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Ridwan Nurazi
Southern Cross University

Michael Evans
Southern Cross University

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Ridwan Nurazi
Doctor of Business Administration
Graduate College of Management
Southern Cross University
and
Associate Professor Michael Evans
Director
Graduate College of Management
Southern Cross University

Abstract

This study investigates whether CAMEL(S) ratios can be used to predict bank failure. Based on the literature review, the study used 13 variables representing CAMEL ratios, one representing sensitivity to market risk, and one representing bank size. Most of the analysis was done using multivariate logistic regression since it is more flexible and relatively free of restrictions. To evaluate for consistency, multiple discriminant analysis was also carried out. The results found that logistic regression in tandem with multiple discriminant analysis could function as an early warning system for identifying bank failure and as a complement to on-site examination. The results suggest that the variables ECTA (adequacy ratio), RORA (assets quality), ROA (management), OEOI (earnings), CBTD (liquidity), and LGBS (bank size) are statistically significant in explaining bank failure. Therefore, stakeholders should focus on these variables to identify and solve banking problems.

Key Words
bank failure, CAMEL(S) ratios, logistic regression, multiple discriminant analysis

Introduction

The economic crisis that hit Indonesia in 1997 meant that many Indonesian banks could not maintain their status as a 'going concern'. Sixteen commercial banks were suspended on 1 November 1997 and the Ministry of Finance liquidated 38 others on 13 March 1999 (Hadad 1999; Kawai 1999). This has become a major issue for the public, the government and banking regulators in Indonesia because bank failure has a greater effect on the economy than other types of corporate failure.

The cause of corporate failure was a popular topic of research in the 1990s (McKee 2000; Estrella et al. 2000; Shah & Murtaza 2000; Mongid 2000). One of the techniques used to analyse possible corporate failure was CAMEL (Capital, Assets quality, Management, Earning and Liquidity) ratios. On 1 January 1997, a sixth component, 'S' (sensitivity to market risk), was included in the CAMEL rating system. Researchers have argued that the CAMEL(S) ratios can help evaluate the financial conditions of a bank, its management quality and its compliance with regulations. That is, the ratios can be used as an effective tool to identify a bank's problems.

The objective of this study is to examine whether CAMEL(S) ratios are accurate predictors of bank failure; what the most influential variables in predicting bank failure are; whether there are any significant differences between publicly held banks and non-publicly held banks; and how the proposed model can be applied in practice. Since bankruptcy research has been neglected in Indonesia, this topic is highly relevant. In addition, this is also a challenging area to explore. According to Bryant (1997), so far, there have been no underlying economic theories of bankruptcy. Research into bankruptcy prediction has been largely a trial-and-error, iterative process of identifying predictor variables and searching for more accurate statistical methods.

This paper is organised in six sections. This section provides an outline of the importance of the study, including research objectives. The next section briefly discusses the literature review. Section three raises research issues. Section four describes the research methodology. Section five reports on and discusses the data analysis and findings. The last section presents the conclusions and implications for future research.

Literature Review and Previous Research

There has been significant prior research on bankruptcy prediction using a wide variety of techniques. In general, these techniques can be divided into two categories, namely, landmark models and developing models. The landmark studies are the work of Beaver (1966) on univariate analysis, Altman (1968) on multiple discriminant analysis and Ohlson (1980), on logistic regression analysis.

Most work, such as the catastrophe model (Scapens et al. 1981), recursive partitioning algorithm (Frydman et al. 1985), proportional hazard model (Henebry 1996, 1997), cased-based reasoning (Bryant 1997), artificial neural network (Shah & Murtaza 2000; Luther 1998; Barniv et al. 1997; Bell 1997), and rough sets theory (McKee 2000), can be considered developing models because most of them use the Beaver (1966), Altman (1968) and Ohlson (1980) studies for comparison.

Each of these models has advantages and disadvantages. The various techniques cannot be easily compared due to possible differences in assumptions, data sets, time periods and failure definitions. After reviewing all of the above approaches, it can be concluded that there is no single model that is superior to the others. Each can be useful in certain conditions, and under certain assumptions.

There is little agreement among researchers regarding the best accounting ratios for determining the likelihood of financial failure. Most researchers who use ratios as predictor variables do so on the basis of their popularity in the literature. There is no basic rule or theory for choosing which variables to use among the literally hundreds of ratios to choose from.

In the case of Indonesia, there was very little information about bankruptcy research. Most of the bankruptcy studies were about the US and Latin America. Some studies were about the UK and Australia. However, there was one Indonesian bankruptcy study by Mongid (2000). Mongid (2000) presented a model for bankruptcy prediction for the Indonesian banking system using accounting data.

