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Bankruptcy Prediction of Industrial Industry in the UK

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Abstract

We make comparison between 6 models including (1) Altman's (1968) z-score; (2) Model 1: z-score model with adjusted coefficients; (3) Model 2: z-score model with modified variables; (4) Model 3: dynamic logic model; (5) Merton distance to default (DD) model (Bharath & Shumway, 2008) and (6) back-propagation network model (Lippman, 1987). We assess the relative information content of these models regarding their bankruptcy prediction capability. Our tests show that dynamic logic model and DD model both provide significantly more information than the others while DD model has the highest prediction accuracy in the out of sample test. It is also worth noticing that altering coefficients and adjusting variables of the original z-score model could not significantly improve the predictive power of z-score model regarding companies in the industrial industry in the UK.

Keywords: Bankruptcy, Altman, Z-score, Dynamic Logic Model, DD Model, Back-propagation network model

INTRODUCTION

Financial distress, also known as financial crisis is the major reason that leads to corporate bankruptcy. However, financial distress and financial bankruptcy are two different financial concepts where financial distress is more of a dynamic process. Excluding unpredictable external environmental factors, most companies will experience financial difficulties prior to bankruptcy with their initially healthy financial situation gradually deteriorated throughout the years. This kind of financial plight of enterprises often come with an omen and could be predictable. Accurately predicting such distress risk could therefore (Charalambous et al., 2000):

1. Protects the interests of investors as shareholders often have the lowest rank in redeeming their investments when companies went bankrupt. If

- investors could obtain prior information regarding the probability of bankruptcy, they could even make positive return by short selling the stocks or by means of other derivative instruments;
2. Gives assistance to creditors when conducting loan appraisals and screens out companies with bankruptcy risk higher than a certain level. It can also be utilized as a periodical assessment in adjusting the required return of loans in order to compensate the corresponding financial distress risk;
 3. Assists the Government in determining and monitoring the quality of listed companies and securities market risk;
 4. Contributes to company's business related decisions. Companies could then keep track of the financial distress risk of its vendors and suppliers in order to ensure a stable supply chain. Companies can also look for other alternative sources of supply in advance once they realize a dramatic increase in bankruptcy risk;
 5. Assists staff in assessing the business situation of the firm they belongs to and act as a warning signal in case of bankruptcy.

However, it is also noticeable that not all companies that experienced financial distress will go bankrupt. Instead, some of the financial distressed firms become financially healthy again by means of restructuring (Charitou et al., 2004). It is therefore of interest that what are some of the factors that play a key role in curing these companies and what measures are the most effective to save them from a financial distress situation. Understanding these factors could then be a reliable measure for management to prevent financial crisis.

Considering financial distress risk in investment purpose, when investors consider a possible investment, it is a norm to consider both risk and return. However, compare to the numerous researches on valuation of firms and equities, there are rather few researches focusing on the methodology to compute the amount of risk, especially when it comes to financial distress risk or probability of bankruptcy. Among the limited amount of existing models, they are also often being criticized to be not sufficiently accurate enough or vulnerable to management manipulations (Aziz & Humayon, 2006). An accurate model is therefore in demand aiming to reduce the possibility of tremendous loss in case of bankruptcy. Over the years, three mainstream financial distress prediction models have been developed: (1) Z-Score model with utilization of traditional accounting information (Altman, 1968); (2) Contingent Claims Model with computations based on market information (Merton 1974); (3) Hazard model with considerations of both accounting and market information in order to predict financial difficulties of enterprises.

Among the three models, Contingent Claims Model was developed by Black & Scholes (1973) and Merton (1974) with their option pricing theory. Their model was then improved as Moody's KMV model (Bharath & Shumway, 2008) and this type of models are often referred as the Merton DD model (Merton default to distance model). Bharath & Shumway (2008) made the following two conclusions regarding DD model: (1)The function used in the Merton DD model

is the most crucial concept in this default prediction model; (2) Traditional Merton DD model could be difficult to calculate but a simplified form of the model, Naïve DD model could have the same or even higher accuracy of prediction but with a relatively simpler calculation process.

In view of the above situation, this paper aims to test the predictive power of (1) traditional Z-score model; (2) traditional naive DD model; (3) model 1 with same variables as Z-score model but with new coefficients; (4) model 2 with all new coefficient and new variables; (5) model 3 dynamic logic model and (6) a more recent development, neutral network analysis, back-propagation network model (BPNN) in the field of industrial industry in the UK. Comparing these six models, the most suitable model with the highest predictive power for the industry will then be identified. Finally, a new model based on Z-score will be proposed for future related investigation, which will be included in the appendix. As prediction and management of enterprise financial distress risk becoming an increasingly important part in business, investment and lending decisions (Beaver et al., 2011), this paper should be of interest to shareholders, creditors and even company employees when considering the risk of bankruptcy.

Major contribution of this article is to (1) applies and compares 6 models (classic Z-score model, naive DD model, model 1, model 2, model 3 and BPNN model) to 700 companies within the industrial industry in the UK; (2) identify the relative strength and weaknesses of these models; (3) investigates 10 financial indicators of financial distress prediction by stepwise discriminant analysis and suggest the potentially best model for the industry; (4) makes suggestion on an innovative concept and a potential model which has not been published in any paper before.

The later part of this paper is organized as follows: Section 2 will deliver lecture review; Section 3 will describe the method of data acquisition; Section 4 will disclose the methodologies and logic behind different models; Section 5 will conclude the results and make comparison between models; Section 6 will discuss the limitations and suggestions.

