

Predicting Egyptian Banks Distress

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Abstract

Purpose – the main purpose of the study is to investigate an accurate prediction method for banking distress applied on a set of Egyptian banks.

Methodology - the researchers have compared the prediction accuracy of the discriminant analysis and logistic regression model, to choose the most appropriate one. The data has been collected from the “Bank scope” data base and for the period of 2002–2016.

Findings – the results of the study revealed that the predictive accuracy of discriminant analysis outperformed that of the logistic regression model.

Originality - The study adds value to the literature as it is one of the few studies that is concerned with predicating the banking financial distress especially in Egypt.

Keywords: Banking distress, Egyptian banking system, Z-score, Type of auditor, Discriminant analysis, Logistic Regression Model

1. Introduction

The central Bank of Egypt completed the first phase of the banking reform program, which started in 2004 and ended in 2008. This stage included four logistic pillars: first, conducting

some privatization and consolidation processes in the banking sector. Second, confronting the problem of nonperforming loans in banks. Third, restructuring public sector banks financially and administratively. Finally, support the supervision sector of the central Bank of Egypt. The political events in Egypt led to major shifts that adversely affected economic activity and financial markets during 2011 and 2012. The Egyptian banking sector ranks fourth among the Arab banking sector, and ranks first among the banking sector of the non- oil Arab countries.

The Prediction of bank distress has been an interest of many researchers. Maghyere (2014) indicated that bank distress has some advantages such as increasing the ability of regulators to forecast the distress and the ability to take actions that prevent distress and to protect healthy institutions and prevent the currency crisis that may generate from the financial sector crisis.

Most studies that have analyzed banking distress focused on the U.S. banks, such as those developed by Altman (1977), Meyer and Pifer (1970), Oshinsky and Olin (2006), and De Graeve et al (2008). However, Laeven (1999), Bongini et al (2001), and Arena (2008). Others studies focused on East Asia such as: Wong (2010) who examined banking distress in an Executive meeting of East Asia Pacific Central Banks (EMEAP); Zaki (2011) who studied banking distress in UAE financial market; Maghereh (2014) who tested banking distress in Gulf Cooperation Council Countries.

Sahut (2011) indicated that banks in the MENA region are characterized by government intervention, highly concentrated and less exposed to subprime loan risk.

The aim of this study is to compare between the prediction accuracy of logistic regression and discriminant analysis to select the most appropriate one and to determine the variables that can be used as a measure of distress.

The contribution of this study stems from the fact that it provides important predicted information for investors, shareholders and regulators regarding the probability of financial distress in the Egyptian banking sector. The study has a limitation that the distress forecast need to be used in both macro and micro prudential approaches.

The study proceeds as follows: the first section is an introduction to the research, the second section presents the literature review, the third section provides the study methodology, the fourth section presents the empirical results, the fifth section presents the main conclusion, finally the sixth section presents the recommendations and future researchers.

2. Literature Review

According to literature review, most of the studies have used discriminant analysis for investigating the causes of bank distress. Altman (1968) study was the pioneer for predicting the firm failure by Multivariate Discriminant Analysis (MDA) over the period from 1946 to 1964. He found that the MDA model was able to provide a high predictive accuracy of 95% one year prior to failure. Sinkey (1975) predicted correctly 72% of banks' distress during the period from 1969 to 1971. Altman (1977) attempted to identify the financial problems in the saving and loan institutions during the period from 1966 to 1973 and found that discriminant analysis has proven effective performance in many previous studies.

Cox and Wang (2014) used linear and quadratic discriminant analysis (LDA) to predict US banks failure during the period of 2007-2010. He found that LDA performs better in predicting the survival of banks within a range of 70.69% to 94.92% and QDA performs better in predicting bank distress within a range of 77.91% to 86.71%. Contrary to the previous study, which relied on annual data for the studied variables, Cleary and Hebb (2016) investigated the failure of 132 US banks during the period from 2002 to 2009 using the MDA analysis. The accuracy of the model's prediction ranged from 90% to 95% when it was used to study the failure of 191 banks outside the sample during the period of 2010-2011.