Based on the literature review, there are some gaps in past research, especially in Indonesia. Some of gaps that needed to be addressed include:

- Most bankruptcy studies are from developed countries or developed economies, so evidence from emerging countries or emerging economies seems to be lacking.

- Since the US regulators introduced the S (sensitivity to market risk) factor in the CAMEL rating system, it has not been tested.
- In the case of Indonesia, since bankruptcy research is still rare, the gaps found are: (a) researchers did not test the size of banks, whereas this variable is significant in other research; (b) when bankruptcy research began in Indonesia, researchers used a very limited sample size; (c) researchers did not make any distinction between public and non-public banks.

Based on the above gaps, this research will examine the S factor together with the other CAMEL indicators, and will analyse the data using multivariate logistic regression.

Research Issues

The research questions addressed in this paper are:

1. What are the most influential variables for predicting bank failure?
2. Can CAMELS ratios be used as predictors of bank failure?
3. Can the proposed models for predicting bank failure be applied in practice?

The research questions and their associated hypotheses are presented in Table 1.

Table 1: Research Questions and Hypotheses

Research questions	Research hypotheses
1. Does the probability of bank failure depend on a bank's capital strength?	• H_o: There is no relationship between a bank's probability of failure and its capital strength. • H_a: there is a relationship between a bank's probability of failure and its capital strength.
2. Does the probability of bank failure depend on a bank's asset quality?	• H_o: There is no relationship between a bank's probability of failure and its asset quality. • H_a: There is a relationship between a bank's probability of failure and its asset quality.
3. Does the probability of bank failure depend on a bank's management quality?	• H_o: There is no relationship between a bank's probability of failure and its management quality. • H_a: There is a relationship between a bank's probability of failure and its management quality.
4. Does the probability of bank failure depend on a bank's earnings?	• H_o: There is no relationship between a bank's probability of failure and a bank's earnings. • H_a: There is a relationship between a bank's probability of failure and its earnings.
5. Does the probability of bank failure depend on a bank's liquidity?	• H_o: There is no relationship between a bank's probability of failure and its liquidity. • H_a: There is a relationship between a bank's probability of failure and its liquidity.

Research questions	Research hypotheses
6. Does the probability of bank failure depend on a bank's sensitivity to market risk?	• H_o: there is no relationship between a bank's probability of failure and its sensitivity to market risk. • H_a: there is a relationship between a bank's probability of failure and its sensitivity to market risk.
7. Does the probability of bank failure depend on a bank's size?	• H_o: There is no relationship between a bank's probability of failure and its size. • H_a: There is a relationship between a bank's probability of failure and its size.
8. Does the probability of bank failure depend on a bank's status (public/non-public banks)?	• H_o: There is no relationship between a bank's probability of failure and its status. • H_a: there is a relationship between a bank's probability of failure and its status.

Research Methodology

The research methodology is in two parts: research design; and data collection and analysis.

Research Design

This study initially examined the cause and effect between CAMEL ratios and failure or bankruptcy. Based on the literature review, research problem and/or objectives, research questions and research hypotheses, a research model was developed (Table 2).

Table 2: Research Model Development

Category	Ratio or Measure		Variable Descriptor
Capital adequacy ratio	• Equity Capital – Fixed Assets/Total Loan + Securities	X_1	CAR
	• Equity Capital/Total Assets (Hirtle & Lopez 1999; Gilbert et al. 1999; Gunther 1999; Sinkey 1975)	X_2	ECTA
Assets quality	• Earning Before Income Tax/ Productive Assets	X_3	RORA
	• Off-Balance Sheet Activities/Equity Capital (Mongid 2000; Bryan 1997; Altman 1968, 1981)	X_4	OBSEQ
Management	• Net Income/Total Assets	X_5	ROA
	• Net Income – Interest Expense/Total Assets (Demirguc-Kunt & Huizinga 2000; McKee 2000; Gilbert et al. 1999; Kane et al. 1998; Bryant 1997)	X_6	NM
Earnings	• Earning After Tax/Operating Income or Sales	X_7	NPM
	• Operating Expense/Operating Income (Routledge & Gadenne 2000; Hermosillo et al. 1996; Sinkey 1975)	X_8	OEOI

