Quest for Research Excellence On Computing, Mathematics and Statistics

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Faculty of Computer and Mathematical Sciences

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Chapters in Book

The 2nd International Conference on Computing, Mathematics and Statistics (iCMS2015)

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4-5 November 2015
Langkawi Lagoon Resort
Langkawi Island, Kedah
Malaysia

Publication by
Faculty of Computer & Mathematical Sciences
UiTM Kedah

ISBN 978-967-0314-26-6

Content

CHAPTER 23
Partial Least Squares Based Financial Distressed Classifying Model of Small Construction Firms

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Abstract. The study on the classification of firms' financial distress was made popular by Altman (1968). Up until today, banks use Altman's ratio to rate credit credibility of potential borrowers. Since then many works replicate, improvise or use different statistical and non-statistical methods to improve the classification rate of financial distress. Most of these works dealt with information gathered from large companies as information on small companies are limited and not easily available. The aim of this research is to fill in the gap and extends the work done in Abd Razak and Wan Asma' (2012) by looking at the predictive ability of information gathered from Malaysian small firms. It tries to determine the financial covariates that can classify the distressed firms from the healthy ones and to investigate whether a partial least squares discriminant analysis (PLS-DA) is a more efficient model than a logit model in classifying the distressed from the healthy ones. The result of Logistic Regression and PLS-DA are found to be close. PLS-DA has the advantage that is not affected by multicollinearity, because its components are orthogonal.

Keywords: logit model; partial least square discrimant analysis; financial ratio; bankruptcy

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1 Introduction

Numerous research have been developed to identify indicators of corporate financial distress. If financial distress cannot be relieved, it can lead to bankruptcy. Bankruptcies affect entrepreneurs, depositors, creditors, auditors and other stakeholders. Therefore, it is very interesting to know factors that leads to bankrupt. Most studies on financial distress were studies on failure of large public firms as financial information of small firms are not easily available and limited. Unlike large public firms, small firm are not required by the regulators to submit full financial report at the end of each financial year.

In the 60's, researchers used statistical models to identify financial ratios that could classify companies into failure or non-failure groups. The statistical approach includes univariate and multivariate models (. According to Gilbert et al., (1990) financial variables used to identify bankrupt firms from non-bankrupt firms are different from those variables used to discriminate financially distressed firms from the bankrupt ones.

Financial ratios are assumed to be powerful prediction models for assessing the financial distress of a firm (Hossari & Rahman, 2005). According to Karas and Reznakova (2012), the ratios that are significant in predicting bankruptcy are quick assets turnover, capital turnover and total assets value. Yazdanfar & Nillson (2008) showed that from MDA result, the three financial ratios solvency, quick ratio and return on assets are significant in discriminating between bankrupt and non-bankrupt firms for a one-year prediction horizon. Abd Razak & Wan Asma' (2012) found that financial ratios will become less predictive when combined with non-financial information in bankruptcy prediction model. Majority of business failure papers as predictors use financial ratios, while in the real life banks combine financial and nonfinancial variables.

This study aims to build a bankruptcy model for financially distressed firms using partial least square discriminant analysis (PLS DA). It involved small construction firms. The firms were based in the United Kingdom. Up until today, banks use Altman's z-score to rate credit credibility of potential borrowers. Since then many works replicate, improvise or use different statistical and non-statistical methods to improve the classification rate of financial distress. Most of these works dealt with information gathered from large companies as information on small companies are limited and not easily available. The main aim of this research is to fill in this gap, that is, to look at the predictive ability of information gathered from small construction companies.Many of these models, however, were constructed based on samples of large firms where financial data were more easily accessible, in contrast to those of privately-owned firms. Hence, only a small number of studies on small and medium-sized enterprises (SME hereafter) apart from Edmister (1972), Altman and Sabato (2007), Behr and Güttler (2007), Lugovskaya (2010) and Pederzoli and Torricelli (2010) were undertaken.However, the main constraint on studies of SMEs is the non-availability of the data. In this study, the variables included in the model represent liquidity, leverage, efficiency and profitability. The model also incorporates a non-financial variable (firm's age) to improve the prediction accuracy (Grunet et al., 2005; Lugovskaya et al., 2010; Pederzoli and Torricelli, 2010).