On the other hand, some studies have been used the regression models to improve banking distress prediction. Martin (1977) used logit analysis to study the early warning system in US commercial banks during the period from 1970 to 1976. He found that the linear composition of independent variables positively correlated to the probability of failure. Among the most important variables for determining the bankruptcy are size, total liabilities to total assets, performance, and current liquidity based on the study of Ohlson (1980). Thomson (1991) correctly predicted 93% of failure of US banks during the period from 1982 to 1989.

Logit or probit models were used widely to investigate bank distress across countries and regions, Barrell et al (2010) developed a prediction model for the OECD economies from 1980 to 2007. Jin et al. (2011) examined the ability of quality audit and accounting to predict US banks from 2006 to 2007. Gungel (2012) used the multivariate logit model to study the banking distress in Northern Cyprus during the period from 1984 to 2008. Betz et al (2014) developed a model to forecast vulnerabilities in European banks from 2000 to 2013. Wong et al (2010) developed a panel probit model to identify indicators of bank distress for banking distress EMEAP countries during the period from 1990 to 2007.

One of the most important models that has been used to predict banks distress during the banks crisis period is the Hazard model. Shumway (2001) predicted distress by hazard model finding that Hazard model was superior to the logic and the MDA models. Männasoo and Mayes (2009) used the discrete time survival model for explaining banking problems in 19 Eastern European countries during the period from 1995 to 2004. The study found that The CAMEL indicators have an important role in predicting distress.

There are many studies that used more than one model, such as, Espahbodi (1991) tested both the MDA analysis and logit model for a sample of 48 US banks that failed in 1983. The study concluded that the logit model outperforms the analysis of discriminant in predicting potential failure. Kolari et al. (2002) used both logit analysis and trait recognition to predict the failure of US commercial banks during the period from 1989 to 1992. Doganay et al (2006) developed models to forecast the failure of Turkish banks using multiple regression model, discriminant analysis, logit model and probit model. During the period from 1997 to 2002. The study found that the most appropriate model is the logit model. Li, et al (2011) compared the predictive power of models by using logit regression, the proportional hazard model and the survival time model for US banks. The study found that the logit model outperformed the prediction accuracy of both the proportional hazard model and the survival time model. Ling (2010) used logistic regression and artificial neural network (ANN), to investigate banking distress in

emerging countries during the period from 1998 to 2006. The study found that the mixed model is suitable for predicting banks' financial distress in emerging markets.

Other studies have been conducted to predict bank distress in MENA countries including: Sahut and Mili (2011) that used a two-level nested logit model to develop a model for linking merger decisions and troubled banks during the period from 2000 to 2007. AL-Saleh and Al-kandari (2012) used logistic regression model to determine the bank's financial distress in Kuwait from 2001 to 2009. He found that 41.7% of the time periods are expected to lead banks in financial distress. Maghyreh and Awartani (2014) used the hazard model In the GCC countries to identify the causes of bank distress from 2000 to 2009. Zaki et al (2011) examined the main drivers of the financial distress of UAE financial institutions during the period 2000-2008 by logit and probit model.

3. Methodology

3.1 Data Source

The data were collected from the Bankscope database during the period from 2002 to 2016.

3.2 Population and the Study Sample

The population is the Egyptian banking system that consists of 40 commercial, non-commercial, private and public sector banks Hafez, 2018. The research sample consists of 22 commercial banks. Our sample divided to "in-sample" analysis from 2002 to 2011 and "out-of-sample" from 2012 to 2016

3.3 Statistical Models

The equation of discriminant Analysis

$$Z_i = \beta_0 + \beta_1 CAR_{it} + \beta_2 EAS_{it} + \beta_3 LLP_{it} + \beta_4 NPL_{it} + \beta_5 CTI_{it} + \beta_6 NIT_{it} + \beta_7 ROAA_{it} + \beta_8 LADF_{it} + \beta_9 Deposits_{it} + \beta_{10} size_{it} + \beta_{11} off\ bs_{it} + \beta_{12} auditor\ type_{it} + \beta_{13} Concentration_{it} + \varepsilon_i$$

