by the U.S. Financial Crisis Inquiry Commission concluded that

> *"the crisis was avoidable and was caused by: Widespread failures in financial regulation, including the Federal Reserve's failure to stem the tide of toxic mortgages; Dramatic breakdowns in corporate governance including too many financial firms acting recklessly and taking on too much risk; An explosive mix of excessive borrowing and risk by households and Wall Street that put the financial system on a collision course with crisis; Key policy makers ill prepared for the crisis, lacking a full understanding of the financial system they oversaw; and systemic breaches in accountability and ethics at all levels.''* (Tucker, 2011, p.1)

Deterring away from this domestic view, monetarist and chairman of the Federal Reserve took a more macroeconomic view coining the famous 'global savings glut' theory. In a statement made at a lecture in Virginia 2005, he spoke about the correlation between excessive savings made in developing countries, particularly China, and the US current account deficit along with low-long term interest rates globally (Bernanke, 2005). Nevertheless, numerous economists are assigning the causations to be rooted "in high interest rates, recession-squeezed profits and heavy debt burdens. Furthermore, industry-specific characteristics, such as government regulation and the nature of operations, can contribute to a firm's financial distress" (Charitou, Neophytou & Charalambous, 2000, p.3). Failure has been also significantly linked to the "prevailing tight monetary policy; the investor's expectations' about economic conditions; and the state of the economy" (Dambolena & Khoury, 1980, p.1019)

At any rate, although there remains a multitude of possible roots, it is without a doubt that the financial crisis raised its aggressive head in the American banking system and crossed the Atlantic in the form of detrimental financial contagion. The 2008 bankruptcy of the Lehman brothers, the largest bankruptcy in US history, spread shock to the whole financial system and to other financial markets. Ireland was one of the first Eurozone countries to slip into recession days after the Lehman Brothers collapse. Ireland had sustained growth achievement for two decades yet it was one of the most severely affected countries in the global crisis. This shows the fragility of the banking system in response to contagion. This has had substantial affects on the credit market leading to a high rate of corporate failures, particularly with highly geared companies.

Simic, Kovac & Simic (2012, p.536) stated ‘corporate failure prediction is essential for the prevention or mitigation of negative economic cycles in a national economy. Particularly after the collapse of large banks during the great depression such as Fannie Mae, Citigroup New York, Merrill Lynch and, of course, Lehman Brothers and Anglo Irish Bank. The importance of bankruptcy prediction has become a significant concern for corporate governance (Gilson, 1989; Gilson, 1990; Datta & Iskandar-Datta, 1995). It is also argued by Daily and Dalton (1994) that there is a relationship between corporate failure and corporate governance characteristics.

The identification of early warning signals in failing firms can deter managers from making poor investment decisions and implementing preventative actions to offset possible future catastrophes. Telmoudi et al (2011) stated:

> ‘‘*Prediction may avoid high social costs affecting stakeholders (i.e. investors, managers, governments, etc. and limit its undesirable impact on a country's economic performance. Firms are always endeavouring to find a countermeasure for undesirable situations where bankruptcy plays an increasingly important role because it has a significant impact on the profitability of business units. It serves to provide owners with a timely early warning system.*’’

Contemporary corporate failure prediction models have been based on the pioneering work of William H. Beaver. Beaver (1966) carried out univariate analysis, comparing the financial ratios of 79 failed firms and 79 non-failing firms. His utilization of the paired-sample approach and the use of a hold-out sample to validate the model has been a benchmark for later researchers (Moghadam, Zadeh, Fard, 2011, p.3). He examined the predictive power of thirty accounting ratios for five consecutive years leading up to the bankruptcy of the tested firms. Beaver applied 3 criteria in selecting these ratios; "widely used in past literature, good performance of ratios in past studies and the capability of ratios to be defined as "cash flow" concept" (Siew Bee & Abdollahi, 2011, p.6826). A misclassification rate was used as an index to gauge the predictive power of the variables. Misclassification could either be a Type I error (classifying a failing firm as non-failing), or Type II error (classifying a non-failing firm as failing) (Bunyaminu & Issah, 2012). The smaller the misclassification rate; the greater the accuracy. The 'cash flow to debt ratio' resulted in being the best predictor of corporate failure with a 78% success rate as

> *"Five years before failure, an optimal prediction criterion (i.e., cutoff value) based on the single accounting ratio misclassified only 22 per cent of the validation; one year prior to failure the criterion misclassified only 13 per cent of the validation sample."* (Salehi & Abedini, 2009, p.399)

The second best indicator was 'net income to total assets' ratio with misclassification rate of 13% for first year before failure and misclassification rate of 28% for the 5th year before failure. The 3rd, 4th, 5th, and 6th ranks belonged to 'total debt to total assets', 'working capital to total assets', current ratio, and no credit interval ratios respectively.

A limitation of Beaver's work is based primarily on the univariate nature of the model he developed. It only allows for one ratio used at a time, this can give inconsistent results for a firm should other ratios be utilized. Not only this, but the financial complexity of a firm cannot be captured by one single ratio. Lastly, the cut-off point determined is chosen post-failure of a company which means that, in reality, the failure status of a company must be predicted resulting in inaccurate classifications.

In 1968 Edward Altman advanced upon Beaver's work by incorporating four more variables into the model to give an overall more precise prediction of manufacturing corporate failure. Altman's multi-discriminant analysis (MDA) model differed to Beavers model in relation to the ratios chosen of highest prediction. Altman classifies the companies into two mutually exclusive groups; bankrupt and non-bankrupt (Altman, 1968, p.591). Altman's discriminate analysis became a dominant model used in corporate failure prediction literature due to its simplicity and accuracy. His multi-discriminant approach allowed him to develop the equation into a combination of five ratios consisting of liquidity, profitability, financial leverage, solvency, and sales activity (sales to total assets). This linear equation distinguished between failing and non-failing companies. The result of the combination of ratios gives rise to a discriminant score otherwise known as the 'Z score'. Altman applied 22 ratios to 66 manufacturing firms (with an equal number of failures and non-failures). From the 22 ratios he utilized, the best five predictors were chosen. These were then presented in the linear equation as shown below.

The original Altman model took the following form:

$$\mathbf{Z=0.012\ X_1 + 0.014\ X_2 + 0.033\ X_3 + 0.006\ X_4 + 0.999\ X_5}$$

Where:
X_1=Working capital/Total assets;
X_2=Retained earnings/ Total assets;
X_3=Earnings before interest and taxes/Total assets;
X_4=Market value of equity/Book value of Total liabilities;
X_5=Sales/Total assets.

Boundary values:
Z > 2.99 Safe Zone: Considered financially healthy
1.81 < Z < 2.99 Grey Zone: Could go either way
Z < 1.81 Distress Zone: Risk that company will go bankrupt within two years
Source: (Altman, 1968, p.594)

A resulting low score suggests the firm is in financial distress. Companies with Z scores below 1.81 would be classified as potential failures; Z scores between 1.81 and 2.99 are said to be in the zone of ignorance or grey area and above 2.99 indicates the company is not in any financial distress. The Z-Score is calculated by multiplying each of the financial ratios by an appropriate coefficient and then adding the results together. The coefficients describe the importance of each ratio, as larger coefficients affect the Z-score more. Using the above model, Altman's Z Score provided evidence to predict bankruptcy of 94% of the failed companies in his sample (Altman, 1968 p.609). However, in a study carried out by Moyer (1977), he tested the effectiveness of Altman's (1968) model on 27 failed and 27 non-failed firms between 1965-1975. The firms paired according to industry and assets ranging from $15million to $1billion. The result of the investigation indicated that the forecasting accuracy on a post-dated sample of firm failure was 75% a year before failure. This is in contrast to a 94% accuracy rate proposed by Altman (1968).

Then in 1977, Altman, Haldeman and Narayanan (1977) used US data to investigate the period between 1969-1975 with a sample of fifty-three failed and fifty-eight non-failed companies. They derived a Zeta value based on seven financial ratios, return on assets, stability of earnings, debt service, cumulative profitability, liquidity, capitalization, and finally size. Like Altman (1968), to test the models rigorously for both failed and non-failed companies, a holdout sample was introduced. The study achieved an overall miss-classification of 7% for type I error and 3% higher (i.e., 10%) type II error a year prior to failure. The predictive power of the model reduced significantly five years prior to failure to 70% and 82% for failed and non-failed companies respectively. This surveillance highlights that the variables are irregular across various studies. Furthermore, these two studies were exceedingly precise in the short-run, but the precision shrinks vividly when the facts were for time periods of more than two years prior to ruin. Overall, the Zeta model did produce significantly improved accuracy compared to the original Z Score model *with 'bankruptcy classification accuracy ranges from over 96% one period prior to bankruptcy'* (Altman et al, 1977, p.49).

Another opponent of Altman's Z score is Hillegeist as he indicated in a (2004) study that the model is 'deficient' and failed to include a measure of asset volatility as "tracking a company's asset volatility is important because it measures the probabilities that the value of a firms assets decline to the extent that it is unable to pay its debts" (Li & Rahgozar, 2012, p.13).

The 'Z score' is a highly accurate corporate failure predictor however it does have its limitations. The model is industry specific, as it was formulated for operating manufacturing companies. This means it cannot make accurate predictions for non-industrial companies such as firms in the financial sector. Another drawback was "regarding the assumptions of similar variance covariance matrices and linear distributions of independent variables that might lead to invalid results."(Abdullah, Halim, Ahmad & Rus, 2008, p.202). Researchers have also criticized Altman's work on the basis of lack of evidence of ex-ante predictive ability of ratios (Appiah, 2011) .

The Z Score performs better with manufacturing companies than with any other industries (Grice and Ingram, 2011). Li and Rahgozar (2012) also found that both "In almost all cases, the average 5-year Z Score is superior in predicting financial distress over one, two, and average of 3-year Z-scores". This being said the Z score is still a very relevant statistical model developed over 40 years ago which has retained its high accuracy for predicting corporate failures.