LITERATURE REVIEW

Traditional accounting ratio based models - Multiple discriminant analysis (MDA)

It is generally considered that Beaver (1966) was the first to use univariate analysis to predict business failure back in 1966. By then, base on the researches of Beaver, Altman (1968) incorporated the multiple discriminant analysis (MDA) method into financial distress prediction and established the well known Z-Score model. This methodology is known as the classical statistical model which utilize accounting ratios to make predictions.

In the early 80s, MDA was then gradually replaced by qualitative response model. In particular, Ohlson (1980) set a precedent by creating the Logit failure prediction method in enterprise applications while Zmijewski (1984) put forward

the Probit analysis method aiming to predict bankruptcy more accurately. These were considered to be the second generation of empirical research. Until now, Altman's (1968) Z-Score model and Ohlson's (1980) Logit model are still widely recognized as a baseline method which are frequently used in academic research (Altman & Narayanan, 1977).

One of the strongest strengths of these traditional accounting ratio based models is their simplicity as a linear function (Taffler, 1983). Since the equations are mainly composed of accounting ratios of different companies, these components could be obtained with ease and are relatively simple in calculation. The simplicity of the algorithm brought also high level of self explanatory power to the model since the resulting score could be traced back directly to the accounting ratio component of the formula. While these models are widely used, they are often being criticized by scholars due to absence of theoretical foundation. Hillegeist et al. (2004) pointed out that data in financial statement are mostly historical and are computed on the basis of ongoing concern. If one is to estimate the risk of bankruptcy, which is a violation of ongoing concern, the model would be inherit with fundamental defect. Agarwal & Taffler (2008) also pointed out that most traditional models were built based on sample period analysis which means the coefficients in the existing models could have been different if given different sample period. It is also worth noticing that some of the inherent characteristics of the financial statements could reduce the effectiveness of accounting ratio models: (1) Financial statements reflect a company's past performance and thus future failure prediction may not be timely; (2) the conservatism principle and historical cost accounting could cause the real value of assets to be different from the book value that are being recorded; (3) Accounting data are vulnerable to earnings management. Furthermore, as stated by Zmijewski (1984), accounting ratio models are biased since bankrupted firms are often over-sampled during the process of modeling business. As a consequence, in order to maintain the predictive power of the model, it would be necessary to rebuild the model over time on a regular basis (Cui, 2014).

Probit Model and Logit model

Since MDA model is subjected to statistical assumptions and preconditions, multivariate conditional probability model is therefore introduced by researchers and is claim to be capable of overcoming these limitations. This type of model estimates its parameters by utilizing maximum likelihood estimation method. Two of the most utilized models are Probit model and Logit model. Probit model estimates probability of default by assuming normal distribution and convert the data with probability density function while Logit model has almost the same idea as Probit model but utilize logistic variables in the probability density function (Balcaen & Ooghe, 2006).

Logistic model method is first used by Ohlson (1980) in predicting corporate financial distress. The sample used by Ohlson consists of 105 bankrupted firms and 2058 active firms randomly drawn in the period between 1970 to 1976 in

the US market. The 9 predictor variables in each of the firms provided the study with prediction accuracy of more than 92%

This type of model not only overcome some of the many weaknesses of linear probability model, studies pointed out that this model is also with a high predictive capability (Peel et al., 1986). Logit model then gradually became one of the baseline methods in a significant number of researches regarding financial distress risk. Early warning system of commercial banks is one of the examples that was developed based on Logit model with factor analysis in the selection process of appropriate financial ratios as predictor variables. These variables then compute the relative scores of distress risk and act as financial indicator of firms. Quality of assets is then found by Logit model to be one of the factors that plays a crucial role in determining financial quality of banks (Keasey and Watson, 1986). It also hinted the possibility of combining traditional factor analysis with Logit model.

Dynamic logit models - Hazard models

Ever since the creation of Logit model, many researches adopted the same approach and predict financial distress risk with such static Logit model, see papers from Ohlson (1980), Zmijewski (1984) and Ward (1994). These studies construct their models with a single period of company data observation and forecast the probability of financial crisis. However, using only one set of observation for each company can cause bias as it failed to observe the factors that change over time and thus ignore cross-sectional data correlation. According to Beck, Katz and Tucker (1998), such ignorance of cross-sectional relevance may underestimate the standard error of Logit model and produce sampling bias.

To overcome the disadvantages of these single-phase model, some studies have chosen to construct dynamic model for financial crisis prediction analysis. Shumway (2001) constructed one of the earliest representative models, discrete time VaR model (discrete time hazard model) to improve the accuracy of bankruptcy prediction. He also proved that dynamic logit model could estimate parameters that are both unbiased and consistent while those estimations of static logic models are inconsistent and biased. Other than the original way that proposed by Shumway (2001) in estimating the model by standard logic program, recent literature (Chava and Jarrow, 2004) also show more manageable ways to have the estimation computed.

Market based models - Merton Distance to default (DD) Model, Moody's KMV model

Targeting the shortcomings of MDA model and logic model, another form of prediction model (Merton DD model) utilizing contingent claims analysis instead of accounting ratio has been developed to predict corporate financial distress. These models were developed based on option pricing theory proposed by Black & Scholes (1973) and Merton (1974). It defines the possibility of business

failure to be the probability that the value of firm would be less than the book value of liability at maturity date. Since inputs of these models were obtained from the capital market, it is also known as a market based model.