Category	Ratio or Measure		Variable Descriptor
Liquidity	• Total Loan/Total Deposit	X_9	LDR
	• Total Loan/Total Assets	X_{10}	TLTA
	• Cash/Total Assets	X_{11}	CTA
	• Cash & Bank/Total Deposit	X_{12}	CBTD
	• Growth in Loan (Routledge & Gadenne 2000; Hirtle & Lopez 1999; Gilbert et al. 1999; Henebry 1997, 1996; Santoso 1996; Boudreaux et al. 1995; Altman 1968)	X_{13}	GRWTH
Sensitivity to market risk	• Market Price per Ordinary Equity Share/Earning Per Share	X_{14}	PE
Size (bank size)	• Natural Logarithm (Ln) (Bell 1997; Hooks 1995; Ohlson 1980)	X_{15}	LGBS

The potential research model is:

$$\mathrm{Ln}\left[\frac{F}{NF}\right] = \alpha + \sum_{n=1}^{n} \beta_n X_n, \text{ or}$$

$$\mathrm{Ln}\left[\frac{F}{NF}\right] = \alpha + \beta_1X_1 + \beta_2X_2 + \ldots + \beta_nX_n, \text{ or}$$

$$\mathrm{Ln}\left[\frac{F}{NF}\right] = \alpha + \beta_1X_1 + \beta_2X_2 + \beta_3X_3 + \beta_4X_4 + \beta_5X_5 + \beta_6X_6 + \ldots + \beta_{14}X_{14}$$

where:

F = NF	=	Failure, Non-failure (log of the odds)
α	=	Intercept
β	=	Slope
X_1, X_2, X3, …	=	Financial accounting ratios (CAMELS rating ratios) and Size

The above linear regression equation is called the logit, or log of the odds, and is the natural log ($\log_e$) of the probability of being in one group divided by the probability of being in the other group. Tabachnick and Fidell (2001, p. 518) state that 'the procedure for estimating coefficients is maximum likelihood, and the goal is to find the best linear combination of predictors to maximise the likelihood of obtaining the observed outcome frequencies'.

Data Collection and Analysis

A number of sources of data were considered, such as the Central Bank of Indonesia, Jakarta Stock Exchange and Association of National Private Banks. The process of data collection was divided into three steps, A, B and C. Step A is data collection for analysing the period before and during the economic crisis (five years before 1997), Step B is data collection for analysing the period during and after the economic crisis (five years before 1999), and Step C is data collection for analysing banks listed in the stock market during and after the economic crisis (five years before 1999).

Steps A, B and C

1. In Step A, the population for the research was all Indonesian commercial banks operating for the calendar years 1992 to 1996 (five years before certain banks were liquidated). In Step B, The population for the research was all Indonesian commercial banks operating for the period during and after the crisis (data from 1993 to 1998, or five years before certain banks were liquidated and/or merged). In Step C, the population for the research was all Indonesian banks listed in the Jakarta Stock Exchange for the period during and after the crisis (data from 1993 to 1998, or five years before listed banks were liquidated). No listed bank was liquidated before and during the economic crisis (1997-1998).
2. In steps A and B, all failed banks were considered as sample data (100% sample). Half (50%) of the successful, or survivor, banks were chosen using a random sampling method. In Step C, about 90% of all failed listed banks in the stock market during this period were considered as sample data. Sixty-eight per cent of survivor listed banks in the stock market were chosen using a random sampling method. The reason for this kind of sampling was due to the data in the stock market not being in a series.

3. The variables were analysed using logistic regression analysis. The analysis of steps A and B was to find out whether the model developed for the data before the economic crisis also applied to data after the crisis. The analysis of Step C was meant to see whether the model developed for listed banks also applied to non-listed banks.

As mentioned previously, most of the analysis of this study is based on multivariate analysis or multiple regression analysis, specifically logistic regression analysis. The benefits of using logistic regression analysis are its flexibility and relative freedom from restrictions. To test the overall model or to measure goodness of fit, the Pseudo R-square or adjusted R-square was used. To evaluate the consistency of the model, it was also compared with the other multiple regressions, in this case, multiple discriminant analysis (MDA).

Data Analysis and Findings

This section is divided into six subsections. Subsection (a) is the normality distribution, Pearson correlation and multicollinearity. Subsection (b) is the logistic regression analysis. Subsection (c) is logistic regression analysis versus MDA. Subsection (d) is practical use. Subsection (e) is practical use with logistic regression analysis, and subsection (f) is practical use with MDA.

(a) Normality Distribution, Pearson Correlation, and Multicollinearity

Evaluating distributions and determining whether the data is acceptable in terms of departures from normality is often the most time consuming action of any data analysis. Since the logistic regression does not require that the predictors should be normally distributed, parametric statistics are still eligible for further analysis. In logistic regression, although assumptions regarding the distributions of predictors are not required, multivariate normality and linearity among the predictors may enhance predictive power. However, since this research also compares logistic regression with MDA, the data will be transformed to a normal distribution using logarithms (log) when analysed using MDA (Tabachnick & Fidell 2001; Hair et al. 1998; Khandwalla 1977; Blau & Schoenherr 1971). Using Pearson correlation, Table 3 shows the correlation among independent variables. Table 3 will also indicate whether multicollinearity among accounting variables exists.