The equation of Logistic regression

$$Z_i = \log\left(\frac{p_i}{1-p_i}\right) = \beta_0 + \beta_1 CAR_{it} + \beta_2 EAS_{it} + \beta_3 LLP_{it} + \beta_4 NPL_{it} + \beta_5 CTI_{it} + \beta_6 NIT_{it} + \beta_7 ROAA_{it} + \beta_8 LADF_{it} + \beta_9 Deposits_{it} + \beta_{10} size_{it} + \beta_{11} off\ bs_{it} + \beta_{12} auditor\ type_{it} + \beta_{13} Concentration_{it} + \varepsilon_i$$

Where, β_0 Is a constant, $(\beta_1: \beta_{13})$ Are the coefficient of the explanatory variables. (i) refers to the bank number and (t) refers the time period. ε_i is the unobservable heterogeneity.

3.4 The research Hypotheses

H.1: " there is a significant correlation between z-score as a dependent variable and the study's independent variables (capital adequacy ratio, equity to total assets, provisions of loan loss to total loans, non-performing loans to total loans, cost to income ratio, non-interest expenses to average assets, pre-tax profits to average assets, Liquid assets to deposits and short term funds,

Deposits to total assets, The logarithm of total assets, off-balance sheet items, auditor type and Concentration".

H.2:" there is an equal relative impact of all the independent variables on the bank's z-score".

H.3:" the discriminant model is more accurate than the logistic regression model in predicting the bank distress in the Egyptian banking sector".

Table 1. Explanatory variables

Dependent variable(Bank risk)			
$z - score_{it} = \log \left(\frac{ROA_{it} + EQ_{it}}{SDROA_{ip}} \right)$			
ROA is pre-tax profits to total assets.		EQ is equity to total assets.	
SD ROA we use data from the two previous years to calculate (ROA) at time t.			
Variables	Measures	Ex. Effect	Source
Explanatory variables			
CAMEL variables			
Capital			
CAR	(Tier 1 + Tier 2 capital) to risk weighted assets.	N	Bankscope
EAS	Equity capital to total asset	N	Bankscope
Asset quality			
LLP	provisions of loan loss to total loans.	P	Bankscope
NPL	Non-performing loans to total loans.	P	Bankscope
Efficiency			
CTA	Cost to income ratio.	P	Bankscope
NIT	Non – interest expenses to average assets.	P	Bankscope
Earning			
ROAA	pre-tax profits to average assets	N	Bankscope
Liquidity			
LADF	Liquid assets to deposits and short term funds.	N	Bankscope
DEPOSIT	Deposits to total assets.	N	Bankscope
Non-CAMEL variables			
SIZE	The logarithm of total assets.	N	Bankscope
Off-BA	Acceptances, documentary credits, loan guarantees, contingent liabilities to total assets.	N	Bankscope
Auditor type	Dummy variable take one for big 4 auditor and zero for non big 4 auditor.	N	Bankscope
Concentration	Herfindahl-Hirschman(HHIIC)	N	Bankscope

Source: prepared by the researcher.

4. Empirical Results

4.1 Descriptive Statistics

The skewness in Table 2 is positive for CAR, EQ, LLP, NPL, ROAA, CTI, NIT, log assets

and off-balance sheet item's. While skewness is negative for LADF, deposits, type of auditor and concentration. The values of kurtosis are deviated from 3 that show data are not normally distributed, rejected the normality assumption at the 5 % level of significance.