Although MDA and market based models are both sensitive to multicollinearity and are subjected to a series of assumptions and preconditions, market based models are claimed to outperform MDA in a number of aspects. According to Agarwal & Taffler (2008), market based models overcame some of the fundamental flaws compared to the traditional models: (1) it is a theoretically reliable model with a solid foundation of BSM model; (2) in an efficient market, stock prices reflect not only the information contained in the financial statements but also market information; (3) input of the model are unlikely to be affected by accounting policies and thus are not as vulnerable to manipulation as accounting ratio model; (4) market prices reflect expectations of future cash flow and therefore are more suitable for prediction purposes; (5) it does not depend heavily on a particular sample period. In practice, Hillegeist et al. (2004), and Duffie et al. (2007) both drawn similar conclusion that market based model provided significantly more information about the probability of bankruptcy than accounting ratio model and thus suggested future research to use BSM model to predict the likelihood of bankruptcy of enterprises.

Moody's KMV model is one of most recognized models developed based on Merton DD model. Kealhofer & Kurbat (2001) pointed out that KMV model captures all traditional rating information and well-known accounting variables as needed while Kurbat & Korablew (2002) also proved the effectiveness of KMV model by utilizing level validation and calibration method. However, KMV model could be difficult to apply and hence could be cost inefficient in some cases. In view of such situation, Bharath & Shumway (2008) proposed a reduced form of Merton DD model, namely naive DD model which is much trouble-free to implement and more cost efficient. They also claimed naive DD model has the same or even better forecasting capabilities to Merton DD model.

Neutral Network Analysis

Neural network is a complex network system composed of numbers of simple processing units which linked to each other. As nonparametric classification method, it (1) overcomes the difficulties in selecting the proper variables for the algorithm and (2) the assumptions are not as strict as in MDA and market based models, ie, the sample no longer have to be restricted in a particular distribution (Atrill & McLaney, 2013). The three most widely recognized neural network analysis for financial distress prediction are namely, back- propagation network (BPNN), probabilistic neural network (PNN) network and learning vector quantization (LVQ).

BPNN is the most widely used neural network in the establishment of financial distress prediction model. It is often composed of three layers: Input layer consists of nodes that are representatives of financial ratios; hidden layer comprises nodes that are determined by empirical trial and error method; output

layer involves only one node which would classify the companies into different groups when comparing the resulting value with a predetermine cutoff value (Iwan, 2005).

PNN classified companies based on mainly the estimated density of each category. When it comes to financial distress prediction, PNN is constructed generally with three layers: Input layer consists of nodes with quantity equal to the number of financial ratios used in modeling; Intermediate layer of nodes equal to the number of samples of the training set; Output layer nodes equal to the number of categories of samples. Compared with BPNN, the advantage of PNN is it has fewer parameters to be estimated, shorter training time and it could output the probability of bankruptcy.

LVQ is a self mapping neural network analysis with supervision as a filter of classification. It allows samples to be inputted according to their classification. LVQ is construed with three layers. Input layer is the first layer with number of nodes equal to the number of financial ratios used while output layer consists of nodes that is correspond to the number of classes that the sample possesses. In contrast to BTNN and PNN, the hidden layer of LVQ classifies input into different category while the output layer is responsible for converting the system defined categories into user-defined categories.

All of these neural network analysis outperform traditional statistical methods in the following ways (Wilson & Chong 1995): the requirement of distribution of the data is not as strict; these models are often with high robustness and adaptability. However, neural network theory lacks a unified mathematical theory and thus it is not as simple in terms of determining the network structure; improving the explanatory model; facing the difficulty of over-learning and the effect of model is not as stable. The computation of the model is also often considered to be in a “black box” as they are computed through computer program in its hidden layer.

To conclude, traditional accounting based models are often utilized as a baseline method to compare with other more recently developed models; dynamic logic models is similar to traditional MDA but takes into account time effect; market based models consider market effect instead of accounting ratios and thus a number of researches claim this method could outperform accounting based models in a number of ways; Neutral network analysis has a slightly more complex calculation stage and its predictive capability is claimed to be the highest in some researches but it is relatively not stable and lacks support of unified mathematical theory.

METHODS

This study aims to examine and compare the predictive power of the following models particularly in the industrial industry, which is listed in the UK. 6 models that are used for performance comparison are as follows:

- (1) Classic Z-score model with ordinary coefficients and variables provided by Z-score. (Based on data that consists of 97 pairs of active and bankrupted firms)
- (2) Model 1: Modifying existing coefficients of the classic model by performing a discriminant analysis. The resulting model would not be a general model that suits all industries; instead it would be a model exclusively useful for the industrial industry. This model will be denoted as Z'-score model in this paper for simplicity. (Based on data that consists of 97 pairs of active and bankrupted firms)
- (3) Model 2: Altering variables of the classic model by considering 10 variables in total using stepwise method. This model will be denoted as Y-score model in this paper for simplicity. (Based on data that consists of 97 pairs of active and bankrupted firms)
- (4) Model 3: Utilizing all 700 companies instead of 97 pairs of companies as the sample and consider again 8 variables in total to build a new model using stepwise method. This model will be denoted as Y'-score model in this paper for simplicity.(based on 700 firms, 7018 observations and 56144 ratios in total)
- (5) DD probability as computed from naive DD model and turned into DD score in order to compare with Z-score. (Based on data that consists of 97 pairs of active and bankrupted firms)
- (6) Back-propagation network (BPNN) model would be constructed and the accuracy of classification result would be used to compare with other models.