Ohlson (1980) wanted to offset the limitations of the discriminant analysis model and he employed logit analysis or a logistic regression model into corporate failure prediction studies. Eisenbeis (1977), Ohlson (1980), and Jones (1987) found that there were some inadequacies in MDA with respect to the assumptions of normality and group dispersion. The assumptions were often violated in MDA. This may bias the test of significance and estimated error rates (Abdullah et al. 2008). Logit uses data averages where a healthy company is given a value of 0 and a distressed company is given a value of 1 (Abdullah et al, 2008). Hence, the logit model treats bankrupt companies as if they were bankrupt ever since their inception. Ohlson analysed 105 bankrupt companies and 2058 non-bankrupt companies from 1970 to 1976 (Ohlson, 1980). The results showed that size, financial structure (total liabilities to total assets), performance and current liquidity were important determinants of bankruptcy (Abdullah et al, 2008). Zmijewski (1984) followed up on Ohlson's study, who first applied the probit function. Research carried out by Collins and Green (1982), Ingram and Frazier (1982), Harrell and Lee (1985) and Gessner, Kamakura, Malhortra, and Zmijewski (1988) all have similar results, showing that the logit model is superior to the discriminant one. The studies by (Chen, Huang & Lin, 2009) stated that: "Logit Regression would have a better theoretical jurisdiction and more diversity and breadth for the independent variables selected." These variables included; Retained Earnings/Total Asset, Net Income/Net Sale, OPBAT/ Shareholder's Fund and Quick ratio (Siew Bee et al. 2011).

Ohlson's (1980) model was further advanced: using the effect of industry-related ratios on the likelihood of corporate failure (Platt and Platt, 1990); discrimination between financially distressed firms and failed firms (Gilbert, Menon and Schwartz, 1990); development of industry-specific model (Platt and Platt, 1994); and the introduction of multinomial logit approach to reduce misclassification error (Johnsen and Melicher, 1994).

Just like Beavers (1966) and Altman's (1968; 1977) model, Ohlson's model also has its fair share of limitations. Hillegeist (2004) points out there are "two econometric problems with the single period logit model". The first is the sample selection bias that arises from using only one, non-randomly selected observation for each bankrupt company, and second, the model fails to include time varying changes to reflect the underlying risk of bankruptcy. These problems demonstrated that the results would be biased, inefficient and inconsistent coefficient estimates. Shumway (2001) “predicted bankruptcy using the hazard model and found that it was superior to the logit and the MDA models” (Abdullah et al., 2008, p.203).

In a (2008) report ‘Predicting Corporate Failure of Malaysia’s Listed Companies: Comparing Multiple Discriminant Analysis, Logistic Regression and the Hazard Model’ written by Abdullah et al., they analysed three corporate failure predictors comparing Altman’s MDA, Ohlson’s logistic regression and Shumway’s hazard model. In this study they examined 26 bankrupt and 26 non-bankrupt companies listed in Bursa Malaysia. Of the 52 companies, twenty companies were the holdout sample. Ten of them were distressed with a matching ten companies in distress of similar size and industry. The hazard model was seen to predict 94.9% and 63.9% of the estimation and holdout sample respectively. The MDA model provided an overall accuracy rate of 80.8 % and 85 % for the estimation and the holdout sample respectively and for the logit model, it could correctly predict 82.7 % and 80% of the respective estimation and holdout sample. In conclusion it was seen the hazard model “provides a higher overall accuracy rate in the estimation model, but when the estimated equation is applied in the holdout sample, MDA gives a higher accuracy rate”(Abdullah et al., 2008, p.215).

The aforementioned corporate failure prediction models are both beneficial and limited, however, “no technique is consistently superior to other techniques” (Collins & Green, 1982; Tam, 1991; Taffler, 1995). A major limitation to research made in relation to predicting corporate failures is the focus exclusive to statistical models (Appiah, 2011).

The fragility of the banking system to economic downturns significantly paves the way for future failures of highly leveraged firms. The tightening of credit conditions, in particular for small and medium firms, can have immense negative effects on corporate survival rates. With the uncertainty surrounding financial markets, particularly for the Eurozone, implicating early warning systems to determine possible failures is advantageous to all stakeholders involved be it an institution or a company. Not only this but auditors also face the threat of a potential lawsuit if they fail to provide early warning signals about failing firms through the issuance of qualified audit opinions (Zavgren, 1983; Jones, 1987; Boritz, 1991; Laitinen and Kankaanpaa, 1999). Majority of the failed banks were caught in the real estate market collapse and because they did not have sufficient capital to ride out the cycle, were forced by the FDIC to merge with or be sold to other institutions (Jordan, Rice, Sanchez, Walker & Wort, 2010).

The focus of this study is to analyse the predictive capability of using the Z" Score applicable to banking institutions and to apply this to failed/nationalised banks and to benchmark these to current banks that may be in financial distress. The traditional and early corporate failure prediction models have been addressed in this study, however, they all lack the industry specific characteristic that makes them ineffective in predicting the failure of non-manufacturing firms.

In (1975) Joseph F. Sinkey carried out a multi statistical analysis of the balance sheet and income statement to identify characteristics of problem banks. MDA was used to test for group mean differences to classify banks as either problematic banks or non-problematic. The newly identified banks were matched with non-problem or control banks.

The empirical findings indicate that measures of banking factors such as asset composition, loan characteristics, capital adequacy, sources and uses of revenue, efficiency, and profitability are good discriminators between the groups (i.e., group mean differences exist). Then in 1977, Sinkey identified large problem/failed banks: in the case of Franklin National Bank. Sinkey utilized univariate, bivariate, and multivariate outlier tests. The results indicated that by year-end 1972 it was time to have been very 'suspicious' about Franklin National Bank. Even as early as year-end 1971, univariate income measures and risk-return analysis indicated that Franklin was a significant outlier (Sinkey, 1977, p.795). Sinkey's (1977) study had demonstrated that "existing, routinely collected banking data, if properly analyzed, should be useful in identifying potential problem banks" (Sinkey, 1977, p.795)

The mainstream definition used to define bankruptcy is "a law for the benefit and the relief of creditors and their debtors, in cases in which the latter are unable and unwilling to pay their debts." Furthermore, Ross, Westerfield, Jaffe, and Jordan (2008, p.853) define "financial distress as a situation where a firm's operating cash flows are not sufficient to satisfy current obligations and the firm is forced to take corrective actions." To avoid bankruptcy, the first step is to identify a 'problem bank'.

Banking authorities characterised a 'problem' bank "to be one with a large volume of adversely-classified (i.e., highest-risk) assets relative to its capital and reserves."(Sinkey, 1977, p.780). Sinkey (1978) advanced this definition further by identifying 'problem' banks as those with "low net capital ratios (NCR); (2) the most important component of the NCR is the volume of "substandard" loans; and (3) banks that failed in recent years almost invariably had low NCRs months before failure, although most banks with low NCRs do not fail."(Sinkey, 1978, p.184). Bank capital and substandard loan classification are important variables as substandard loans conveyed in a low NCR account for approximately 80 percent of a problem banks classified loans. It has been observed that the NCR has been a favoured predictor of most bank failures.

As previously mentioned using Altman's Z score model it is accompanied by Type-I and Type-II failure errors. Sinkey was also concerned with identifying Type-I failure errors (classifying a bank as failing or as non failing) and Type-II errors (problem banks that do not fail or require financial assistance). Regarding the financial difficulties of billion-dollar banks, the FDIC has had a zero Type-I error (Sinkey, 1978). These banks had low net capital ratios (i.e., 0.0 and -1.0) and large volumes of "substandard" loans. Of course, given their goal of failure prevention, the banking authorities try to correct a bank's financial difficulties and thus NCR predictions will be biased towards becoming Type-II errors (Sinkey, 1978).

Prior to Sinkey's (1975;1977) study regarding identifying problem banks, Meyer and Pifer (1970) took a different perception of predicting Bank Failures. They listed four factors that explain bank failures (1) local economic conditions, (2) general economic conditions, (3) quality of management, and (4) integrity of employees. They positioned each failed bank as "matched" with a comparable solvent bank. The banks comparability requirements, in order of importance were that the banks (a) were in the same city, or in the case of a one-bank town, in the same economic area, (b) were approximately the same size and age, and (c) had the same regulatory requirements. Data for a solvent bank covered the same period as its matched closed bank.

Apart from Sinkey's, Meyer's and Pifer's studies, there was limited early literature regarding the corporate failure of banks until the emergence of the recession in the mid-twenty first century. Ozkan-Gunay and Ozkan (2007) analyzed 59 Turkish banks, 23 of which were failed banks and 36 were non-failed using a non-linear artificial network approach. They found that 66% of the failed banks were correctly indicated and 90% of the non-failed banks were correctly indicated. Using a hybrid artificial neural network Yim (2007) predicted firm failure of Australia's financial services sector. Yim (2007) successfully predicted 100% of failed firms a year before failing but only predicted 33.3% of failed firms two years before failure. Schaek (2008) used a quantile regression approach to compare high-cost to low-cost bank failures. (Jordan et al, 2010, p.6)**.** Then in 2009 Ercan and Evirgen investigated the factors that are of imperative to the failure of Turkish banks using a principal component analysis methodology. Furthermore to studies in 2009, Jesswein compared a sample of 37 failed banks from 2008 and 2009 compared to 7, 075 non-failed banks using the "Texas Ratio". The Texas Ratio is calculated "by dividing the bank's non-performing assets (non-performing loans plus other real estate owned) by the sum of its tangible equity capital and loan loss reserves" (Jesswein, 2007). Moreover, it was noted that "such a measure offers important insights but may not be sufficient as a general, all-purpose tool." (Jesswein, 2007).

The first statistical discriminant model used to predict company failure by Beaver (1966) using a univaritate approach has certainly been adapted to the contemporary business environment; however, the basic linear model has remained fairly constant in the form of:

$\mathbf{Z=A_1X_1+A_2X_2...A_NX_N,}$

Where Z = Overall Score

A_1... A_N = Discriminant Coefficients

X_1...X_N = Discriminant Variables

Since then, the univariate model has evolved into a multi discriminant model which utilizes many financial ratios at the same time (Altman, 1968). The primary purpose of this was to discriminate between a sample of bankrupt firms with a matched control sample (healthy firms).

The first MDA devised by Altman (1968) took the following form:

$\mathbf{Z = .012X_1 + .014X_2 + .033X_3 + .OO6X_4 + .999X_5}$

Where,

X_1 = Working capital/Total assets

X_2 = Retained Earnings/Total assets

X_3 = Earnings before interest and taxes/Total assets

X_4 = Book Value of Equity/Total Liabilities

X_5 = Sales/Total assets

Z = Overall Index

(Source: Altman, 1968, p.594)

This model was then revolutionised by Altman, Haldeman and Narayanan creating the Zeta® Credit Risk Model (1977) as a second generation discriminant model which "appeared to be quite accurate for up to five years prior to failure" (Altman, 2000). The Zeta® model consists of seven variables: (1) return on assets, (2) stability of earnings, (3) debt service, (4) cumulative profitability, (5) liquidity, (6) capitalization, and (7) asset size. The major limitation to Altman's first two models was the fact they were only useful for manufacturing firms and they did not work well for financial corporations or institutions such as banks.