2 Literature Review

The study on the prediction, or rather the classification, of firms' distress started with the seminal work by Beaver (1966). Beaver uses a univariate prediction model to show the significance of certain financial ratios in classifying bankrupt firms. While Beaver started it all, it was Altman's (1968) work using multiple discriminant analysis (MDA) with five financial ratios as covariates that becomes the benchmark of future work until to this day. Since then many authors based their work on Altman's. They replicate, improvise or use different statistical and non-statistical methods to improve the classification rate. Some works which become benchmarks on their own are works by Ohlson (1980) and Shumway (2001). Ohlson uses conditional logit model while Shumway uses the hazard model. Both studies show an improvement in classification rate over Altman's MDA model.

Latest work on the prediction of firms' bankruptcies and financial distress include Bae (2012), Yang et al. (2011) and Lin (2009). Bae develops a financial distress prediction model based on radial basis function support vector machines and found that this model outperformed a model based on artificial intelligence in predicting financial distress. Yang et al. explores the predictive ability of a model based on partial least squares and support vector machines and found that not only the model can select significant financial indicators but it can also identify the role of each variable in the prediction process. Lin compares the predictive ability of four models and found that artificial neural networks model outperforms Altman's and Ohlson's models in predicting corporate bankruptcies. Other works on the prediction of firms' bankruptcies and financial distress are Cao (2012) and Cao and Chen (2012).

In this proposed work, we extend the work of Abd Razak and Wan Asma' (2012) and Abd Razak and Zubir (2010). While both works identified significant predictors of corporate failure of large firms, we will investigate possible predictors of failure for both large and small construction firms by using Partial Least Squares. Large public firms are required to submit full account of their financial statements to the regulator while small firms submit abridged account. As such, most studies on corporate failure use large firm sample as less information can be gathered about small firms. Ours will be one of the few that will be using financial and non-financial information from small firms sample.

3 Methodology

This study used Partial Least Square Discriminant Analysis (PLS-DA) to predict bankruptcy. This method used for constructing predictive models when there is a lot of independent variables and high multicollinearity while the sample size is not enough. It combines the merits of Principal Component Analysis, Canonical Correlation Analysis and Multiple Linear Regression in the course of modeling (Tobias & Others, 1995). According to Serrano-Cinca and Gutiérrez-NietoIt (2011), it was found that PLS-DA results are very close to those obtained by Linear Discriminant Analysis and Support Vector Machine results. Its components are orthogonal so that PLS-DA is not affected by multicollinearity.

PLS-DA also allows the series of equations to be analyzed simultaneously while traditional regression may require separate regression equations to analyze. Therefore, many financial covariates that can classify the bad bankrupt firms can be analysed simultaneously and the same constructs can be tested for UK small construction firms.

The sample will consists of small UK firms which involved in construction. It contain 768 financially distressed firms. 53.52% went into bankrupt and 46.48% firms are not. The data is divided into training which is 70% of the firms and validation samples is 30%. The PLS-DA method is then compared with logit model to determine the most efficient model. Twenty-four financial ratios are used in this study. Based on past research, they are categorized into five different groups which are cash-flow, leverage, liquidity, activity and profitability. Table 1 defines the variables.

Table 1. Financial ratio and it definition.

Information	Variable	Ratio
Activity	Asset_ut181	Turnover / total assets
	Cred_day159	Payment period = 365 x trade creditors / turn over
	Debtor_d158	Debtor ratio = 365 x trade debtor / turnover
	Sales_tf182	Turnover / total fixed assets
	Stock_tu157	Stocks / turnover
	Wkg_k_sa188	Working capital / turnover
Leverage	Netwh_cl196	Net worth / current liabilities
	Netwh_tl150	Net worth / total liabilities

	Tlia_sfund205	Total liabilities / shareholders' fund
	Cap_gear222	Total liabilities / total assets
Liquidity	Current207	Current assets / current liabilities
	Quick206	Current assets – stocks / current liabilities
	Cass_tot163	Current assets / total assets
	Cliab_st187	Current assets / stocks
	Ncash_cl165	Net cash / current liablities
	Wkgcap_tass214	Working capital / total assets
	Clia_tasset219	Current liabilities / total assets
	Wrkcap_clia220	Working capital / current liabilities
Profitability	Gross_tover208	Gross profit / turnover
	Prof_cli160	Pre-tax proft / current liabilities
	Prof_mar154	Pre-tax proft / turnover
	Rtn_on_a153	Pre-tax proft / total assets
	Rtn_on_c152	Pre-tax proft / capital employed
	Rtn_shar180	Pre-tax proft / shareholders' fund
	Tlia_cbit212	Total liabilities / earning before tax and interest

4 Results and Discussion

Table 2 shows summary statistic, mean and test of significance of financial variables. From the result, we can see bankruptcy firms have less liquidity, less profitability and higher leverage.