The exact methodology is as follows:

- (1) Data within the period of 1989-2008 that are needed to compute both models would be collected to determine which model exhibit a higher predictive power.
- (2) Empirical Tests would be conducted to modify the models in order to improve their forecasting power.
- (3) Z-score model, DD model, Model 1, Model 2 and Model 3 would then be tested with the data in the period 2009-2012 as out-of sample test to verify their effectiveness.

Original Z-score model

The original formula of Z-score model is computed and reported based on the following expression:

$$Z = 0.012X_1 + 0.14X_2 + 0.033X_3 + 0.006X_4 + 0.999X_5 \quad (1)$$

Where,

X₁ = Working capital/Total assets

X₂ = Retained Earnings/Total assets

X₃ = Earnings before interest and taxes/Total assets

X₄ = Market value equity/Book value of total debt

X₅ = Sales/Total assets Z = Overall Score

For which,

Z < 1.8 bankruptcy zone;

1.8 < Z < 2.99 grey zone;

2.99 < Z safe zone

According to further researches of z-score model (Cui, 2014), one has to update the coefficients in the original z-score model depending on different markets and different countries. The updated model, which will be presented as model 1 and model 2 are supposed to have higher prediction capability. Original Z score model in this paper is supposed to have the lowest prediction power and is therefore used as a baseline method for prediction comparison.

Model 1 (Z'-score model)

The objective of model 1 is to alter solely the coefficients of ordinary Z-score model and result in a model that is suitable for the industrial industry. The coefficients are computed to optimize the classification capability of the model based on the 97 pairs of companies.

Resulting formula of Model 1 would be expressed in the following format:

$$Z' = W_1X_1 - W_2X_2 + W_3X_3 + W_4X_4 + W_5X_5 \quad (2)$$

Where,

W_i = Weight of predictor variables X_i X₁ = Working capital/Total assets

X₂ = Retained Earnings/Total assets

X₃ = Earnings before interest and taxes/Total assets

X₄ = Market value equity/Book value of total debt

X₅ = Sales/Total assets

Z' = Overall Score of Model 1

Hypothesis of Model 1

The coefficients of original Z-score model are updated based on the 97 pairs of companies in industrial industry in the UK during the period between 1989 to 2012. These coefficients are therefore not as general as in the original z-score model and thus is expected to exhibit a higher prediction capability (Hillegeist, 2004).

Model 2 (Y-score model, discriminant analysis)

Model 2 aims to predict whether a company would have a certain characteristics to go bankrupt and figure out what are some of the quantitative variables that would help differentiate group membership. We gathered 10 predictor variables that could possibly discriminant why bankrupted firms went bankrupt and why active firms remained active.

The logic behind the model is to identify uncorrelated linear combinations of these predictor variables, which can discriminate companies between group memberships. This is similar to multiple regression and factor analysis in using variables to predict a single outcome that is categorical. In this discriminant model, raw score of each original variable are multiplied by assigned weights and sum together to obtain its discriminant score. These scores would then act as indicators to discriminate companies.

Resulting formula of model 2 is expected to be in the following format:

$$Y\text{-score} = W1X1 + W2X2 + W3X3 + W4X4 + W5X5 + W6X6 + W7X7 + W8X8 + W9X9 + W10X10 \quad (3)$$

The predictor variables are as listed below:

W_i = Weight of predictor variables X_i

X1: WCTTA = Working capital / Total assets

X2: RETTA= Retained Earnings / Total assets

X3: EBITTA = Earnings before interest and taxes / Total assets

X4: ETTD = Market value equity / Book value of total debt

X5: STTA = Sales / Total assets

X6: FFOTTA = Funds from operation / Total assets

X7: CRTTA = (Cash and short term investments + receivables) / Total assets

X8: EBITDATA = Earnings before interest, taxes, depreciation and amortization / Total assets

X9: ETLSSL = Market value equity / (Long term liability + current liability)

X10: SMEDTTA = (Sales - Total debt) / Total assets

Y = Overall Score of Model 2

Predictor variables selection - stepwise method, forward selection (SPSS)

Stepwise method for discriminant analysis would then be utilized to decide on predictor variables that should be retained among all the potential variables. This process is to filter and retain solely those predictors or group of predictors that could significantly contribute to the criterion variable (Sloan, 1996).

Hypothesis of Model 2

Model 2 is inputted initially with 10 predictor variables, including the 5 variables that have been covered by z-score model and Model 1. The new variables are added in order to figure out the best combination that could increase its predictive capability (Cui, 2014). Model 2 is therefore supposed to have a higher predictive accuracy than the previous mentioned models.

Tests to be conducted to compare results between Model 1 and Model 2

There are several tests to be conducted in comparing between Model 1 and Model 2. (1) The significant level of all of the predictor variables would be tested and those with a significant level below 0.05 would be considered as significant; (2) Box's M test will be conducted and if the p-value is higher than 0.05, the model will be considered to have equal variance between the two groups and thus would be following normal distribution (Duffie et al., 2007). However, although the data is assumed to follow a multivariate normal distribution with the variance-covariance matrix of the group, we would not be too concerned with the significant results for this test since discriminant analysis is rather robust against violation of these assumptions; (3) Canonical correlation would be tested which refers to the correlation between the discriminant score and the levels of the dependent variables (McFadden, 1973). The square of the value of canonical correlation could be viewed as a similar indicator as R-squared value. Thus, the higher the value of canonical correlation indicates the function discriminant well between subjects. (4) Wilks' Lambda would be tested where it is a multivariate statistic and is computed as $(1 - \text{canonical correlation}^2)$.