This limitation was then progressed into a new model created by Richard J. Taffler (1983) which used a UK-based Z score model and has shown the ability to predict failure (Agarwal & Taffler, 2007)

The Z score model is being constantly updated by (Altman, 1983; 2002; Altman, Hartzell, and Peck, 1995) to adapt to different parameters and the changing corporate landscape. This is key considering the service industry is now larger than the manufacturing sector. In 1983, Altman devised the Z score to be adapted for private companies 'The Z' Score'. This model took the following form:

$$\mathbf{Z' = 0.717X_1 + 0.847X_2 + 3.107X_3 + 0.420X_4 + 0.998X_5}$$

Where:

X_1: Working Capital/Total Assets

X_2: Retained Earnings/Total Assets

X_3: EBIT/Total Assets

X_4: Book Value Equity/Total liabilities

X_5: Sales/Total Assets

Source: Altman (1983:122)

This model was further developed to create the Z” Score model (Altman, 1995). This was adapted to predict corporate failures for developing countries firms (Mexican companies), emerging market companies and for non-manufacturers. This model kept the first four variables as the previous Z’ Score model with the exclusion of the sales/total assets activity ratio ‘X_5’ in the following form with different weighted coefficients (in order to filter the function from the possible distortion related to the sector and country):

$$Z'' = 6.56X_1 + 3.26X_2 + 6.72X_3 + 1.05X_4$$

Where:

X1: Working Capital/Total Assets

X2: Retained Earnings/Total Assets

X3: EBIT/Total Assets

X4: Book Value Equity/Total liabilities

Source: Altman, Hartzell and Peck (1995:3)

In order to standardise the Z” Score results Altman, Hartzell and Peck (1995) added a constant (+3.25) so that the scores that equal or less than zero would be ‘equivalent to the default situation’ (Altman, Danovi, and Falini, 2013:4) from this proposal, Altman and Hotchkiss (2006) translated this score to Standard and Poors ratings. This bond rating equivalent (BRE) of the Z” Score makes the model very relevant and useful for investors. This is displayed in the following table.

Correspondence between Z" Score and Standard and Poor Rating

<table>
<tr><td rowspan="11">Safe Zone</td><th>Rating</th><th>Z" Score Threshold</th><th>Rating</th><th>Z" Score Threshold</th><td rowspan="6">Grey Area</td></tr>
<tr><td>AAA</td><td>>8.15</td><td>BB+</td><td>5.65</td></tr>
<tr><td>AA+</td><td>8.15</td><td>BB</td><td>5.25</td></tr>
<tr><td>AA</td><td>7.60</td><td>BB-</td><td>4.95</td></tr>
<tr><td>AA-</td><td>7.30</td><td>B+</td><td>4.75</td></tr>
<tr><td>A+</td><td>7.00</td><td>B</td><td>4.50</td></tr>
<tr><td>A</td><td>6.85</td><td>B-</td><td>4.15</td><td rowspan="5">Distress</td></tr>
<tr><td>A-</td><td>6.65</td><td>CCC+</td><td>3.75</td></tr>
<tr><td>BBB+</td><td>6.40</td><td>CCC</td><td>3.20</td></tr>
<tr><td>BBB</td><td>6.25</td><td>CCC-</td><td>2.50</td></tr>
<tr><td>BBB-</td><td>5.83</td><td>D</td><td><1.75</td></tr>
</table>

(Source: Altman and Hotchkiss, 2006:314)

Another adaptation was the introduction of the Z-Metrics System (Altman and Rijken et. al., 2010). It refines the original model, includes both market equity levels and volatility, as well as macro-economic variables. The parameters are not made explicit, considering the proprietary nature of this technique. The Z-Metrics approach was used by the authors to assess the sovereign risk, particularly in Europe today, with encouraging results (Altman and Rijken, 2010).

III. Methodology

The focus of my study is to apply the most suitable Z score model to 4 distressed and non-distressed Eurozone banks between 2005 and 2012. From the outset of the financial trouble, the banks have been at the centre of the financial crisis due to the frail capital structure of banks to provide liquidity to both borrowers and lenders (Diamond and Rajan, 2001, p.289). Failed Eurozone banks were forced to merge with other banks or became nationalised. In particular, the Eurozone has been awash with (negative) mainstream media. The onset of the uncertainty surrounding the euro has made the financial market trading conditions difficult to attract investors. The primary reason for this investigation is not just verify the validity of the Z" Score model but to predict possible 'future' failures. To identify a trend in the Z" Score of the failed banks and to see if this is parallel to a current bank. The development of an early warning system is imperative to Eurozone traders in such financial circumstances.

The Z score model is a form of discriminant analysis. This is a multivariate technique utilized in the social and physical sciences for many decades. The first application of discriminant analysis to the problem of failure prediction in business was performed in 1966 (Beaver, 1966) and concentrated on the manufacturing sector of the economy (Altman & Loris, 1976). Since then, the model has evolved to pertain to the contemporary business environment. In the Euro-area the services industry has the largest share of total output '73.1% GDP' (ECB Report, 2012). Along with the model being a valid indicator of corporate failure, it is imperative that it has adapted to suit a wider range of firms. This flexibility to modification is the main reason it is one of the most widely used corporate predictors today and is as relevant today as it was in the late sixties. In this case the evolution of the Z Score that will be used in this study is Altman's Z" Score.

The analysis undertaken in this study requires a comparison be made between 'failed' and 'non-failed' Eurozone banks. The best suited analysis is discriminant analysis as it 'seeks to combine and weight several independent variables in such a way as to maximize the discrimination between two or more clearly identifiable groups.' (Altman and Lorris, 1976, p.1203)

The importance of the going-concern concept was emphasized by William J. Casey, then Chairman of the Securities and Exchange Commission, in a speech' to the National Investor Relations Institute on October 3, (1972):

> *"Auditors sometimes find themselves so dubious about a company's viability as a going concern that they find themselves unable to give an opinion as to the overall fairness of the financial statements, which rest after all on the implicit assumption that there is a going business here which can reasonably be expected to continue operating for an indefinite period in the future."*

We think it imperative that such prime candidates for bankruptcy or reorganization proceedings be spotted at the earliest possible moment so that investors may guide themselves accordingly. The most fundamental judgment by an auditor concerning the future in relation to an enterprise is its ability to continue to operate as a going concern.

Dataset

In the United States, the Federal Deposit Insurance Corporation (FDIC) keeps a public log of all the failed/nationalised banks which can be accessed from: http://www.fdic.gov/bank/individual/failed/banklist.html. However, information regarding the actual number of failed Eurozone banks since the crisis has not been collected or disclosed in any type of log. The only source found was an independently created blog which featured known Eurozone bank failures. This can be accessed from:

https://docs.google.com/spreadsheet/pub?key=0AkitojFFyvjCdC1lcmRhRU9WWExSdmJ6OFpySExzb3c&single=true&gid=0&output=html.

The banks required for this research had to meet the following characteristics:

1) Euro area bank
2) Failed or nationalised between 2007 to 2012
3) Banks had to be in operation for at least five years before the collapse
4) For each closed bank, there is a comparable(control) bank
5) Financial statements for five years prior to the failed banks collapse had to be publically available

It was imperative that the bank be of Eurozone origin as this analysis is to validate the Z" Score as a predictor of bank failure even in financially turbulent markets. The banks analysed had to have failed during the 2007-2012 period as this model needed to forecast failure withstanding recession induced stress. In order to confirm the Z" Score can predict failure five years prior to failure, it was paramount that the banks examined had to be of going concern at least five years prior to failure. To discriminate between the two data sets, comparable banks were required to identify any similar or dissimilar trends. Entirely public data was required as this Z" Score model is to prove it can be used by any stakeholders that can utilize ratio analysis. Data required to carry out ratio analysis was extracted from the statement of comprehensive income and statement of financial position of the banks analysed. "The basic objective of financial statements is to provide information useful for making economic decisions"' (AICPA,1973, p.13). This is why it was important that financial statements were accessible.

The Statistical Model

The statistical model used in this analysis is the Z” Score model is outlined below.

$$\mathbf{Z'' = 6.56X_1 + 3.26X_2 + 6.72X_3 + 1.05X_4}$$

Where:

X_1: Working Capital/Total Assets

X_2: Retained Earnings/Total Assets

X_3: EBIT/Total Assets

X_4: Book Value Equity/Total liabilities

Source: Altman, Hartzell and Peck (1995:3)

It was first used in 1995 to predict the corporate failures of non-manufacturing and developing countries firms (Altman, Hartzell and Peck, 1995). Then recently in 2013, (Altman, Danovi & Falini, 2013) applied this model to predict the corporate failure of Italian banks subject to extraordinary administration. The results of the Z” Score predicted 95.5% of failure a year before declaring bankruptcies. The main reason for choosing the Z” Score as a statistical model was due to it’s the high predictive ability that it produced for Italian banks. This made the model very relevant for my analysis considering it had worked correctly on a Eurozone bank. The weightings of the variables did not change for my study as the objective was to use the original existing model to verify its validity as a corporate predictor for other Eurozone banks.

Variables Explained

X_1: Working Capital/Total Assets

The first variable in Altman's Z" Score model is the working capital to total assets ratio. This liquidity ratio calculates the ability of the bank to finance its short term obligations. It is the measure of the net liquid assets of the firm relative to capitalisation. An increasing liquidity figure shows a positive sign. A decreasing figure will suggest and increase in liabilities and thus distress caused to a bank. If a bank is experiencing operating losses its current assets will be shrinking in relation to total assets. It has proven to be the most valuable of the liquidity ratios in a Merwin study "which rated the net net working capital to total asset ratio as the best indicator of ultimate discontinuance" (Altman, 1968, p.595).

X_2: Retained Earnings/Total Assets

The second variable indicates the ability of a bank to accumulate earnings using its assets. The higher the ratio the better as it suggests the bank can accumulate earnings. A young firm will usually display a very low RE/TA as it has not had the time to build up cumulative profits hence "the incidence of failure is much higher in a firm's earlier years" (Altman, 1968, p.595).