Table 3a: Correlation Matrix Among Variables (Step A)

Variable	F/NF	CAR	ECTA	RORA	OBSEQ	ROA	NM	NPM	OEOI	LDR	TLTA	CTA	CBTD	GRWTH	LGBS
CAR	-.083	1.000													
ECTA	-.158**	.857**	1.000												
RORA	-.110**	.070	.119**	1.000											
OBSEQ	.000	-.132**	-.180**	-.026	1.000										
ROA	.090*	-.208**	-.189**	.231**	.012	1.000									
NM	-.102**	.199**	.271**	.330**	-.015	.235**	1.000								
NPM	-.078*	.110**	.179**	.817**	.041	.074	.207**	1.000							
OEOI	.068	-.161**	-.229**	-.368**	-.059	.045	-.365**	-.667**	1.000						
LDR	-.052	-.022	-.006	.041	.000	-.019	-.003	.026	-.028	1.000					
TLTA	.035	-.513**	-.345**	-.070	.139**	.122**	-.006	-.071	.002	.090*	1.000				
CTA	-.108**	-.151**	-.141**	.130**	-.014	.148**	.214**	.069	-.065	-.100**	.009	1.000			
CBTD	-.100*	-.018	-.011	.073	.003	.037	.067	.055	-.059	.117**	.006	.316**	1.000		
GRWTH	-.041	-.049	-.051	-.046	.005	-.005	.047	-.133**	.115**	.049	.157**	-.038	.073	1.000	
LGBS	-.060	-.460**	-.526**	-.083*	.227**	-.010	-.241**	-.025	-.017	.071	.306**	.021	.064	.012	1.000

Table 3b: Correlation Matrix Among Variables (Step B)

Variable	F/NF	CAR	ECTA	RORA	OBSEQ	ROA	NM	NPM	OEOI	LDR	TLTA	CTA	CBTD	GRWTH	LGBS
CAR	-.001	1.000													
ECTA	-.006	.862**	1.000												
RORA	-.199**	.134**	.169**	1.000											
OBSEQ	-.068	-.120**	-.165**	-.040	1.000										
ROA	-.009	-.049	.002	.200**	-.022	1.000									
NM	-.164**	.288**	.363**	.418**	-.019	.278**	1.000								
NPM	-.136**	.118**	.167**	.807**	.027	.043	.347**	1.000							
OEOI	.125**	-.180**	-.218**	-.382**	-.034	.039	-.504**	-.654**	1.000						
LDR	.058	-.038	-.020	.010	-.002	-.051	-.052	.016	-.019	1.000					
TLTA	.045	-.467**	-.223**	-.103	.091*	.042	-.054	-.079	.009	.144*	1.000				
CTA	-.187**	-.063	-.059	.175**	-.008	.227**	.307**	.059	-.087*	-.114**	-.016	1.000			
CBTD	-.148**	.049	.038	.194**	-.016	.094*	.184**	.091*	-.123**	.267**	.004	.742**	1.000		
GRWTH	.020	-.058	-.034	-.031	-.036	-.001	-.005	-.133**	.115**	.099*	.175**	-.029	.144**	1.000	
LGBS	-.052	-.475**	-.537**	-.130**	.169**	-.074	-.303**	-.025	-.017	.090	.258**	-.026	.063	.015	1.000

Table 3c: Correlation Matrix Among Variables (Step C)

Variable	F/NF	CAR	ECTA	RORA	OBSEQ	ROA	NM	NPM	OEOI	LDR	TLTA	CTA	CBTD	GRWTH	PE	LGBS
CAR	.183	1.000														
ECTA	.135	.914**	1.000													
RORA	-.173	.378**	.469**	1.000												
OBSEQ	-.068	-.494**	-.457**	-.445**	1.000											
ROA	-.100	-.003	-.002	-.022	.003	1.000										
NM	-.037	.214*	.309**	.318**	-.197*	.031	1.000									
NPM	-.084	.366**	.428**	.875**	-.283**	-.130	.154	1.000								
OEOI	.086	-.189*	-.228**	-.511**	.233*	.088	.007	-.405**	1.000							
LDR	.212*	.199*	.125	.175	-.136	-.012	.063	.099	.013	1.000						
TLTA	.083	-.134	.012	-.079	.102	-.079	.188	-.023	.113	-.083	1.000					
CTA	-.063	-.159	-.157	-.086	-.054	.067	.126	-.230*	-.018	-.193*	-.023	1.000				
CBTD	-.193*	.067	-.044	-.014	-.182	.011	.066	-.160	.015	.515**	-.114	.632**	1.000			
GRWTH	-.078	-.105	-.065	-.085	.118	.052	-.048	-.090	.072	.085	.028	.010	.004	1.000		
PE	.035	.111	.156	.195*	-.027	.083	.039	.182	-.129	.020	-.201*	-.072	-.135	.058	1.000	
LGBS	-.149	-.526**	-.545**	-.275**	.476**	.035	-.053	-.211*	.063	-.188*	-.165	.286**	.055	-.106	-.226*	1.000