The lower the value of the significance level of Wilks' Lambda, the stronger the models would be and thus would indicate the predictor variables could make predictions at a statistically significant level in terms of accuracy (McFadden, 1973); (5) coefficients of the predictor variables would be computed and the larger the value of the coefficients, the higher the predictive capability of the variable; (6) correlation between the predictor variables would be investigated. With this test, existence of consistency could be claimed if the ranking of the correlation follow a similar trend of the magnitude of the variables coefficients; (7) Chi-square test would be conducted. The null hypothesis of this test is the model being tested (Model 1 and Model 2) relative to a model with no predictors has the same prediction capability. This null hypothesis could be rejected only if the significant level is smaller than 0, which could also prove the models, are significantly effective; (8) Classification test would be conducted where the percentage of type 1 and type 2 error would be identified. Type 1 error refers to those members that should be classified as bankrupt firms but is predicted to be in active group while type 2 error refers to those that should be classified as active forms are predicted to be in bankrupt group. The average value of these error would be computed and the lower the value of error the better the model would be (Deakin, 1972).

Model 3 (Y'-score model, dynamic logit model)

Model 3 is built as a dynamic logit model with the software STATA. The sample used in this model contains 700 companies including 603 active firms and 97 bankrupted firms. Each company will have 8 ratios each year, which are computed, based on data obtained from Bloomberg and Thomson Reuters. The sample thus consists of 7018 data set and therefore 56144 data point in total.

The resulting formula of model 3 is expected to be in the following format:

$$Y'\text{-score} = W1X1 + W2X2 + W3X3 + W4X4 + W5X5 + W6X6 + W7X7 + W8X8 \quad (4)$$

The predictor variables are as listed below:

W_i = Weight of predictor variables X_i

X1: WCTTA = Working capital / Total assets

X2: RETTA= Retained Earnings / Total assets

X3: EBITTA = Earnings before interest and taxes / Total assets

X4: ETTD = Market value equity / Book value of total debt

X5: STTA = Sales / Total assets

X6: FFOTTA = Funds from operation / Total assets

X7: CRTTA = (Cash and short term investments + receivables) / Total assets

X8: EBITDATA = Earnings before interest,taxes,depreciation and amortization / Total assets

The sample set is then treated with the following processes: (1) Filter outliers by winsorizing the top 5% and bottom 5% of data. This implies that top 5% and bottom 5% of each ratios are being replaced by the mean value of each corresponding ratios (Lennox, 1999). (2) The combination of the predictor variables that has the highest prediction capability is determined by utilizing stepwise analysis method. This means some of the variables would be eliminated and only those predictor variables with significant influence will be remained. (3) Revise the formula obtained from stepwise method with other significant predictor variables that has not been selected. To be more specific, univariate test for those unselected predictor variables would be conducted and if those variables were proved to be significant, we would add them back into the model.

Hypothesis of Model 3

Model 3 is different from other previous models as it is computed with a much larger sample size while it did not require paring up of companies. According to Shumway (2001), compare to the models computed in the previous sections, model 3 (dynamic logic model) accounted for the factors that change over time and takes into account cross-sectional data correlation. Model 3 thus is supposed to produce prediction without sample bias and should have a higher prediction accuracy.

Naïve DD model

Naïve DD model is developed based on Merton DD model. According to Bharath & Shumway (2008), Merton DD model is an application of classical finance theory that inherited with a series of assumptions. However, if some of the assumptions are ignored, it is possible to construct a more accurate but relatively simpler formula models with the same input variables as Merton DD. As a consequence, they constructed Naive DD model and proved its superiority over Merton DD model. Expression of Naive DD model is illustrated as follow:

$$NaiveDD = \frac{\ln \frac{E+F}{F} + (r_{t-1} - 0.5 naive \sigma_v^2)}{naive \sigma_v \sqrt{T}} \quad (5)$$

$$DD P_{def} = N(-NaiveDD) \quad (6)$$

Where,

T= Time to maturity (Normally assume T=1)

Naive DD model is a reduced form of Merton DD model but is considered to be more practical with similar or even superior predictive power against Merton DD.

Finally, in order to compare the prediction power between Z score model and DD model, probability of bankruptcy computed from DD model is then translate into DD score based on a translation formula as suggested by Hillegeist (2004). Expression of DD score is as follow:

$$DD score = \ln \left(\frac{DD P_{def}}{1-DD P_{def}} \right) \quad (7)$$

Hypothesis of DD Model

According to Agarwal & Taffler (2008), DD Model is a market based models and overcame some of the fundamental flaws compared to the models mentioned in the previous sections: (1) it is a theoretically reliable model with a solid foundation of BSM model; (2) input of the model are unlikely to be affected by accounting policies and thus are not as vulnerable to manipulation as accounting ratio model; (3) market prices reflect expectations of future cash flow and therefore are more suitable for prediction purposes; (4) it does not depend heavily on a particular sample period. DD model is therefore used in this paper as a comparison to the previously mentioned accounting based models. Since market based models outperform accounting based models in a number of researches (Hillegeist et al., 2004), we expect DD model to have a higher prediction accuracy than Model 1, 2 and 3.