X_3: Earnings before Interest and Taxes/Total Assets

Earnings before interest and tax (EBIT) to total assets ratio indicates a proportion between the measure that shows company's profitability and company's assets. It measures the productivity of the firm's assets notwithstanding any tax or leverage factors. "Since a firm's ultimate existence is based on the earning power of its assets, this ratio appears to be particularly appropriate for studies dealing with corporate failure" (Altman, 1968, p.595). In short, it represents general profitability of the company's assets. EBITDA would not be a very accurate measure of a bank's financial position as it takes into account depreciation and amortization which would not be applicable to the nature of a bank's operations.

X_4: Book Value Equity/ Total Liabilities

The final variable expresses the financial leverage i.e. the proportion of equity. "The measure shows how much the firm's assets can decline in value (measured by market value of equity plus debt) before the liabilities exceed the assets and the firm becomes insolvent" (Altman, 1968, p.595). A high value depicts firm's aggressiveness in financing its growth with debt. If the cost of the debt financing outweighs the return that the company generates on the debt, it could even lead to the possible bankruptcy. This ratio adds a market value dimension which other failure studies did not consider. It also appears to be a more effective predictor of bankruptcy than a similar, more commonly used ratio: Net worth/Total debt (Altman, 1968).

IV. Empirical Results

Z" Score Results

	Anglo Irish Bank	BRE	Banca D'Italia	BRE	Dexia	BRE	Proton	BRE
YE 1	-1.67791813	D	0.520948689	B-	-0.2913136	CCC-	0.266671417	CCC
YE 2	0.596302337	CCC+	0.820345294	CCC+	-0.4340555	CCC-	0.197624157	CCC
YE 3	0.642211501	CCC+	0.39423437	CCC	-0.5279191	CCC-	0.340833957	CCC
YE 4	0.612608571	CCC+	0.280897174	CCC	-0.5353641	CCC-	0.551694481	CCC+
YE 5	1.133891456	B-	1.178578682	B-	-0.0545136	CCC+	4.806	AA

The above table are the Z" score results and bond related equivalents (BRE) of the failed/nationalised banks analysed in this study. Year end 1 'YE 1' is the year prior to bankruptcy onwards to year end 5 'YE 5' which is five years ex ante failure. Anglo Irish Bank is seen to have a decreasing Z" Score from 'YE 5' through to the penultimate year in

'YE 1'. With this the BRE has also decreased from B- in 'YE 5' to D in the year of its collapse. However, it is seen that it had a constant BRE of CCC+ for three years prior to its D- rating.

Banca D'Italia had a dissimilar trend as it's Z" Score took upswings and downswings throughout the five years, varying from a Z" Score of 1.179 to 0.28. The BRE also varied and even showed a positive increase in its BRE a year prior to its bankruptcy. Even so, the Z" Score has kept Banca D'Italia in the distress zone.

Belgian bank Dexia had a very steadily decreasing Z" Score from 2007 through to 2011. The BRE did not converge from the CCC- rating in the four years prior to Dexia's bankruptcy.

Similar to the Irish and Belgian bank, Greek bank Proton was noted to have a degrading Z" score from YE 5 to the year of its demise. Nevertheless, in YE 5 it made a large decrease in Z" Score from 4.806 to 0.266. There was also very little divergence in its BRE from YE 4-YE1 as it degraded from CCC+ to CCC and had this grade till the year of its collapse.

	AIB	**BRE**	**Danske Bank**	**BRE**	**Santander**	**BRE**	**Deutsche Bank**	**BRE**
YE 1	0.581541138	CCC+	3.494825565	A-	0.534706394	CCC+	0.156084062	CCC
YE 2	1.055304576	B-	3.605562769	A	0.402582189	CCC	0.286575594	CCC
YE 3	-0.21490060	CCC-	3.592252973	A-	0.270528183	CCC	0.10477709	CCC
YE 4	0.670081938	CCC+	3.770023354	A+	0.357228169	CCC	-2.67224596	D
YE 5	0.537263374	CCC+	3.445638896	A	0.519940526	CCC+	3.863090325	A+

The second table consists of the Z" Score results for non-failed banks with the accompanying BRE's. And as these banks have not failed 'YE 1' represents the current year and 'YE 5' is the banks Z" Score and BRE five years ago.

In the first column, the Z" Score shows AIB is in a distressed position and continues to be with a slight improvement in YE 2 with an increase in grade to B-. However, this is then offset in 'YE 1' with a large decrease in Z" Score and a degradation to CCC+.

Danish Danske Bank has shown the highest current Z" Score for 'YE 1' compared to the other three peer control banks with a Z" Score of 3.494. It is a consistently stable bank with the BRE ranging from A- to A+ for the five years.

The third control bank analysed is Spanish bank Santander. The Z" Scores show the bank to be in a distressed position with low Z" Scores and low BRE's of CCC and CCC+. It is in quite a similar position to AIB with the same BRE.

The final control bank analysed is German Deutsche Bank. This has had the most variance in relation to Z" Score and BRE. The Z" Score in 2008 was positively high at 3.863 giving Deutsche bank a credit rating of A+, however, the following year left Deutsche bank with a dramatic downgrade to the lowest grade of D. The reason for this was due to Deutsche bank putting risky assets into the CDO. And also put mortgage bonds that its own mortgage department had but couldn't sell. The CDO was marketed as a good product, described as having A level ratings. By 2009, the entire CDO was worthless and all the investors had lost all of their funds. This is reminiscent of the credit rating given to Anglo Irish Bank in its penultimate year before bankruptcy. The following year it quickly regained CCC status and has remained so for the past three years.

Book Value of Equity to Total Liabilities

	Anglo Irish Bank	Banca D'Italia	Dexia	Proton
YE 1	0.042250833	0.044320018	-0.00077467	0.122289865
YE 2	0.018321976	0.070754345	0.019294721	0.156767839
YE 3	0.043904652	0.077805796	0.021193617	0.183978805
YE 4	0.038131392	0.079947271	0.008704841	0.320150712
YE 5	0.131031444	0.428312859	0.027872894	4.244845221

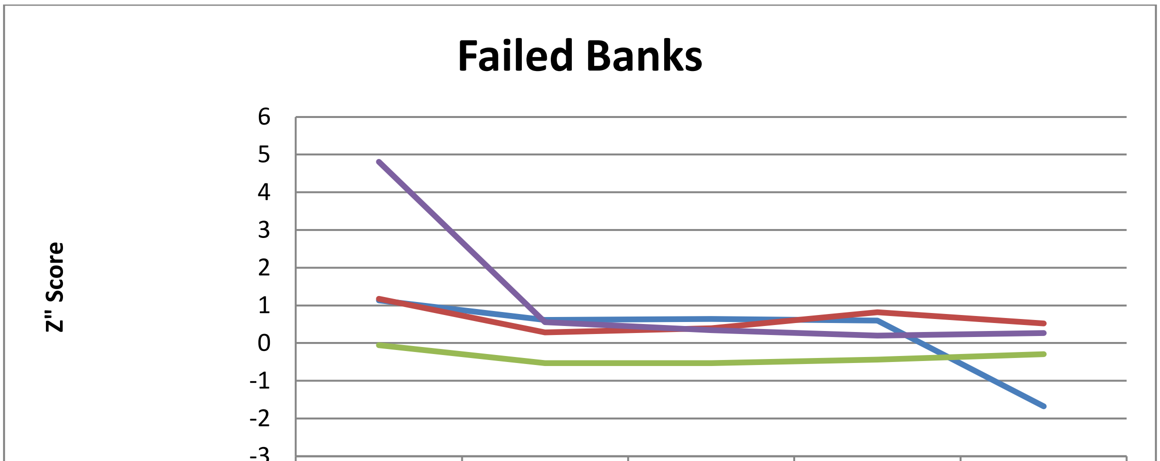
The resulting values for the book value of equity to total liabilities ratio appeared to show a decrease from 'YE 1' to 'YE 5'. This showed true for Banca D'Italia, Dexia and Proton but with some variance for Anglo Irish Bank.

Looking at the table below showing the book value of equity to total liabilities values, there is a slight improvement for Danske, Santander and Deutsche Bank, with a minor deviation for AIB which slightly decreased for 'YE 1'.

Perhaps even more significant, the book value of equity to total liabilities ratio is showing a negatively correlated trend between these two data sets as the BVE/Tl ratio is shown to decrease for the failed banks and the BVE/TL is shown to increase for the control banks.

	AIB	Danske Bank	Santander	Deutsche Bank
YE 1	0.101019996	0.04130152	0.071143	0.0205791
YE 2	0.118366779	0.038154667	0.0709	0.0185223
YE 3	0.030871778	0.033688372	0.071191	0.0212326
YE 4	0.069548838	0.033577422	0.071258	0.0150172
YE 5	0.059827419	0.028512706	0.060631	0.0093922

V. Discussion

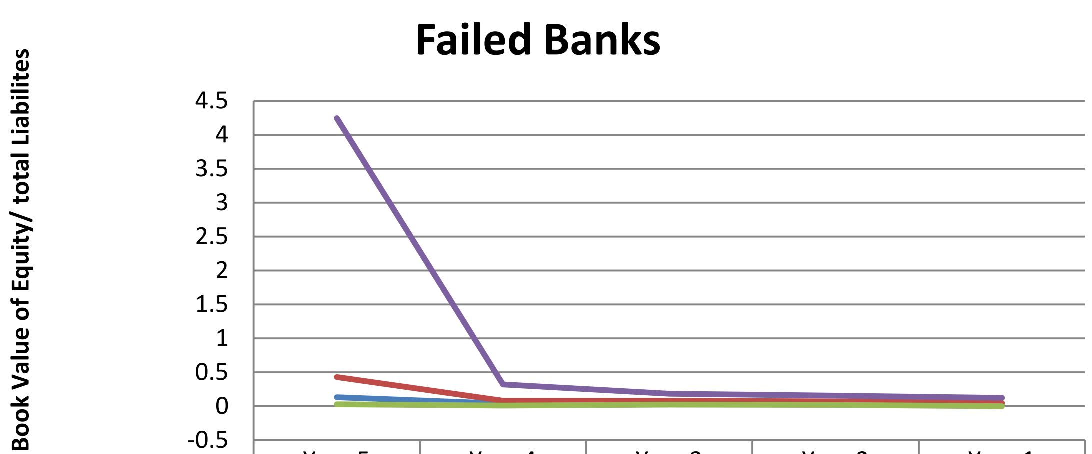


	YE 5	YE 4	YE 3	YE 2	YE 1
Anglo Irish Bank	1.13	0.612	0.642	0.596	-1.677
Banca Di Italia	1.179	0.281	0.394	0.820	0.521
Dexia	-0.055	-0.535	-0.527	-0.434	-0.291
Proton	4.806	0.552	0.34	0.197	0.266

From the above graph you can see Anglo Irish Bank was already showing distress signals between ‘YE 5’ and ‘YE 4’. It had taken a deep plunge from a Z” Score of 1.13 to .612. This trend is very similar to Dexia in the same ‘YE 5’ to ‘YE 4’ in the lead up to their collapse. Considering a Z” Score of less than 1.81 signals insolvency, Anglo Irish Bank and Dexia were already very much on the road to bankruptcy. This shows the Z” Score could predict a high risk of bankruptcy five years prior to collapse. The trend between ‘YE 4’ and ‘YE 3’ are again quite similar between Dexia and Anglo Irish bank as their Z” Score remains quite constant. However, in ‘YE 2’ to ‘YE 1’ Anglo Irish Bank makes a very steep fall with a Z” Score of -1.667. From this data you can see the Z” Score made an accurate prediction in the five year lead to the demise of Anglo Irish Bank. On the other hand, Dexia was already deemed with a high level risk of bankruptcy from ‘YE 5’. Dexia’s Z” Score improved slightly from -.434 to -.291 in the penultimate year of its bankruptcy.