* : Correlation is significant at the 0.05 level (2-tailed)
** : Correlation is significant at the 0.01 level (2-tailed)

where:

CAR	=	Equity Capital – Fixed Assets/ Total Loan + Securities	LDR	=	Total Loan/Total Deposit
ECTA	=	Equity Capital/Total Assets	TLTA	=	Total Loan/Total Assets
RORA	====	Earning Before Income Tax/ Productive Assets	CTA	===	Cash/Total Assets
OBSEQ		Off-Balance Sheet Activities/ Equity Capital	CBTD		Cash & Bank/ Total Deposit
ROA		Net Income/Total Assets	GRWTH		Growth in Loan
NM		Net Income – Interest Expense/Total Assets			
NPM	==	Earning After Tax/Operating Income	PE	=	Market Price per Ordinary Equity Share/Earn. P Share
OEOI		Operating Expense/ Operating Income	LGBS	=	Natural Logarithm (Ln) of Bank Assets size

Source: Developed for this study.

Tables 3a, 3b and 3c, show that the highest correlation among independent variables is between CAR and ECTA. Their correlation is high because of the similarity of their numerators. Another reason some of the other variables have a high correlation is because the nature of the CAMELS components themselves cause the ratios to be related. However, this is unlikely to create statistical problems (multicollinearity) since when additional analysis was performed by omitting one related variable, the result was still consistent with the full model. Multicollinearity must be recognised but need not diminish the importance of the study.

(b) Logistic Regression (Backward Stepwise Method)

Logistic regression allows the researcher to use the backward stepwise/conditional method. This allows the inclusion or removal of predictors from the equation to obtain a better result (Cohen 2001; Tabachnick & Fidell 2001). Table 4 shows selected results of the backward stepwise/conditional logistic regression method.

Table 4 shows that the variables ECTA, RORA, NPM, CBTD and LGBS in Step A rejected the null hypothesis for each component of CAMELS represented. Variables RORA, OBSEQ, OEOI, LDR and CBTD in Step B rejected the null hypothesis for each component of CAMELS represented. Variables ECTA, RORA, NPM, CTA and CBTD in Step C rejected the null hypothesis for each component of CAMELS represented. Table 4 also shows that there is a relationship between a bank's probability of failure and its status (publicly and non-publicly held banks). The Exp (B) number (2.26) shows that non-publicly held banks are 2.26 times more likely to fail than publicly held banks.

Table 4: Selected Results of Logistic Regression (Backward Stepwise/Conditional Method)

		Variable in the equation						*Model if term removed*[a]			
Variable		B	SE	Wald	df	Sig	Exp (B)	Model log likelihood	Change in –2 log-likelihood	df	Sig. of the change
Step	ECTA	-.285	.051	31.674	1	.000	.752	-175.159	57.716	1	.000
A:	RORA	-.331	.148	5.029	1	.025	.718	-150.044	7.485	1	.006
	NPM	.046	.020	5.355	1	.021	1.047	-151.485	10.368	1	.001
	OEOI	.036	.022	2.761	1	.097	1.037	-147.973	3.343	1	.067
	CBTD	-.481	.122	15.563	1	.000	.618	-159.249	25.896	1	.000
	LGBS	-.574	.138	17.372		.000	.563	-157.785	22.968		.000
Step	LISTE	.816	.267	9.299	1	.002	2.260	-	-	-	-
B:	D (1)	-.182	.060	9.115	1	.003	.834	-345.779	12.278	1	.000
	RORA	.000	.000	2.125	1	.145	1.000	-341.848	4.867	1	.027
	OBSE	.044	.013	11.328	1	.001	1.045	-345.529	12.230	1	.000
	Q	.004	.002	5.995	1	.014	1.004	-345.741	12.652	1	.000
	OEOI	-.160	.042	14.602	1	.000	.853	-347.579	16.630	1	.000
	LDR				1						
	CBTD										
Step	ECTA	.209	.089	5.502	1	.019	1.233	-50.287	5.912	1	.015
C:	RORA	-2.266	.856	7.004	1	.008	.104	-52.258	9.854	1	.002
	NPM	.256	.131	3.832	1	.050	1.291	-49.482	4.302	1	.038
	CTA	-.509	.295	2.975	1	.085	.601	-49.485	4.308	1	.038
	CBTD	.412	.154	7.156	1	.007	1.509	-53.404	12.147	1	.000