Tests to be conducted to compare results between Model 1, Model 2, Model 3 and DD model

The following tests would be conducted to compare results of the models: (1) Classification (type I and type II) test would be conducted where the

percentage of type 1 and type 2 error would be identified. Type 1 error refers to those members that should be classified as bankrupt firms but is predicted to be in active group while type 2 error refers to those that should be classified as active forms are predicted to be in bankrupt group. The average value of the these error would be computed and the lower the value of error the better the model would be; (2) Likelihood ratio test where the larger the value of log likelihood statistic would indicate a stronger predictive capability; (3) goodness-of-fit test which will include a table of 10-decile predictive accuracy as presented in the paper of Chava and Jarrow (2004).

Hypothesis of BPNN Model

Neutral network analysis is relatively new compare to the models mentioned in the previous sections. A number of recent research claimed neutral network analysis to have a higher predictive capability (Jain and Barin, 1997). This model is therefore expected to be outperforming the entire previously mentioned model in classification test.

Tests to be conducted on BPNN Model

Among all the paired companies being considered, 70% of them are used as training set and the remaining ones are used for forecasting. The following tests would be conducted to test the efficiency of the model: (1) Classification test for both training set and forecast set; (2) Convergence of mean squared error (mse).

Bankruptcy rate of industrial industry in the UK

Actual bankruptcy ratios in the period between 1989-2012 are shown below with an average ratio of 1.38%. It is also noticeable that the trend show three bulges during 1998- 2000, 2002 and 2007-2010 while 2 of which are in the period of economic downturn (1998- 2000 and 2007-2010). This could act as a proof that bankruptcy rate of industrial industry in the UK is significantly correlated to the global economy. This is consistent with other research findings regarding industrial industry of other countries (Berzkalne, 2013).

Table 1. Trend Of Bankruptcy Rate

Year	Number of Total Firms	Number of Bankrupt Firms	Percent of Bankrupt Firms
1989	211	0	0.00%
1990	303	0	0.00%
1991	359	0	0.00%
1992	357	3	0.84%
1993	351	1	0.28%
1994	353	2	0.57%
1995	361	2	0.55%
1996	360	2	0.56%
1997	360	2	0.56%
1998	345	3	0.87%
1999	348	4	1.15%
2000	320	3	0.94%
2001	308	3	0.97%
2002	315	7	2.22%
2003	322	3	0.93%
2004	316	5	1.58%
2005	311	5	1.61%
2006	324	8	2.47%
2007	134	6	4.48%
2008	325	12	3.69%
2009	316	11	3.48%
2010	304	8	2.63%
2011	223	3	1.35%
2012	283	4	1.41%
Average			1.38%

Source: Thomson Reuters Database

Data collection process

Stocks included in the computation of this paper are located from Thomson Reuters database system based on the following constrains:

- Status: all, include both active, dead and suspended,
- Category: Equities,
- Exchange: London,
- Market: UK,
- Instrument Type: Equity,
- Sector: 2350 Construction & Materials, 2710 Aerospace & Defense, 2720 General Industrials, 2730 Electronic & Electrical Equipment, 2750

Industrial Engineering, 2770 Industrial Transportation, 2790 Support Services

- Primary Quote: Yes,
- Major Security: Yes.

In the period from 1989 to 2012, there are initially 1251 companies located. These companies are then filtered based on LSPD G10 code, which is an approach, used by Agarwal and Taffler (2007, p.288).

Since we are interested in corporate failures that are in their most extreme form, we classified companies with code 0 (active) and 5 (acquisition or merger) as active firms. We then defined those with code 6,7,10,11,16,20,21 as bankrupted firms. These bankrupted firms are with one of the following death type: (1) Suspension or cancellation with shares acquired later (2) Liquidation (usually valueless, but there may be liquidation payments) (3) Quotation suspended - if suspended for more than three years, this may lead to automatic cancellation (4) Voluntary liquidation, where value remains and was/is being distributed (5) Receiver appointed/liquidation. Probably valueless, but not yet certain (6) in Administration or administrative receivership (7) Cancelled and assumed valueless or suspended but assumed valueless.

Companies with code other than those stated above are excluded from the sample. Exact death time of bankrupt firms is retrieved based on G12 code and the data used in the computation for bankrupt firms are collected one year before bankruptcy.

It is also worth noticing that:

- Bankrupted firms with missing data will have data replaced by the most recently available data from two years before bankruptcy Chava and Jarrow (2004) and
- Bankrupted firms that are recorded with 0 total debt are replaced with a small value (0.1) and are winsorised for outliers.

With the above treatment, 700 firms were remained while 99 of those are bankrupted firms and 601 of them are active firms. With reference to the 99 bankrupted firms, another 99 active firms are filtered and paired up with the bankrupted group. Below are the rules in picking the active firms:

- a. The differences in the size of total capital between the paired active firm and bankrupt firm have to be smaller than 15%.
- b. Active firms selected must have at least three full years of financial data available.
- c. When more than one active firm are qualified, the one with a length of lifetime that is similar to its paired bankrupted firm is selected.