The three banks Banca D'Italia, Proton and Dexia converged very closely in 'YE 1'. Which can be seen later on in relation the their Book value of equity to total liabilities ratio results.

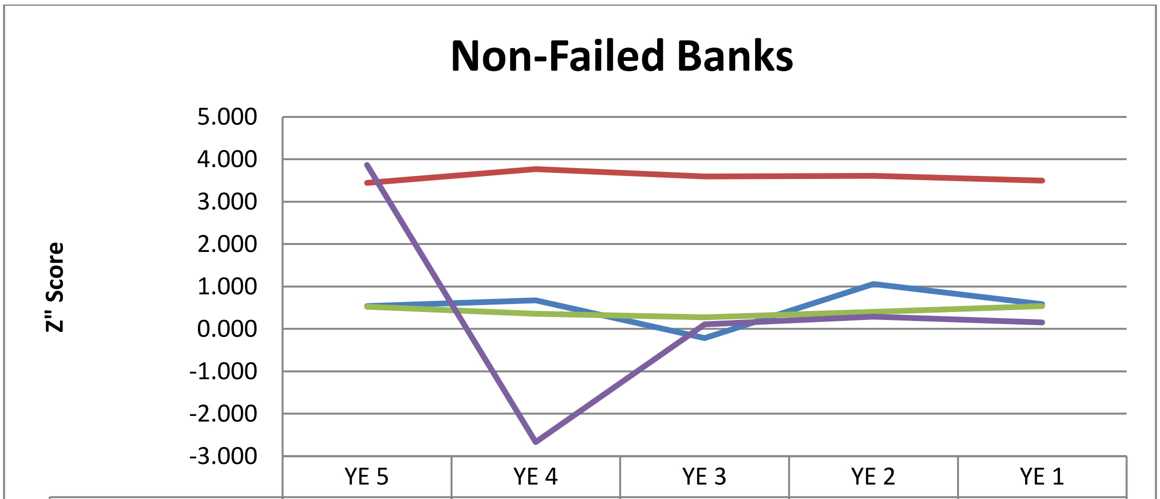
From 'YE 5', or five years before the collapse of the failed banks, the Z" Scores already depicted these banks in the distress zone. This is a 100% bankruptcy prediction value from 'YE 5', which even over predicts Altman's Italian bank study in which '72.3% were classified in the distress zone' five years before bankruptcy (Altman et al, 2013:132). Altman's results suggests that the Z-Score is an accurate forecaster of bankruptcy up to two years prior to distress and that accuracy diminishes substantially as the lead time increases. Nevertheless, the trend towards bankruptcy can be seen straight away from 'YE 5' on the graph using the Z" Score results of the failed banks.



	Year 5	Year 4	Year 3	Year 2	Year 1
Anglo Irish Bank	0.131	0.038	0.044	0.018	0.042
Banca Di Italia	0.428	0.080	0.078	0.071	0.044
Dexia	0.027	0.008	0.021	0.019	-0.001
Proton	4.244	0.32	0.183	0.156	0.122

The Z" Score encompasses four ratios to give the best prediction of corporate failure. However, the ratio 'book value of Equity to total liabilities'(BVE/TL) also appears to give quite accurate prediction capabilities in terms of banking failures. As you can see from the graph above there is a declining trend from 'YE 5' to 'YE 1' apart from a slight upturn for

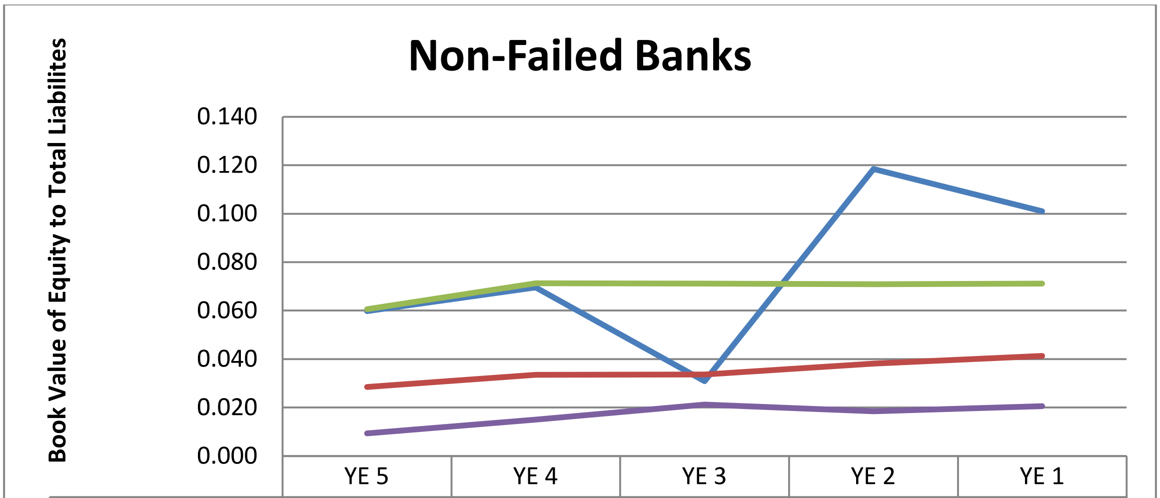
Anglo Irish Bank between ‘YE 2’ and ‘YE 1’. The BVE/TL ratio has displayed considerable bank failure predictive abilities. Like the Z” Score graph, it is also showing very similar trends towards the bank’s failure. All four banks converge between ‘YE 3’ and ‘YE 1’. This movement could suggest the BVE/TL is a significant indicator. Altman (1968) also suggests in his pioneering study that the book value of equity/total liabilities ‘appears to be a more effective predictor of bankruptcy than a similar, more commonly used ratio: Net worth/Total debt’ (Altman, 1968, p.595). It is widely known that a banks debt-to-equity structure affects the probability of insolvency. The results of this ratio have proven it to be a considerable indicator in this analysis.



	YE 5	YE 4	YE 3	YE 2	YE 1
AIB	0.537	0.670	-0.215	1.055	0.582
Danske	3.446	3.770	3.592	3.606	3.495
Santander	0.520	0.357	0.271	0.403	0.535
Deutsche Bank	3.863	-2.672	0.105	0.287	0.156

Above is a graph depicting the Z” Score values of the non-failed banks data set for five years. The trend is divergent compared to the failed-banks data set. There is considerably more variance, with the control banks not converged as much as the trend to its failed counterparts. Straight away, it can be seen Danske has the best Z” Score and has a constant flat progression compared to Deutsche Bank which took a large downswing in 'YE 4'. In 'YE 3', Santander, AIB and Deutsche bank have become intersected, which could be due to sharing the same financial environment. They remain close through to their current period 'YE 1'.

Risk-averse investors utilising this information can evidently see from this graph that perhaps the best bank to trade with would be Danske. Other stakeholders could also benefit from this information as the Z" Score does place Santander, AIB and Deutsche bank in the distress zone.



	YE 5	YE 4	YE 3	YE 2	YE 1
AIB	0.060	0.070	0.031	0.118	0.101
Danske	0.029	0.034	0.034	0.038	0.041
Santander	0.061	0.071	0.071	0.071	0.071
Deustche Bank	0.009	0.015	0.021	0.019	0.021

The graph above again highlights a major difference between the control banks and their failed counterparts. The BVE/TL ratio has shown the control banks to vary from each other and also to have a constant BVE/TL progression apart from a large plummet in 'YE 3' for AIB. The trends are very promising as they convey the BVE/TL ratio to be a valid predictor of corporate failure.

These graphs have emphasised the predictive power of Eurozone bank failures utilizing the Z" Score and the BVE/TL.

Bank (Failed)	**Z"Score (+3.25=BRE) 1 year prior to bankruptcy**	**Bond Rate Equivalent (Standard & Poor Rating)**
Anglo Irish Bank	**-1.677(1.572)**	**D**
Banca Di Italia	**.521(3.77)**	**B-**
Dexia	**-0.291(2.958)**	**CCC**
Proton	**0.266(3.516)**	**CCC+**
Mean	**-0.569(2.680)**	**CCC**
Standard Deviation	**.818**	
Standard Error	**.408**	

Banks(non-distressed)	**Present Z" Score (+3.25, BRE)**	**Bond Rate Equivalent (Standard & Poors Rating)**
AIB	**0.581(3.832)**	**CCC+**
Dankse Bank	**3.495(6.745)**	**A**
Santander	**0.535(3.785)**	**CCC+**
Deutche Bank	**0.156(3.406)**	**CCC**
Mean	**1.192(4.442)**	**B-**
Standard Deviation	**1.547**	
Standard Error	**0.774**	

The mean, standard deviation and standard error were calculated for failed and non failed banks. The results were only calculated on the year before bankruptcy 'YE 1' and the current year for the control banks. The mean Z" Score for the failed banks was -.569 compared to a mean value of 1.192 for the control banks. This shows a large discrimination between the two data sets. Nevertheless, the control banks still have a mean Z" Score of less than 1.81 which implies that they are also currently in the distress zone. The standard deviation for the failed banks was also showed a lot less variation from the mean unlike the control banks. There is a large dispersion within the control banks in relation to their mean. This can be seen straight from the BRE's as two of the banks are 'A' and 'B-'rate whereas the other two banks are

‘CCC’ and ‘CCC+’. The standard error for the failed banks resulted in a smaller error compared to the control banks which suggests the sample of failed banks is more representative of the overall population. This is mainly due to the fact that the control banks are made up of ‘thriving’ and ‘surviving’ banks which causes a large gap in the data collected.