a. Based on conditional parameter estimates.
Source: Developed for this study

where:

.	=	Equity Capital – Fixed Assets/ Total Loan	LDR	=	Total Loan/Total Deposit
	=	+ Securities	TLTA	=	Total Loan/Total Assets
		Equity Capital/Total Assets			
ROR	=	Earning Before Income Tax/ Productive	CTA	=	Cash/Total Assets
A	=	Assets	CBTD	=	Cash & Bank/ Total Deposit
OBS	=	Off-Balance Sheet Activities/ Equity	GRWTH	=	Growth in Loan
E	=	Capital			
Q		Net Income/Total Assets			
ROA		Net Income – Interest Expense/Total			
NM		Assets			
NPM	=	Earning After Tax/Operating Income	PE	=	Market Price per Ordinary Equity
OEOI	=	Operating Expense/ Operating Income	LGBS	=	Share/Earn.
					P Share
					Natural Logarithm (Ln) of Bank
					Assets Size

The results from the backward stepwise/conditional logistic regression regarding predictive ability are shown in Table 5. They show the predictive ability of steps A, B and C in the Fail/Not Fail classification. In Step A, the percentage for predicting survivor banks is 98.9%, with five cases of β (type II error), and the percentage for predicting bank failure is 26.6%, with 47 cases of α (type I error). In Step B, the percentage for predicting survivor banks is 89.2%, with 40 cases of β, and the percentage for predicting bank failure is 37.1%, with 132 cases of α. In Step C, the percentage for predicting survivor banks is 96.5%, with 3 cases of β, and the percentage for predicting survivor banks is 24%, with 19 cases of α.

Table 5: Classification of Predictive Ability Using Logistic Regression[a]

			Predicted		
			F/NF		
Observed			**Not Fail**	**Fail**	**Percentage Correct**
Step A:	Backward stepwise	**Not Fail**	459	5	98.9
		Fail	47	17	26.6
		Overall Percentage			90.2
Step B:	Backward stepwise	**Not Fail**	330	40	89.2
		Fail	132	78	37.1
		Overall Percentage			70.3
Step C:	Backward stepwise	**Not Fail**	82	3	96.5
		Fail	19	6	24.0
		Overall Percentage			80.0

a. the cut value is .500

Table 6 shows the Pseudo R-square, using the Nagelkerke R-square, and the goodness of fit, using the Hosmer and Lemeshow test.

Table 6: Pseudo R-Square and Goodness of Fit

Observed	Model summary		Hosmer & Lemeshow test		
	-2 Log Likelihood	Nagelkerke R-square	Chi Square	Df	Sign.
Step A:	285.267	.323	32.072	8	.000
Step B:	688.872	.157	18.783	8	.016
Step C:	94.662	.290	2.979	8	.936

Table 6 shows that the Pseudo R-square is quite a good result for steps A and C; however, the Pseudo R-square of Step B is not so good (less than .200) (Cohen 2001). The chi square of the Hosmer and Lemeshow test indicates significant results for steps A and B, but it is not significant for Step C. The Nagelkerke R-squared, result also indicates that the data used has a better fit to the model in steps A and C but not in Step B, which means the data during and after the crisis is not good enough to predict, or explain, the dependent variables (Failed/Not-failed). However, the logistic regression model can still be considered an early warning system for identifying bank failure. In other words, the logistic regression model can be included as a decision aid in solving banking problems.

(c) **Logistic Regression vs MDA**

As mentioned previously, this research also aims to determine the consistency of the logistic regression model compared to other multiple regressions, in this case, MDA. Unlike logistic regression, MDA requires the data to be normally distributed. To fulfil the requirement of normal distribution, the data should be transformed to normal distribution using logarithms (log) (Tabachnick & Fidell 2001; Hair et al. 1998). The significant variables for predicting bank failure with logistic regression and MDA are shown in Table 7.