Table 2. Descriptive statistics

Variables	Min	Max	Mean	Median	Skew	Kurto	SD	Ja-Bera
Dependent Variable								
Z-score	0.000	1.000	0.509	1.000	-0.036	1.001	0.501	36.667
Independent Variables								
CAR	0.080	0.249	0.161	0.154	0.501	2.142	0.041	15.942
EQ/TA	0.039	0.188	0.097	0.091	0.527	2.439	0.043	13.078
NPL	0.014	0.349	0.122	0.110	0.925	3.227	0.089	31.873
LLP	0.000	0.038	0.013	0.010	0.661	2.314	0.011	20.347
CTI	0.256	0.989	0.540	0.514	0.724	2.872	0.201	19.348
NIT	0.009	0.034	0.019	0.019	0.307	2.283	0.007	8.161
ROAA	-0.011	0.034	0.010	0.008	0.295	2.453	0.012	5.940
LADF	0.077	0.719	0.436	0.456	-0.142	2.049	0.178	9.034
DEPOS	0.707	0.884	0.801	0.805	-0.182	1.971	0.053	10.924
LOG TA	3.277	5.267	4.047	4.000	0.498	2.468	0.547	11.702
OFF-BA	0.052	0.468	0.169	0.137	1.466	4.447	0.111	97.935
TYPE	0.000	1.000	0.805	1.000	-1.536	3.359	0.397	87.687
HHIC	0.000	1.000	0.900	1.000	-2.667	8.111	0.301	500.206

Source: prepared by the researcher.

Table 3. Pearson's Correlations Matrix

	z- score	CAR	EQ	NPL	LLP	CTI	NIT	ROA A	LA D F	DEP O	LO G TA	OF F
z- score	1											
CAR	0.19 ***	1										
EQ	-0.06	0.33 ***	1									
NPL	0.02	0.17 **	-0.07	1								
LLP	0.01	-0.12 *	-0.17 ***	0.27 ***	1							
CTI	0.11	0.14 **	0.11	0.03	-0.13 *	1						
NIT	0.12 *	0.37 ***	0.27 ***	-0.13 *	0.01	0.43 ***	1					
ROA A	-0.07	0.02	0.34 ***	-0.40 ***	-0.26 ***	-0.47 ***	-0.02	1				
LADF	0.20 ***	0.31 ***	0.23 ***	0.16 **	-0.11	0.04	0.19 ***	0.09	1			
DEPO	0.12 *	-0.24 ***	-0.49 ***	-0.09	-0.21 ***	0.04	0.04	-0.15 **	-0.30 ***	1		
LOG TA	-0.08	-0.29 ***	-0.54 ***	-0.10	-0.03	-0.22 ***	-0.25 ***	-0.02	-0.25 ***	0.32 ***	1	
OFF	0.00	-0.15 **	-0.12 *	-0.15 **	-0.07	-0.02	-0.08	0.11 *	-0.07	-0.05	0.3 ***	1

*** Significant at the 0.01 level.

** Significant at the 0.05 level.

* Significant at the 0.10 level.

Source: prepared by the researcher.

From Table 3, there is no correlation between the independent variables as that indicating no multicollinearity between variables (field, 2009, P.224). It is obvious that the CAR ratio, LADF ratio, NIT and Deposits have a significant positive relationship with the Z-score. The ratio OF NPL, LLP ratio, CTI ratio, and OFF-balance sheet items have a positive relationship with the Z-score but not significant. ROAA, and log of total assets have an inverse relationship with the Z-score but not significant.

So, we can accept the first hypothesis partially as the CAR ratio, LADF ratio, NIT ratio and Deposits are significantly correlated with the Z-score.

4.2 Estimation

Table 4. Estimation logistic and discriminant analysis (2002 to 2011)