In relation to the BRE’s, there was very little variance to what you might expect. Out of the four failed banks, only Anglo Irish Bank had a BRE of “D” or default status in the entity’s final year. This is 25% of the banks analysed compared to ‘65.9% of the companies’ with a “D” rating in Altman’s study in their final year before bankruptcy (Altman, 2013, p.132).

Benchmarking the failed to the control banks, you can see there are similarities regarding the Z” Scores and BRE’s. Taking Anglo Irish Bank and its most compatible control bank AIB due to size and location, AIB’s present BRE is the same compared to Anglo Irish Bank’s BRE YE 2, two years before its demise. This result is quite significant as it could possibly predict perhaps AIB’s fate is on the path to bankruptcy also considering its predecessor was declared bankrupt a year later. And given the accuracy of the Z” Score it should probably be a one to watch for future problems.

Belgian and French bank Dexia collapsed the same weekend as Proton in November 2011. It is interesting to compare the two Z” Scores and BRE’s as the BRE for Dexia and Proton was shown to be “CCC-“ unstable and “CCC” neutral respectively. This result demonstrates that there is no real difference between an unstable or neutral rating as there is still the possibility a neutral rated bank can also become bankrupt. Keeping this in mind this could have also proven the two may have failed due to interbank contagion.

The failed bank with the highest BRE and Z” Score prior to the year of bankruptcy was Banca D’Italia with grade B- and 0.521 respectively. This is quite a high BRE for the year of collapse considering currently AIB, Santander and Deutsche bank have a lower BRE. Perhaps, a singular BRE or Z” Score is not enough to determine a failure in the year prior, an overall trend or progression needs to be analysed to determine if a bank has possibility of failing.

Danske bank has the leading Z” Score and BRE, with a current grade of “A-” and is currently the only bank analysed in the ‘safe zone’. It has had consistently high Z” scores varying between ‘3.44’ and ‘3.77’ in the past five years. From an investor’s point of view, it would be classed as a financially sound bank to invest in.

The results have predicted the bankruptcy of the failed banks as far back as ‘YE 5’, but it also has classed 75% of the control banks in distress zone also. As indicated by the author (Altman, 1970), the model is not probabilistic but descriptive-comparative. It should be used as a warning device rather than as a definitive prediction tool since the score indicates the proximity of a firm to one group or the other (Teodori, 1989, p.129)

VI. Limitations

No singular model can possibly explain every detail of a corporate failure phenomena. There are many limitations associated with the Z” Score model used in this study. The public information used in the ratio analysis extracted from these failed and ongoing banks financial statements could have been possibly subject to creative accounting or manipulated in some way. There is an inherent problem with accounting data being manipulated as companies’ are motivated by the benefits of concealing failure signals to the public. It has been found in a study that during recession’s companies tend to omit the bad and exaggerate the good. (Tilden & Janes, 2012, p.5) (Altman et al., 2013, p.135). This would greatly affect the results of the Z” Score model and ultimately create void results. As the ratio analysis depends on the accuracy of the financial statements completely.

Another large limitation the Z" Score produces is the fact it is only a valid corporate prediction model five years prior to a firm or banks collapse. This is unfortunate as analysing a banks Z" Score without recession induced stress would have been beneficial. Considering the predictive power is only viable five years prior to bankruptcy, even if the Z" Score forecast the failure at YE 5. This may not give the company enough time to force an organization to review its strategic processes and practices Shukla (1994).

A major limitation utilising the Z" Score and which accompanies most accounting models is the fact is is largely based on historical information. The determination of future results is based on analysing past trends. Moreover, aggregate factors (such as interest rates, FX rates, inflation) in the macro economy can substantially affect the viability of a company. Notwithstanding the use of accounting information as a primary predictor has a major fault lying in its ability to account for uncontrollable macro elements. . The euro area has become particularly prone to volatile stocks and with the ever-deteriorating investor confidence it is a very unpredictable market. Heavily geared companies are non-resilient to the effects emerging from the macroeconomy. Unstable macro variables in the global economy have significant effects on the going concern of euro companies, in particular, SME's. Harsh credit conditions have distressed corporate performance, particularly in the case of financially "distressed companies that are usually small and bank-dependent" (Platt and Platt, 1994). Investor confidence in European markets has greatly eroded due to the uncertainty surrounding the instability of European countries. There are a number of reasons to believe that accounting data-based failure prediction models are sensitive to recession-induced changes in the risk of default and firm failure. First, Rose, Andrews, and Giroux (1982) studied the effect of economic developments on the probability of failure. From an initial listing of 28 business cycle indicators, they applied correlation analysis, leadlag relationships, and stepwise regression to arrive at a failure prediction model consisting of six macroeconomic variables that had an R-squared of 0.912. They concluded that macroeconomic conditions are significant factors in the process of business failure. Second, Kane (1994) found that the associations of accounting data with subsequent abnormal returns are acutely sensitive to the occurrence of recession-associated market valuation periods. Similarly, Lev and Thiagarajan (1993) and Johnson (1993) report that the abnormal return associations of "unexpected" information components of accounting data are sensitive to the business cycle. These studies document that accounting data have information content about stock returns that is conditional across varying stages of the business cycle.

Another limitation to this study was the actual access to information. not only was it difficult to find a list of failed banks but public information required i.e. financial statements in some cases did not exist. A larger sample size would have been more beneficial to the results as it would have given a clearer and more defined picture to verify the validity of the Z" Score as a predictor of bank failures. A larger sample size would have also decreased the standard error.

A limit associated with this analysis is that the data set for failed banks are based on ex post applications, on a sample of companies whose destiny was already known. (Altman et al, 2013, p.132).

The Z" Score model has been proven to have a 100% predictive Eurozone bank failure capability. However, this model may not be as accurate in another industry or non-Euro area institution.

VII. Conclusion

In conclusion, empirical results suggest the Z" Score model is a reliable predictor of Eurozone bank failure within five years prior to bankruptcy. In this study it has predicted 100% of banking failures from five years to the year of their demise. The Z" Scores of the control banks (AIB, Deutsche Bank and Santander) are currently relatively low compared to Danske Bank with a high Z" Score. These low Z" Scores could possibly mean future failures as they are trending the same way as their failed counterparts. It also depicts that the current Eurozone financial climate is harsh and banks are just about surviving.

The Z" Score has predicted the banking failures successfully but a number of factors could suggest that the analysis was somewhat biased considering the fate of the failed banks were already known. Nevertheless, this study was to verify the Z" Score as a valid predictor and it required the data set consist of failed and non-failed banks. The Z" Score is only valid five years prior to bankruptcy, perhaps a model with an increase in predictive capabilities of up to ten years or more would be beneficial to stakeholders.

The Z" Score model used entirely historical results, going forward models should encompass not only accounting but also macro determinants of corporate failure. There is a major dearth of economic literature providing evidence to suggest macroeconomic variables enormously affect a company's going concern. It should be recognised that volatile shocks created in the external environment such as the escalation in oil prices, high exchange rates, tight credit, inflation and high interest rates can have devastating effects on the health of a bank. And it is evident from the recessionary years that "low or negative economic growth occurs during periods of economic stress, which is most devastating to vulnerable entities" (Altman, 1983).

From this study it was perceived that the ratio 'Book value of equity to total liabilities' had significant results to prove it possessed bank failure prediction capabilities .

Further analysis should be carried out on this ratio on a larger sample size to verify if it is itself a valid bank failure predictor.

With the uncertainty surrounding the future of the Eurozone and the common currency, it is an important time to be forward thinking to avoid making poor investment decisions. A bank's deterioration to problem status (or failure) is not an overnight transition but a gradual financial retrogression which can be predicted up to five years using Altman's Z" Score model. The Z" Score has revealed a great predictive power which can be beneficial to many stakeholders.

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Appendix

Financial Statements

Allied Irish Bank

Annual Report 2012:

http://ir2.flife.de/data/allied_irish_banks/igb_html/index.php?bericht_id=1000001&lang=EN G

Annual Report 2011:

http://online.morningstarir.com/ir/aib/ar_2011/ar.jsp

Annual Report 2010:

http://online.hemscottir.com/ir/aib/ar_2010/ar.jsp

Annual Report 2009:

http://online.hemscottir.com/ir/aib/ar_2009/ar.jsp

Annual Report 2008:

http://online.hemscottir.com/ir/aib/ar_2008/ar.jsp

Anglo Irish Bank

Annual Report 2005:

http://www.ibrc.ie/About_us/Financial_information/Archived_reports/Annual_Report_2005.pdf

Annual Report 2009:

http://www.rte.ie/news/2010/0331/angloreport1.pdf

Annual Report 2008:

http://www.ibrc.ie/About_us/Financial_information/Archived_reports/Annual_Report_2008.pdf

Annual Report 2007:

http://www.ibrc.ie/About_us/Financial_information/Archived_reports/Annual_Report_2007.pdf

Annual Report 2006:

http://www.ibrc.ie/About_us/Financial_information/Archived_reports/Annual_Report_2006.pdf

Annual Report 2005:

http://www.ibrc.ie/About_us/Financial_information/Archived_reports/Annual_Report_2005.pdf

Banca D'Italia

Annual Report 2011:

http://www.bancaditalia.it/pubblicazioni/relann/rel11/rel11en/en_rel_2011.pdf

Annual Report 2010:

http://www.bancaditalia.it/pubblicazioni/relann/rel10/rel10en/en_rel_2010.pdf

Annual Report 2009:

http://www.bancaditalia.it/pubblicazioni/relann/rel09/rel09en/en_rel_2009.pdf

Annual Report 2008:

http://www.bancaditalia.it/pubblicazioni/relann/rel08/rel08en/Text%20book_internet.pdf

Annual Report 2007:

http://www.bancaditalia.it/pubblicazioni/relann/rel07/encf07/rel_07_abr_anrep.pdf

Danske Bank

Annual Report 2012:

http://www.danskebank.com/Documents/Publications/AnnualReport-2012.html

Annual Report 2011:

http://www.danskebank.com/en-uk/ir/Documents/2011/Q4/Annualreport-2011-online.pdf

Annual Report 2010:

http://www.danskebank.com/Flash/ePages/Reports/Q42010/Report-UK/index.html

Annual Report 2009:

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Annual Report 2008:

http://www.danskebank.com/en-uk/ir/Documents/2008/Q4/Annualreport2008.pdf

Deutsche Bank

Annual Report 2012:

https://annualreport.deutsche-bank.com/2012/ar/servicepages/welcome.html

Annual Report 2011:

https://www.db.com/ir/en/download/DB_Annual_Report_2011_entire.pdf

Annual Report 2010:

https://www.db.com/ir/en/download/Deutsche_Bank_Annual_Report_2010_entire.pdf

Annual Report 2009:

https://www.db.com/ir/en/download/Annual_Report_2009_entire.pdf

Annual Report 2008:

https://www.db.com/ir/en/download/DB_Annual_Review_2008_entire.pdf

Dexia

Annual Report 2011:

http://www.dexia.com/EN/shareholder_investor/individual_shareholders/publications/Documents/RA_2011_EN.pdf

Annual Report 2010:

http://www.dexia.com/EN/shareholder_investor/individual_shareholders/publications/Documents/annual_report_2010_UK.pdf

Annual Report 2009:

http://www.dexia.com/EN/shareholder_investor/individual_shareholders/publications/Documents/annual_report_2009_UK.pdf

Annual Report 2008:

http://www.dexia.com/EN/shareholder_investor/individual_shareholders/publications/Documents/annual_report_2008_UK.pdf

Annual Report 2007:

http://www.dexia.com/EN/shareholder_investor/individual_shareholders/publications/Documents/annual_report_2007_UK.pdf

Santander

Annual Report 2012:

http://www.santander.com/csgs/StaticBS?ssbinary=true&blobtable=MungoBlobs&blobkey=id&SSURIsscontext=Satellite+Server&blobcol=urldata&SSURIcontainer=Default&SSURIsession=false&blobwhere=1278692235367&blobheader=application%2Fpdf&SSURIapptype=BlobServer

Annual Report 2011:

http://www.santander.com/csgs/StaticBS?ssbinary=true&blobkey=id&SSURIsscontext=Satellite+Server&blobcol=urldata&blobheadervalue0=application%2Fpdf&blobheader=application%2Fpdf&blobheadervalue1=inline%3B+filename%3D588%5C553%5CInforme+anual_ingles.pdf&blobwhere=1278681725312&SSURIsession=false&SSURIapptype=BlobServer&blobtable=MungoBlobs&SSURIcontainer=Default&blobheadername0=content-type&blobheadername1=content-disposition#satellitefragment

Annual Report 2010:

http://www.santander.com/csgs/StaticBS?ssbinary=true&blobkey=id&SSURIsscontext=Satellite+Server&blobcol=urldata&blobheadervalue0=application%2Fpdf&blobheader=application%2Fpdf&blobheadervalue1=inline%3B+filename%3DAnnual+report_ENG%2C3.pdf&blobwhere=1278680670554&SSURIsession=false&SSURIapptype=BlobServer&blobtable=MungoBlobs&SSURIcontainer=Default&blobheadername0=content-type&blobheadername1=content-disposition#satellitefragment

Annual Report 2009:

http://www.santander.com/csgs/StaticBS?ssbinary=true&blobkey=id&SSURIsscontext=Satellite+Server&blobcol=urldata&blobheadervalue0=application%2Fpdf&blobheader=application%2Fpdf&blobheadervalue1=inline%3B+filename%3DInforme+anual_ENG.pdf&blobwhere=1278680652317&SSURIsession=false&SSURIapptype=BlobServer&blobtable=MungoBlobs&SSURIcontainer=Default&blobheadername0=content-type&blobheadername1=content-disposition#satellitefragment

Annual Report 2008:

http://www.santander.com/csgs/StaticBS?ssbinary=true&blobkey=id&SSURIsscontext=Satellite+Server&blobcol=urldata&blobheadervalue0=application%2Fpdf&blobheader=application%2Fpdf&blobheadervalue1=inline%3B+filename%3D01+SAN_AnnualReport_Complete_WEB.pdf&blobwhere=1278680481513&SSURIsession=false&SSURIapptype=BlobServer&blobtable=MungoBlobs&SSURIcontainer=Default&blobheadername0=content-type&blobheadername1=content-disposition#satellitefragment

Proton

Annual Report 2009:

https://www.proton.gr/uploaded/downloads/6M_FEK_ENGLISH.pdf

Annual Report 2008:

http://www.athex.gr/content/gr/companies/listedco/annualreports/files/00950_2008_EN.PDF

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Annual Report 2006:

https://www.proton.gr/uploaded/downloads/Proton_Bank_Eng_12M_2006.pdf

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Z" Score Model Excel Workings (See disc attached for files)

AIB

AIB 2008-2012								
				CA	**CL**	**TA**	**X,**	
X,: Working Capital/Total Asset			**YE 2012**	14463	5301	122516	0.074782	
			YE 2011	16600	5123	136651	0.083988	
			YE 2010	13200	8383	145222	0.03317	
			YE 2009	21283	9493	174314	0.067637	
			YE 2008	18105	9286	182143	0.048418	
				RE	**TA**		**X2**	
X2: Retained Earnings/Total As			**YE 2012**	3145	122516		0.02567	
			YE 2011	4367	136651		0.031957	
			YE 2010	330	145222		0.002272	
			YE 2009	330	174314		0.001893	
			YE 2008	698	182143		0.003832	
X3: EBIT/Total Assets								
				OR	**OE**	**Non-operating in**	**EBIT**	**X3**
			YE 2012	621	1,937	485	-1,801	-0.0147
			YE 2011	4340	1720	2990	5610	0.041053
			YE 2010	3357	1649	5201	-10207	-0.07029
			YE 2009	4106	1522	1234	3818	0.021903
			YE 2008	5068	2357	1201	3912	0.021478
X4: Book Value Equity/Total liabilities								
				BVE(TA-TL)	**TL**	**X4**		
			YE 2012	11241	111,275	0.101019996		
			YE 2011	14,463	122,188	0.118366779		
			YE 2010	4349	140,873	0.030871778		
			YE 2009	11335	162,979	0.069548838		
			YE 2008	10282	171861	0.059827419		
			3.25					
			Z" = 6.56X, + 3.26X2 + 6.72X3 + 1.05x4			**Addition 3.25**		
			Z'' YE 2012	0.581541138		3.831541138		
			Z''YE 2011	1.055304576		4.305304576		
			Z''YE 2010	-0.214900604		3.035099396		
			Z"YE 2009	0.670081938		3.920081938		
			Z"YE 2008	0.537263374		3.787263374		

Anglo Irish Bank

ANGLO IRISH BANK 2005-2009								
				CA	**CL**	**TA**	**X,**	
X,: Working Capital/Total Assets			**YE 2009**	54175	86885	92851	-0.35228	
			YE 2008	102053	96495	103166	0.053874	
			YE 2007	90019	84270	96652	0.059481	
			YE 2006	70385	66077	73290	0.05878	
			YE 2005	6810.8	956.7	48263.6	0.121294	
				RE	**TA**		**X2**	
X2: Retained Earnings/Total Assets			**YE 2009**	9258	92851		0.099708	
			YE 2008	3389	101321		0.033448	
			YE 2007	2883	96652		0.029829	
			YE 2006	1971	73290		0.026893	
			YE 2005	399.6	48263.6		0.00828	
X3: EBIT/Total Assets								
				OR	**OE**	**Non-operating income**	**EBIT**	**X3**
			YE 2009	2774	380	1,249	3,643	0.039235
			YE 2008	1972	328	84	1728	0.017055
			YE 2007	1761	393	195	1563	0.01617
			YE 2006	1240	328	171	1083	0.01477
			YE 2005	977	291.8	21.8	1247	0.02583
X4: Book Value Equity/Total liabilities								
				BVE(TA-TL)	**TL**	**X4**		
			YE 2009	3764	89087	0.042250833		
			YE 2008	1823	99,498	0.018321976		
			YE 2007	4065	92587	0.043904652		
			YE 2006	2692	70598	0.038131392		
			YE 2005	5591.4	42672.2	0.131031444		
		BRE Constant	**3.25**					
			Z" = 6.56X, + 3.26X2 + 6.72X3 + 1.05x4			**Addition 3.25**		
			Z'' YE 2009	-1.67791813		1.57208187		
			Z''YE 2008	0.596302337		3.846302337		
			Z''YE 2007	0.642211501		3.892211501		
			Z"YE 2006	0.612608571		3.862608571		
			Z"YE 2005	1.133891456		4.383891456		

Banca D’Italia

Banca D'Italia 2007-2011						
		CA	**CL**	**TA**	**X,**	
X,: Working Capital/Total Asset	**YE 2011**	49,297	19,932	538,978	0.0545	
	YE 2010	47,485	18,862	332,961	0.0860	
	YE 2009	49,688	44,611	301,256	0.0169	
	YE 2008	45,700	46,331	267,431	-0.0024	
	YE 2007	88,683	61,032	324,200	0.0853	
		RE	**TA**		**X2**	
X2: Retained Earnings/Total As	**YE 2011**	21,744	538,978		0.040343796	
	YE 2010	21,149	332,961		0.063518719	
	YE 2009	20,079	301,256		0.066649823	
	YE 2008	19,622	267,431		0.073373115	
	YE 2007	17,300	324,200		0.053361641	
X3: EBIT/Total Assets						
		OR	**OE**	**Non-operating**	**EBIT**	**X3**
	YE 2011	590	1,863	109	-1,163	-0.00216
	YE 2010	613	1921	73	-1235	-0.00371
	YE 2009	1,249	2005	71	-685	-0.00227
	YE 2008	907	2,049	77	-1065	-0.00398
	YE 2007	1403	1687	62	-222	-0.00069
X4: Book Value Equity/Total liabilities						
		BVE(TA-TL)	**TL**	**X4**		
	YE 2011	22,874	516,104	0.044320018		
	YE 2010	22,002	310,959	0.070754345		
	YE 2009	21,747	279,509	0.077805796		
	YE 2008	19,798	247,633	0.079947271		
	YE 2007	97,219	226,981	0.428312859		
	3.25					
	Z" = 6.56X, + 3.26X2 + 6.72X3 + 1.05x4			**Addition 3.25**		
	Z'' YE 2011	0.520948689		3.770948689	B-	
	Z''YE 2010	0.820345294		4.070345294	CCC+	
	Z''YE 2009	0.39423437		3.64423437	CCC	
	Z"YE 2008	0.280897174		3.530897174	CCC	
	Z"YE 2007	1.178578682		4.428578682	B-	