As a result, 2 bankrupt firms with no qualified pair that meet the above criteria are excluded from the sample and 97 pairs remained. Thus, the sample consists of 97 pairs of bankrupted and active companies. Among which, 28 pairs have total capital size difference in between 10% -15%; 37 pairs in

between 5%-10%; 32 pairs in between 0-5%. The data of bankrupt firms one year before bankruptcy are indicated as in bankrupt group (group 1) while the data of active firms are indicated as in active group (group 0).

FINDINGS

Table 2. Occurrence Of Type I and II Error Among 142 Firms (In Sample)

Result (Z) in sample	Type I Error	Type II Error
1992	2	0
1993	1	0
1994	2	0
1995	2	0
1996	2	0
1997	2	0
1998	2	0
1999	4	0
2000	3	0
2001	2	0
2002	4	1
2003	3	0
2004	4	1
2005	3	0
2006	6	1
2007	3	1
2008	10	1
Accuracy rate	61.27%	96.48%
Overall rate	78.87%	

Source: the author's calculations based on Thomson Reuters Data

Table 3. Occurrence of Type I and II Error Among 52 Firms (Out of Sample)

Results (Z) out sample	Type I Error	Type II Error
2009	8	0
2010	7	0
2011	2	0
2012	4	0
Accuracy Rate	59.62%	100%
Overall Rate	79.81%	

Source: the author's calculations based on Thomson Reuters Data

Z-score model has a significantly larger type I error than type II error in both in sample and out-of- sample test. During the period of economic downturn, percentage of both errors is generally higher which is a consistent result as shown in a number of researches regarding industrial industry outside the UK (Berzakalne and Zelgalve, 2013). According to their research, average error of z-score model in countries outside the UK is generally smaller than 20%. This is also consistent to the result of z-score model in the UK as shown above.

Classification result of model 1 and 2

Both Model 1 and Model 2 show similar characteristic of original Z-score model. (1) They both have a significantly larger type I error than type II error; (2) During the period of economic downturn, both rate of error increase significantly. According to Berzakalne and Zelgalve (2013), similar models had shown a significant increase of error, which exceeds 60% in 2008. In our case, we have error occurrence significantly higher than 60%, which is consistence in some sense.

Resulting formula of Model 1

Resulting formula of Model 1 is expressed as follows:

$$Z' = 0.296X1 - 0.031X2 + 0.758X3 + 0.431X4 + .482X5 \quad (8)$$

Where,

X1: WCTTA = Working capital / Total assets

X2: RETTA= Retained Earnings / Total assets

X3: EBITTA = Earnings before interest and taxes / Total assets

X4: ETTD = Market value equity / Book value of total debt

X5: STTA = Sales / Total assets

Resulting formula of Model 2

Resulting formula of model 2 is expressed as follows:

$$Y = 0.874X6 + 0.577X7 + 0.451X9 \quad (9)$$

Where,

X6: FFOTTA = Funds from operation / Total assets

X7: CRTTA = (Cash and short term investments + receivables) / Total assets

X9: ETLSSL = Market value equity / (Long term liability + current liability)

For Model 1, it is our intention to keep all 5 variables, which neglects the effect of significance level and correlations between variables. For Model 2, the result indicates that among the 10 variables that input into stepwise computational process, only three variables are significant enough and should be used to compute the discriminant score. Among which, predictor variable X6 has the highest prediction capability in predicting group membership. The major distinction between model 1 and model 2 is the input of variables. Model 1 is constructed with the 5 predictor variables based on the traditional Z-score model but with new coefficients. Model 2 is constructed with an initial input of 10 variables but the final output would have less than 10 variables by processing stepwise analysis. Among the 5 variables in Model 1, only EBITTA (0.00) and STTA (0.044) are relatively significant while for the Model 2, it is noticeable that except ETTD (0.146), RETTA (0.097) and WCTTA (0.072), all mean values of the variables in the active group are significantly different from the fail group.

Hillegeist et al. (2004) reported negative coefficients for X1, X3 and X4 after updating the coefficients, which is inconsistent as reported in Model 1. However, the research of Berzakalne and Zelgalve (2013) shown rather similar signs as Model 1 when they compute the model based on solely industrial industry. One of the reasons could be there exists factors that affect solely industrial industry.

The significant level of Box's M test for both Z'score and Y-score are both less than 0.001 which means the assumption of equal variance among active and bankrupted groups is not held and thus the assumption of normal distribution is not valid (Deakin, 1972). This would therefore be one of the potential limitations when conducting further interpretation of the results. Comparing the two models, the canonical correlation of Y score (0.376) is higher than that of Z' score (0.335) which indicates a better performance of Y score in regard of classifying subjects into different groups. Wilks' Lamda is a multivariate statistic which is computed as $(1 - \text{canonical correlation}^2)$ The significance level of Wilks' Lambda for both models are 0.000 which indicates both of them are strong models and the predictors variables could make predictions at a statistically significant level in terms of accuracy.

For Model 1, excluding X5 which has a value (0.297) slightly less than 0.3, all other 4 variables are with values higher than 0.3. Among which, X1 and X2 ranked first and second which is consistent with the magnitude of the canonical coefficients. For Model 2, the variables included in the formula (X6,

X7, X9) are all with a relatively high correlation coefficient and none of which has value less than 0.3. Consistency is therefore exists between the discriminant function coefficient as well as the correlation between these individual variables. The null hypothesis of the Chi-square is the model being tested (Z'-score and Y-score models) relative to a model with no predictors has the same prediction capability. Since the resulting significant level is 0 (smaller than 0.05), the null hypothesis could be rejected and thus both Z'-score and Y-score models are significantly effective.