Table 7: Significant Variables Using Logistic Regression and MDA Compared

Logistic regression			MDA		
Step A	Variable	Sig	Step A	Variable	Sig
	ECTA	.000		ECTA	.000
	RORA	.025		NPM	.000
	NPM	.021		OEOI	.000
	CBTD	.000		CBTD	.000
	LGBS	.000		LGBS	.000
Step B	Variable	Sig	Step B	Variable	Sig
	LISTED (1)	.002		LISTED (1)	.001
	RORA	.003		NM	.000
	OEOI	.001		NPM	.000
	LDR	.014		CTA	.000
	CBTD	.000		LGBS	.000
Step C	Variable	Sig	Step C	Variable	Sig
	ECTA	.019		LDR	.022
	RORA	.008			
	NPM	.050			
	CBTD	.007			

Table 7 shows that MDA gives the same results as logistic regression, in terms of significant variables, in steps A and B (both give four significant variables). However, in Step C, logistic regression gives a better result (four out of 15 variables are significant, while only one is significant with MDA).

Table 8 shows the predictive ability of logistic regression and MDA.

Table 8: Predictive Ability of Logistic Regression and MDA Compared

	Logistic regression			MDA		
	Predicted F/NF			Predicted F/NF		
Observed	Not Fail	Fail	Percentage Correct	Not Fail	Fail	Percentage Correct
Step A:						
Not Fail	459	5	98.9	568	12	97.9
Fail	47	17	26.6	12	26	32.5
Overall			90.2			90.0
Step B:						
Not Fail	330	40	89.2	331	39	89.5
Fail	132	78	37.1	114	96	45.7
Overall			70.3			73.6
Step C:						
Not Fail	82	3	96.5	85	0	100.0
Fail	19	6	24.0	23	2	8.0
Overall			80.0			79.1

Table 8 shows that the overall correct percentage in predicting bank failure using logistic regression is marginally better than MDA in steps A and C (90.2% to 90% in Step A; 80% to 79.1% in Step C). Only in Step B is the overall correct percentage better in MDA compared to logistic regression (73.6% to 70.3%). For Step C, MDA can correctly predict survivor banks by 100%, but it is very poor in predicting bank failures (8%). From tables 7 and 8 it can be concluded that the ability to predict bank failure is marginally better using logistic regression rather than MDA. Tables 7 and 8 are also consistent with previous research (Kane et al. 1998; Ohlson 1980), in that, most of the significant variables found earlier have a similar pattern to the significant variables found here.

(d) Practical Use

To obtain practical use from the above findings is not easy. Earlier it was seen that the findings in steps A, B and C gave slightly different significant variables in predicting bank failure, even though the pattern is similar. One way to develop these findings for practical use is to combine the whole data set and then make simulations to obtain a final result that can be applied in practice.
Before deriving an optimal result, the researchers made some simulations to try and group the variables using factor analysis. This process was in order to examine which group of variables had a high correlation, or was interrelated. Using this process, it was found that variables CAR, ECTA, OBSEQ, TLTA and LGBS could be considered as group 1, NPM, RORA, OEOI as group 2, and ROA, NM, LDR, CTA, CBTD and GRWTH as group 3. Each group was then run using logistic regression analysis (direct, forward and backward methods) to find the most significant variables from each. The entry order to the logistic regression analysis was also changed several times. This was done to see whether changing the order influenced the results. From the above simulations and processes, it was found that the variables CAR, ECTA, RORA, ROA, OEOI, CBTD and LGBS most often had significant results. This is similar to the combination of the best predictors from Table 7, except for CAR and ROA. So, these variables were used for the next analysis.

(e) Practical Use with Logistic Regression

After finding the most significant or best predictors above, the next step was to run these variables in the logistic regression (backward/stepwise) method in order to obtain the model or final results that can be applied in practice. Table 9 shows the results.

Table 9: Selected Results with Logistic Regression for Practical Use

			Variable in the equation			
Variable	**B**	**SE**	**Wald**	**df**	**Sig**	**Exp (B)**
ECTA	-.094	.029	10.371	1	.001	.911
RORA	-.171	.059	8.311	1	.004	.843
ROA	.054	.016	11.670	1	.001	1.055
OEOI	.068	.017	16.142	1	.000	1.070
CBTD	-.096	.045	4.612	1	.032	.908
Constant	-5.785	2.013	8.257	1	.004	.003

From Table 9, the model for practical use is as follows:

$$\text{Ln (F/NF)} = -5.785 - .094\ (\text{ECTA}) - .171\ (\text{RORA}) + .054\ (\text{ROA}) + .068\ (\text{OEOI}) - .096\ (\text{CBTD}).$$

where:

L_n (F/NF) = Log of the odds, natural logarithm of failed/not-failed
ECTA = Equity Capital/Total Assets
RORA = Earning Before Income Tax/ Productive Assets
ROA = Net Income/Total Assets
OEOI = Operating Expense/Operating Income
CBTD = Cash and Bank/Total Deposit

In relation to the hypothesis proposed in Section 3, Table 9 shows that the variables ECTA, RORA, ROA, OEOI, and CBTD can reject the null hypothesis (H_0).

f. Practical Use with MDA

Using the same process as logistic regression and based on the best predictors found, Table 10 shows the results of MDA for practical use.