Table 2. Variable mean and test of significance.

Financial ratio	Bankrupt (mean)	Non-bankrupt (mean)	t-stat	p-value
stock_tu157A	39.3638	40.7824	-0.357	0.721
debtor_d158A	47.3653	49.4586	-0.259	0.759
cred_day159A	51.4042	49.8705	0.098	0.922
asset_ut181A	385.4027	320.8240	3.178**	0.002
sales_tf182A	4013.8355	3893.6077	0.298	0.766
wkg_k_sa188A	15.8032	46.0438	-4.013**	0.000
netwh_tl150V	32.3064	112.6838	-5.811**	0.000
netwh_cl169V	42.6946	129.1150	-5.633**	0.000
tlia_sfund205V	15.1597	7.6154	4.632**	0.000

cap_gear222V	1.8072	0.9870	1.790*	0.074
rtn_on_c152p	139.5317	136.7905	0.104	0.917
rtn_on_a153p	32.9792	32.7293	0.07	0.944
prof_mar154p	11.2037	19.9403	-2.467**	0.014
rtn_shar180P	192.0981	157.6107	0.97	0.332
prof_cli160P	34.6056	61.6695	-4.92**	0.000
gross_tover208P	0.3125	0.3492	-2.420**	0.016
tlia_ebit212P	15.1288	11.3134	1.509	0.132
clia_tasset219Q	1.0913	0.85	0.818	0.413
wrkcap_clia220Q	2.2290	2.7963	-0.68	0.497
cass_tot163Q	76.9698	76.2303	0.504	0.614
ncash_cl165Q	23.3843	61.2950	-5.538**	0.000
cliab_st187Q	12.7188	11.2132	0.977	0.329
liquid206Q	0.6632	1.1899	-5.126**	0.000
current207Q	0.9906	1.7392	-5.480**	0.000
wkgcap_tass214Q	0.3987	0.4013	-0.044	0.965

Note: *, ** significant at 10 and 5 percent respectively

Table 3 presents summary of stepwise logistic and partial least square discriminant analysis model. Model 1 shows stepwise logistic regression model and model 2 shows partial least square discriminant analysis model. From stepwise logistic, there are seven financial ratio that are significant with the bankruptcy firms, which are asset_ut181A, wkg_k_sa188A, netwh_tl150V, wrkcap_clia220Q, ncash_Cl165Q, liquid206Q, wkgcap_tass214Q. The coefficients of the variable show the expected sign. It means that, lower profitability and higher leverage will become higher probability of bankruptcy firm. This study used model of fit like a Hosmer and Lemeshow Test, Cox & Snell R Square and Nagelkerke R Square. Hosmer and Lemeshow test show, the model are adequate and effective to predicting the dichotomous variable. Then Cox & Snell R Square and Nagelkerke R Square are 0.172 and 0.23 respectively. Sign of coefficient in Model 2 as expected for all financial ratios.

Table 3. Summary of model.

Model 1 Pred(fail195) = 1 / (1 + exp(-(0.4978-1.0955E-03*asset_ut181A-8.725E-03*wkg_k_sa188A-7.928E-03*netwh_tl150V-0.0239*wrkcap_clia220Q-6.4429E-03*ncash_cl165Q+0.5167*liquid206Q+0.5872*wkgcap_tass214Q)))	
Goodness of fit	642.129
-2 Log likelihood	0.172
Cox & Snell R Square	0.23
Nagelkerke R Square	7.420
Hosmer and Lemeshow Test (d.f, p-value)	(8,0492)