We noticed that apart from the 3 variables (X6, X7, X9) included in Model 2, mean values of X8 and X10 are also significantly different between active group and bankrupted group. We therefore attempted to include the two variables into Model 2 as predictor variables. However, it turns out both ratios would reduce the predictive capability of Model 2. Model 2 with predictor variables X8 and X10 included could only correctly identified 62.2% of group 0 (active firm group) members and 68% of group 1 (bankrupted firm group). The new overall "hit" rate (63%) is lower than the original Model 2 (77.46%).

Resulting formula of Model 3

The result is computed by stepwise analysis method and the formula is indicated as:

$$Y'\text{-score} = -5.7157X6 - 2.6555X8 - 3.8283 \quad (10)$$

Where,

X6: FFOTTA = Funds from operation / Total assets

X8: EBITDATA = Earnings before interest, taxes, depreciation and amortization / Total assets

Significance level of the input predictor variables

Among the input of all 8 variables, result of Z test indicates only X6 is significant. This is consistent with the resulting formula of Model 3 as X6 is selected to be one of the two-predictor variables in the model.

Result of DD Model

Regarding the out of sample test, DD Model exhibit the highest predictive capability than all other models. During the period of economic downturn, DD model outperform all other models and have no predictive type I error. This is consistent to the research of (Hanley & McNeil, 1983) where it shows market based models should have the highest predictive capability compared to accounting based models. However, DD model has the same issue of Model 3 in which it has a relatively high type II error when compare to the other models. Thus, this could be one of the weaknesses of DD Model where in some cases, if the cost of type II error is significantly higher than type I error, it

might still be beneficial to adopt Model 1 or Model 2.

Result comparison between 5 models

Our analysis compares the information content of Z-score, Z'-score, Y-score, Y'-score and DD score. In all five models, it is noticeable that their mean values are significantly different between active group and bankrupted group.

Table 4. Summary Statistic of 5 Models

Score	Status	Mean	Std Dev
Z-score	Active	264.4	1478.8
	Bankrupt	42.3	218.1
Model 1 (X')	Active	18867.5	106229.6
	Bankrupt	2945.1	15668.0
Model 2(Y)	Active	2183.2	10256.3
	Bankrupt	239.2	1020.8
Model 3 (Y')	Active	-3.9	2.2
	Bankrupt	-2.1	3.8
Naïve DD	Active	14.1	10.0
	Bankrupt	7.3	9.2

Source: the author's calculations based on Thomson Reuters Data

The above table shows that DD score model has the strongest prediction capability, which is indicated by its largest value of, log likelihood statistic (-116.87) and pseudo R2 (0.13). The Y'-score is the second best model with log likelihood of 125.339 and pseudo R2 0.068. The significant level of the difference is verified by Vuong test at 5% significant level. This finding is consistent with the view that market based models are incorporate with more information than accounting based models (Hudson, 1987). Apart from the comparison between market based models and accounting based models, we also realized Z score model and Z' score model have almost the same value of log likelihood statistic (-32.27 vs -132.29) and pseudo R2 (0.0163 vs 0.0162). The significant level of this difference is also verified by Vuong test at 5% significant level, which means varying the coefficients of Z score model could not make a significant difference.

Result of PBNN Model

The predictive capability of PBNN model is the lowest among all models. Compare to the result of (Jain and Nag, 1997) where BPNN has 10% accuracy rate higher than both MDA and dynamic logistic model, the result of our model is not consistence. One of the reasons could be the selection of transfer function in the two hidden layers. Since BPNN is relatively a trail and error analysis, the transfer function selected in this paper may not necessarily be the best function. Since BPNN model is solely utilized as one of the baseline method and is not the focus of this paper, we did not carry out further

computations on other functions. However, it is worth noticing that BPNN model could have improved accuracy if one carry on investigating the issue.

CONCLUSION

This paper seeks to assess the predictive capability of 6 models including (1) Altman's (1968) z-score; (2) Model 1: z-score model with adjusted coefficients; (3) Model 2: z-score model with modified variables; (4) Model 3: dynamic logic model; (5) Merton distance to default (DD) model (Bharath & Shumway, 2008) and (6) back-propagation network model (Lippman, 1987). Our tests show that dynamic logic model and DD model both provide significantly more information than the others while DD model has the highest prediction accuracy in the out of sample test. However, each of the models has their own strength and weakness.

Model 1 and Model 2 both show similar prediction accuracy as original Z-score model. Therefore, considering effectiveness, one may use original z-score model directly without altering the coefficients and variables. All of the MDA models in this paper made a significantly less amount of type II than type I error. Thus, these models would be especially useful in the case of high cost type II error. However, during the period of economic downturn, both rate of error increased significantly and hence one should avoid applying these models in the period of economic downturn.

Notwithstanding the fact that Model 3 scored slightly lower than DD model in the out of sample classification test, Model 3 indeed has a lower type II error compare to DD model and the performance of Model 3 is rather stable. If one is interested in a stable performance and to strike a balance between type I and type II error, Model 3 could have an outstanding performance.

DD model has the highest overall accuracy in the out of sample test. It has exceptional performance regarding type I accuracy in general and especially in the period of economic downturn. It is therefore best to use during economic crisis and in the cases where type I error is costly. However, since it has the lowest accuracy regarding term II error, one should avoid using DD model if the cost of type II error is exceptionally high.

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