Table 10: Selected Results with MDA for Practical Use

		Variable in the analysis		
Variable	**Coefficient**	**Wilks' Lambda**	**F**	**Sig.**
ECTA	1.513	.857	14.141	.000
RORA	1.762	.968	47.386	.000

ROA	-3.510	.902	21.096	.000
CBTD	.940	.857	18.398	.000
LGBS	4.380	.852	0.251	.000
Constant	-2.886			

Table 10 shows almost the same results as logistic regression analysis, except for OEOI and LGBS. Variable OEOI is not significant in MDA while it is significant in logistic regression. On the other hand, LGBS is significant in MDA while it is not significant in logistic regression.

The model for practical use in discriminant function is:

$$Z(F/NF) = -2.886 + 1.513\ (ECTA) + 1.762\ (RORA) - 3.510\ (ROA) + .940\ (CBTD) + 4.38\ (LGBS)$$

where:

Z (F/NF)	=	Discriminant function of failed/not-failed
ECTA	=	Equity Capital/Total Assets
RORA	=	Earning Before Income Tax/ Productive Assets
ROA	=	Net Income/Total Assets
CBTD	=	Cash and Bank/Total Deposit
LGBS	=	Natural Logarithm (Ln) of Bank Assets Size

In relation to the hypothesis proposed in Section 3, Table 10 shows that variables ECTA, RORA, ROA, CBTD and LGBS can reject the null hypothesis (H_0).

Further analysis (Table 11) found that the Z-score to evaluate bank failure or survival using MDA is as follows:

Table 11: Z-Score to Evaluate the Bank (functions at group centroids)

	Function
Group	1
Not Fail	0.182
Fail	-0.985

Table 11 shows that a bank will be considered to be a survivor bank if its Z-score is greater than 0.189. On the other hand, a bank will be considered to have failed if its Z-score is less than -1.027. As discussed previously, in the logistic regression analysis, MDA can also be included as a decision aid in solving banking problems.

Conclusion

This study discussed descriptive findings of the most influential or significant variables in predicting bank failure in the period before and during the economic crisis (Step A), during and after the economic crisis (Step B) and during and after the economic crisis for banks that are listed in the stock market (Step C). It also discussed the possible practical use of the model developed.

Logistic regression in tandem with MDA can act as an early warning system to identify bank failure as a complement to on-site examination. Logistic regression model and MDA can be included as a decision aid in solving banking problems.

Using logistic regression and MDA, the results suggest that the variables ECTA (capital adequacy ratio), RORA (assets quality), ROA (management), OEOI (earnings), CBTD (liquidity), and LGBS (bank size) are statistically significant in explaining bank failure. The results also show that non-publicly held banks have a greater chance of failure than publicly held banks.

The variable PE for measuring sensitivity to market risk is not significant in predicting bank failure. Related variables or ratios to measure the sensitivity to market risk could be further explored by future research.

A clear distinction between the model developed for before and during the economic crisis (Step A), the model developed for during and after the economic crisis (Step B), and the model developed for during and after the economic crisis for listed banks (Step C) cannot be found. However, a possible practical use for these models has been proposed. Finally, the results found that the predictive ability and contribution of the significant variables are better in the logistic regression analysis than with MDA.

Implications for Public Policy

This research is significant for government or banking regulators, the public and academics. The significance for government or banking regulators is that it could: (a) be used as an early warning of bank failure; (b) provide the Indonesian Banking Supervisory Agency with a tool that may help predict future problems in the Indonesian banking system; (c) be used to supervise and monitor the quality of a bank's assets to prevent bank failure; and (d) be used to maintain a safe and sound banking system.

The significance for society is that this research could: (a) become an early warning signal for bank problems; (b) confirm investors' concern or confidence on whether to continue to invest or not; (c) provide information on whether there is substantial doubt about a bank's ability to continue as a going concern for a reasonable period of time.

The significance for academics is that this research could: (a) be compared with previous research; (b) improve future research; (c) be used to solve banks' problems; and (d) be useful for teaching.

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