Model 2

F(0) = 0.4119-7.1538E-05*stock_tu157A+2.866E-05*debtor_d158A+9.3521E-06*cred_day159A-8.8458E-05*asset_ut181A-1.6630E-07*sales_tf182A+1.9671E-04*wkg_k_sa188A+1.7928E-04*netwh_tl150V+1.3363E-04*netwh_cl169V-7.2268E-04*tlia_sfund205V+3.6363E-05*cap_gear222V-1.6363E-05*rtn_on_c152P-1.9637E-05*rtn_on_a153P+2.6081E-04*prof_mar154P-2.1363E-05*rtn_shar180P+2.588E-04*prof_cli160P+6.0482E-02*gross_tover208P-1.7966E-04*tlia_ebit212P+1.3211E-03*clia_tasset219Q+1.0408E-03*wrkcap_clia220Q-7.6690E-05*cass_tot163Q+3.0590E-04*ncash_cl165Q-3.2598E-04*cliab_st187Q+1.9953E-02*liquid206Q+1.4296E-02*current207Q-7.029E-03*wkgcap_tass214Q

F(1) = 0.5881+7.1538E-05*stock_tu157A-2.866E-05*debtor_d158A-9.3521E-06*cred_day159A+8.8458E-05*asset_ut181A+1.6630E-07*sales_tf182A-1.9671E-04*wkg_k_sa188A-1.7928E-04*netwh_tl150V-1.3363E-04*netwh_cl169V+7.2267E-04*tlia_sfund205V-3.6363E-05*cap_gear222V+1.6363E-05*rtn_on_c152P+1.9636E-05*rtn_on_a153P-2.6081E-04*prof_mar154P+2.1363E-05*rtn_shar180P-2.588E-04*prof_cli160P-6.0482E-02*gross_tover208P+1.7966E-04*tlia_ebit212P-1.3211E-03*clia_tasset219Q-1.0408E-03*wrkcap_clia220Q+7.6690E-05*cass_tot163Q-3.0590E-04*ncash_cl165Q+3.2598E-04*cliab_st187Q-1.9953E-02*liquid206Q-1.4296E-02*current207Q+7.0294E-03*wkgcap_tass214Q

Table 4 summarize the results of classification accuracy of two models. Model 2 has the lowest of accuracy rate (AR) in estimation and validation sample compared to model 1 but the different is too small. The difference of accuracy rate in estimation is 2.8% and validation is 0.87%. The area under the curve of receiver operating characteristic (ROC) most appropriate to examine the validation of model (Agarwal and Taffler,, 2014). The result show AUC of model 1 is 74.9% and model 2 is 73.3%. There has a slightly difference by 1.6% in AUC.

Table 4. Summary of classification accuracy.

Classification	Measurements	Model 1	Model 2
Estimation	Accuracy rate (AR)	0.6989	0.6710
	Type I error	0.1538	0.073
	Type II error	0.4683	0.619
Validation	Accuracy rate (AR)	0.6348	0.6261
	Type I error	0.16	0.08
	Type II error	0.6095	0.7238
	Area under curve	0.749	0.733

Table 5 shows the results of classification training and validation sample. Model 2 presents a lower accuracy rate compared to model 1 for both classification estimation and validation. Percentage of corrected model 1 is 69.89% for training and 63.48% for validation. Then, estimation of model 2 is 67.10% and 62.61% for validation. However the different between these two models are small.

Table 5. Classification estimation and validation sample.

Model 1

Classification table for the estimation sample

Status	0	1	Total	% correct
0	134	118	252	53.17%
1	44	242	286	84.62%
Total	178	360	538	69.89%

Classification table for the validation sample

Status	0	1	Total	% correct
0	41	64	105	39.05%
1	20	105	125	84.00%
Total	61	169	230	63.48%

Model 2
Confusion matrix for the estimation sample

Status	0	1	Total	% correct
0	96	156	252	38.10%
1	21	265	286	92.66%
Total	117	421	538	67.10%

Confusion matrix for the validation sample

Status	0	1	Total	% correct
0	29	76	105	27.62%
1	10	115	125	92.00%
Total	39	191	230	62.61%

5 Conclusion

This paper compares Partial Least Square Discriminant Analysis (PLS-DA) with logistic regression. It was perform on data of the UK small construction firm. In performance terms, the techniques obtain different results depending on the performance measures chosen. Some techniques have more accuracy than others.

This justifies the use of performance measures like the t-test and the arithmetic mean of precision. The study examines what is behind performance, by analyzing how each firm is classified. With this aim, a contingency table has been calculated to compare, in a paired way,the classifications of each technique. This paper has also analyzed the scores assign to each firm by these two techniques.

The result of Logistic Regression and PLS-DA are found to be close. PLS-DA has the advantage that is not affected by multicollinearity, because its components are orthogonal.

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iCMS 2015

ISBN 978-967-0314-26-6