	Logistic regression(2002-2011)			MDA (2002-2011)		
	Beta	Wald	Sigh.	Beta	F	Sigh.
C	-6.962	3.922	.048**			
CAR	11.55	6.882	.009**	.620	8.550	.004***
EAS	-7.794	2.312	.128	-.419	.816	.367
NPL	-1.477	.559	.454	-.166	.081	.776
LLP	4.293	.072	.789	.061	.034	.853
CTI	.719	.447	.504	.199	2.683	.103
NIT	-12.27	.173	.678	-.105	2.944	.088*
ROAA	-1.509	.005	.942	-.006	.598	.440
LADF	2.734	8.092	.004***	.615	8.820	.003***
DEPOS	8.565	6.136	.013**	.608	3.335	.069*
LOGT	-.569	1.986	.159	-.423	1.516	.220
OFF	1.599	1.251	.263	.240	.000	.982
TYPE	-.024	.003	.959	-.034	2.776	.097*
HHIIC	-.129	.070	.791	-.057	.128	.721
No. of crisis			74			75
No. of observation			220			220
% correct			64.8			64.8
% distress correct			66.1			67.0
Overall Percentage			65.5			65.9
% type I error			35.2			34.6
% type II error			33.9			33.6

Source: prepared by the researcher.

The researchers conducted the panel logistic regression model and discriminant analysis to explore determinants of the z-score from 2002 to 2011. We used SPSS version (20) and Eviews software version following the study of El-Ansary and Hafez (2015).

Table 4 reports the logistic regression model and discriminant analysis to test the second hypothesis. Both of two models agree that the CAR ratio, LADF ratio, and Deposits have a significant positive relationship with the probability of distress, but the NIT ratio and type of auditor have a significant negative relationship with the probability of distress when using discriminant analysis.

So, we can't accept the second hypothesis as all of the independent variables jointly have an equal relative impact on the bank's z-score.

From the table above it is obvious that the predictive accuracy of the discriminant analysis model (MDA) is 65.9 slightly outperforming the logistic regression model which is 65.5 and MDA model can classify distress period with 67% with type I error and type II error lower than that of the logistic regression model.

4.3 Prediction

Table 5. Prediction Classification Accuracy for the Banks (from 2012 to 2016)

	Logistic regression(2012- 2016)	MDA (2012-2016)
No. of crisis	12	17
No. of observation	110	110
% correct	94.3	97.7
% distress correct	52.2	73.9
Overall Percentage	85.5	92.7
% type I error	11.8	6.6
% type II error	29.4	10.5
Root mean squared error	.372	.322
Mean absolute error	.293	.261

Source: prepared by the researcher.

The objective of this article is to investigate the predictive accuracy of the logistic regression model and discriminant analysis to achieve this objective the researchers ran data from 2012 to 2016. Table 5 shows that the predictive accuracy of the discriminant analysis model (MDA) in holdout sample is 97.7% outperforming the logistic regression model which is 94.3% and MDA model can classify distress period at 73.9% with type I and type II errors lower than that of the logistic regression Using a cutoff value of 0.5. The performance achieved by the MDA model was equal to 92.7% versus 85.5% to for logistic regression. Thus, we can accept the third hypothesis that MDA model is more accurate than the logistic regression model in predicting the bank distress in the Egyptian banking sector.

5. Conclusion

Investigating predicting distress for Egyptian commercial banks was core of the article. The data set comprised 22 banks in Egypt over the period from 2002 to 2016. A logistic regression and discriminant analysis were used to choose the most appropriate one. In the study, 13 variables are used as explanatory variables that have been proven to influence bank risk. The study was used z-score that represents a more comprehensive measure of bank distress that capture more than credit risk.

The empirical findings show that EAS, ROAA, NIT and size are inversely related to bank risk. However, LLP, LADF and deposits are positively related to bank risk. We also find that less concentrated markets, auditor otherwise big 4, and increase off-balance sheet items increase bank risk.

The performance achieved by the MDA model was equal to 92.7% versus 85.5% to of the logistic regression model. This indicates the ability of the study model to differentiate between the financially healthy banks versus distressed or financially unhealthy ones.

6. Recommendations and Future Research

6.1 Recommendations

First: it is recommended for regulators and rating agency to early discriminate between healthy and troubled banks. Second: it is recommended to use discriminant analysis for predicting banking distress in Egypt. Third: it is recommended to use z-score as a proxy of probability of distress.

6.2 Future Research

- Using other methods for prediction such as neural networks.

Using macroeconomic variables to choose the leading indicators of distress.

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