Danske Bank

Danske Bank 2008-2011								
				CA	**CL**	**TA**	**X,**	
X,: Working Capital/Total Asset			**YE 2012**	2,016,010	204795	3485181	0.51969037	
			YE 2011	2027953	184668	3424403	0.53827923	
			YE 2010	1928860	207880	3213886	0.53548259	
			YE 2009	1923319	190970	3098477	0.55909694	
			YE 2008	1991135	167893	3543974	0.51446258	
				RE	**TA**		**X2**	
X2: Retained Earnings/Total As			**YE 2012**	1723	3485181		0.00049438	
			YE 2011	276	3424403		8.0598E-05	
			YE 2010	1713	3213886		0.000533	
			YE 2009	1036	3098477		0.00033436	
			YE 2008	14,870	3543974		0.00419585	
X3: EBIT/Total Assets								
				OR	**OE**	**Non-operating income**	**EBIT**	**X3**
			YE 2012	47685	26,588	0	21,097	0.006053
			YE 2011	43377	25987	0	17390	0.005078
			YE 2010	46,277	26010	0	20,267	0.006306
			YE 2009	59339	28907	0	30432	0.009822
			YE 2008	43043	28726	0	14317	0.00404
X4: Book Value Equity/Total liabilities								
				BVE(TA-TL)	**TL**	**X4**		
			YE 2012	138234	3,346,947	0.04130152		
			YE 2011	125,855	3,298,548	0.038154667		
			YE 2010	104,742	3,109,144	0.033688372		
			YE 2009	100,659	2,997,818	0.033577422		
			YE 2008	98,247	3445727	0.028512706		
			3.25					
			Z" = 6.56X, + 3.26X2 + 6.72X3 + 1.05x4				**Addition 3.25**	
			Z'' YE 2012	3.494825565			6.74482557	
			Z''YE 2011	3.605562769			6.85556277	
			Z''YE 2010	3.592252973			6.84225297	
			Z"YE 2009	3.770023354			7.02002335	
			Z"YE 2008	3.445638896			6.6956389	

Deutsche Bank

Deutche Bank 2008-2012								
				CA	**CL**	**TA**	**X,**	
X,: Working Capital/Total Asset			**YE 2012**	80204	45582	1723459	0.020089	
			YE 2011	117985	44004	1869074	0.039582	
			YE 2010	69253	48918	1620164	0.012551	
			YE 2009	673149	1303710	1,538,623	-0.40982	
			YE 2008	1349904	30117	2,250,665	0.586399	
				RE	**TA**		**X2**	
X2: Retained Earnings/Total As			**YE 2012**	6114	1723459		0.003548	
			YE 2011	5434	1869074		0.002907	
			YE 2010	5144	1620164		0.003175	
			YE 2009	4420	1538623		0.002873	
			YE 2008	4080	2250665		0.001813	
X3: EBIT/Total Assets								
				OR	**OE**	**Non-opera**	**EBIT**	**X3**
			YE 2012	2553	4,828		-2,275	-0.00132
			YE 2011	4544	5102		-558	-0.0003
			YE 2010	2344	4804		-2,460	-0.00152
			YE 2009	804	2853		-2,049	-0.00133
			YE 2008	2,123	1,941		182	8.09E-05
X4: Book Value Equity/Total liabilities								
				BVE(TA-TL)	**TL**	**X4**		
			YE 2012	34,752	1,688,707	0.0205791		
			YE 2011	33,990	1,835,084	0.0185223		
			YE 2010	33,685	1,586,479	0.0212326		
			YE 2009	22,764	1,515,859	0.0150172		
			YE 2008	20,942	2,229,723	0.0093922		
			3.25					
	3.25		**Z" = 6.56X, + 3.26X2 + 6.72X3 + 1.05x4**			**Addition 3.25**		
	3.25		**Z'' YE 2012**	0.156084062		3.4060841		
	3.25		**Z''YE 2011**	0.286575594		3.5365756		
	3.25		**Z''YE 2010**	0.10477709		3.3547771		
	3.25		**Z"YE 2009**	-2.67224596		0.577754		
	3.25		**Z"YE 2008**	3.863090325		7.1130903		

Dexia

DEXIA 2007-2011								
				CA	CL	TA	X,	
X,: Working Capital/Total Assets			YE 2011	52,231	65193	412759	-0.0314	
			YE 2010	61850	99830	566735	-0.06702	
			YE 2009	54914	103571	577630	-0.08424	
			YE 2008	70449	123657	645388	-0.08244	
			YE 2007	69376	79002	604564	-0.01592	
				RE	TA		X2	
X2: Retained Earnings/Total Asse			YE 2011	965	412759		0.002338	
			YE 2010	-3,548	566735		-0.00626	
			YE 2009	-4,194	577630		-0.00726	
			YE 2008	-870	651,006		-0.00134	
			YE 2007	-1,951	604564		-0.00323	
X3: EBIT/Total Assets								
				OR	OE	Non-operating	EBIT	X3
			YE 2011	-4,383	1,114	-161	-5,658	-0.01371
			YE 2010	1562	1,136	56	482	0.00085
			YE 2009	6163	3607	-314	2,242	0.003881
			YE 2008	3556	4119	629	66	0.000101
			YE 2007	6896	3834	-256	2,806	0.004641
X4: Book Value Equity/Total liabilities								
				BVE(TA-TL)	TL	X4		
			YE 2011	-320	413,079	-0.00077467		
			YE 2010	10,728	556,007	0.019294721		
			YE 2009	11,988	565,642	0.021193617		
			YE 2008	5,618	645,388	0.008704841		
			YE 2007	16,394	588170	0.027872894		
			3.25					
			Z" = 6.56X, + 3.26X2 + 6.72X3 + 1.05x4			Addition 3.25		
			Z'' YE 2011	-0.291313623		2.958686377		
			Z''YE 2010	-0.434055593		2.815944407		
			Z''YE 2009	-0.527919165		2.722080835		
			Z"YE 2008	-0.535364171		2.714635829		
			Z"YE 2007	-0.054513673		3.195486327		

Proton

Proton 2005-2009								
				CA	**CL**	**TA**	**X,**	
X,: Working Capital/Total Asset			**YE 2009**	131.086	65.939	2904.402	0.02243	
			YE 2008	101.016	63.058	1979.807	0.019173	
			YE 2007	82.497	69.299	2,365.43	0.00558	
			YE 2006	73.558	68.705	1,586.50	0.003059	
			YE 2005	60.883	55.24	290.234	0.019443	
				RE	**TA**		**X2**	
X2: Retained Earnings/Total As			**YE 2009**	-40.892	2904.402		-0.01408	
			YE 2008	-56.2	1979.807		-0.02839	
			YE 2007	18.579	2365.431		0.007854	
			YE 2006	16.612	1586.503		0.010471	
			YE 2005	-6.172	290.234		-0.02127	
X3: EBIT/Total Assets								
				OR	**OE**	**Non-operating ir**	**EBIT**	**X3**
			YE 2009	79.634	-66.743	3.1100	16.0010	0.005509
			YE 2008	45.199	-45.262	0.0000	-0.0630	-3.2E-05
			YE 2007	94.23	-64.156	0.0000	30.0780	0.012716
			YE 2006	65.183	-27.094	0.0000	38.0890	0.024008
			YE 2005	21.284	-8.723	0.0000	12.5610	0.043279
X4: Book Value Equity/Total liabilities								
				BVE(TA-TL)	**TL**	**X4**		
			YE 2009	316.477	2587.925	0.122289865		
			YE 2008	268.308	1,711.50	0.156767839		
			YE 2007	367.565	1997.866	0.183978805		
			YE 2006	384.744	1201.759	0.320150712		
			YE 2005	234.897	55.337	4.244845221		
			3.25		sale of proton in 2009			
			Z" = 6.56X, + 3.26X2 + 6.72X3 + 1.05x4			**Addition 3.25**		
			Z'' YE 2009	0.266671417		3.516671417	CCC	
			Z''YE 2008	0.197624157		3.447624157	CCC	
			Z''YE 2007	0.340833957		3.590833957	CCC	
			Z"YE 2006	0.551694481		3.801694481	CCC+	
			Z"YE 2005	4.80614128		8.05614128	AA	

Santander

Santander 2008-2012								
				CA	**CL**	**TA**	**X,**	
X,: Working Capital/Total Asset			**YE 2012**	131,359	57684	1269628	0.058029	
			YE 2011	117700	71402	1251526	0.036993	
			YE 2010	98443	77385	1217501	0.017296	
			YE 2009	123935	111473	1110529	0.011222	
			YE 2008	153215	110917	1049632	0.040298	
				RE	**TA**		**X2**	
X2: Retained Earnings/Total As			**YE 2012**	37153	1269628		0.029263	
			YE 2011	32980	1251526		0.026352	
			YE 2010	28307	1217501		0.02325	
			YE 2009	61071	1110529		0.054993	
			YE 2008	55,707	1049632		0.053073	
X3: EBIT/Total Assets								
				OR	**OE**	**Non-oper**	**EBIT**	**X3**
			YE 2012	3,908	-6,585	-575	-3,252	-0.00256
			YE 2011	9,719	-8,032	-1,776	-89	-7.1E-05
			YE 2010	12,278	-8,089	-2,923	1,266	0.00104
			YE 2009	22,960	-16,421	-1,311	5,228	0.004708
			YE 2008	18,540	-14,949	-426	3,165	0.003015
X4: Book Value Equity/Total liabilities								
				BVE(TA-TL)	**TL**	**X4**		
			YE 2012	84,326	1,185,302	0.071143		
			YE 2011	82,859	1,168,667	0.0709		
			YE 2010	80,915	1,136,586	0.071191		
			YE 2009	73,870	1,036,659	0.071258		
			YE 2008	60,002	989,630	0.060631		
			3.25					
			Z" = 6.56X, + 3.26X2 + 6.72X3 + 1.05x4				**Addition 3.25**	
			Z'' YE 2012	0.534706394			3.784706	
			Z''YE 2011	0.402582189			3.652582	
			Z''YE 2010	0.270528183			3.520528	
			Z"YE 2009	0.357228169			3.607228	
			Z"YE 2008	0.519940526			3.769941	

Statistics

Data set 1		**Data Set 2**	
Failed Bank	**Z"Score**	**Banks (not Failed)**	**Z"Score**
Anglo Irish Bank	-1.67792	AIB	0.581541
Banca Di Italia	-0.57559	Danske Bank	3.494826
Dexia	-0.29131	Santander	0.534706
Proton	0.266671	Deutche Bank	0.156084
Mean	-0.56954		1.191789
Standard Deviation	0.817557		1.547129
Standard Error	0.408778		0.773564