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Predicting Banks' Failure: The Case of Banking Sector in Sudan for the Period (2002-2009)

Khalafalla Ahmed Mohamed Arabi

Professor of Econometrics, Department of Econometrics and Social Statistics, Faculty of Economics and Administrative Sciences University of Bakht Alruda Sudan

E-mail:khalaf_arabi@yahoo.com, Tel.:+249911811733

Abstract

The purpose of this paper is to estimate bank's failure by logistic regression and discriminant analysis. Both the logistic regression and discrimenant analysis showed that earning (E) was the most influential measure on banks's failure followed by asset quality (A) liquidity (L) and capital adequacy (C). *The estimated discrimenant function without cross validation obtained the following ratios 0.957, 0.872, 0.764, 1.000, 0.961 for fair, marginal, satisfactory, strong, and unsatisfactory respectively. While using cross validation it obtained 0.941, 0.872, 0.764, 1.000, and 0.961 respectively. Averages for the first and second method were 0.878 and 0.756 respectively. It is obvious that the estimated function without cross validation is the best for predicting fiscal situation of banks and the most efficient early warning system. A new bank is identified as being of a particular rating depends upon which discriminant function value is higher*

Key words: logistic regression, discriminant, failure, indicator, prediction, rating, supervision.

Introduction

Banks as profit maxizers are financial mediator between savers and investors i.e. an important source for most businesses, and provide other important financial services which contribute towards the development of any economy. These tasks necessitate the existence of a supervisory body to preserve community savings. Supervision is an ongoing process achieved by the use of the core assessment and expanded procedures, and communicating examination findings are integral parts of the supervision process (Comptroller's Handbook 2010). The leading indicators of bank distress can be grouped into three main categories. The first category consists of standard balance sheet and income statement financial ratios. This includes the so-called CAMEL variables (where CAMEL stands for "capital, asset quality, management, earnings, and liquidity"). The second category of leading indicators of bank distress consists of market prices of financial instruments, such as bank stocks and subordinated debt. The third category of potential leading indicators contains other, somewhat less common, measures of bank risk and financial strength, such as deposit rates or indicators characterizing the economic environment in which the banks operate. CAMEL variables are very popular in the "supervisory risk assessment and early warning systems" (Poghosyan and Cihak 2008). Regulators assess the financial condition of banks through on-site and off-site surveillance. They rely on two analytical tools for off-site surveillance: supervisory screens and econometric models. Supervisory screens are combinations of financial ratios, derived from bank balance sheets and income statements that have in the past given forewarning of safety and soundness problems. Econometric models use sets of variables from banks' financial statements and economic environment to compute the probability that a bank will fail in a future period. In both methods, relevant variables have to be identified (Said & Saucier 2003). The fast advances in the creation of financial instruments and the accompanied technology, and globalization expose financial institutions to operations risks that can spread quickly leading to global financial crisis highlighted the importance of early identification of weak institutions: when problems are identified late, solutions are much more costly. The most important types of risks considered by Basel first and second Committee are: credit, market, and operations risk. Operations risk is defined as risks which result from financial corruption, inappropriate internal operations systems, inadequacy of human capital, and external factors such rising interest and inflation rates. All banks conducting international transactions are required under the Basel Accord to hold assets with no more than 8% aggregated risk. Generally the central bank (CB) assumes three authorities on behaves of the government that is legislative and supervision and excucative on every matter concerns finance and banking sector. The CB imposes full dominance and firm control on financial institutions (Ahmed 2005).

The existence of banking sector in Sudan dates back to 1903 when a branch of Barclays Bank was opened. The Banking sector in Sudan is divided into four categories of scheduled banks. The banking sector was operating in the traditional way, and in the late seventies some Islamic banks were established. In 1984 with the application of Islamic Sharia laws a dual systems of banking was found that is Islamic and traditional banks. Since 1991 the whole banking sector has been operating according to Islamic Sharia laws. The banking sector is composed of four types of banks: Government Owned Commercial Banks (GOCBs), Government Owned Specialized Banks (GOSBs), Private Commercial Banks (PCBs), and Foreign Commercial Banks FCBs (Goosi 2006). The total number of operating banks in Sudan is 33, 7 of them are foreign banks, 4 specialized public banks and the rest are private commercial banks. The central bank of Sudan took two steps toward applying the international supervision measures. The first step was in 1994 commenced with the application of the recommendations of Basle Committee on Banking Supervision concerning capital adequacy and capital regulatory standards project (bank reform). The second was in late 2002 where CAEL measure was fully applied. There is a relatively broad agreement in the literature and among practitioners that the CAMEL indicators are useful in grading banks in terms of their financial vulnerability, and supervisors often combine these indicators to come up with an assessment of a bank's soundness. Basel committee proposed 20% of total capital should be assigned to meet operations risk and banks are allowed later to assess operations risks according to their experience (Alhussain). The banking sector has been exposed to many risks and faced difficulties caused by internal and external factors. Many methods for predicting banks' failure has been used based on internal or external data. External data include variety of economic measures bank's income, cost, and asset value that is solvency. Internal data are collected from capital adequacy, asset quality, management, equity, liquidity, and sensitivity to risk. Due to the uniqueness of banks and their potential fragility it is important to determine which banks are likely to default or experience distress, taking into account that bank supervisors and regulators aim to maintain a prudent and stable banking system. The CB has been committed to solve banks distress by imposing regulatory capital adequacy standards To the best of my knowledge only descriptive statistics were used to evaluate the bank failure, this paper will has apply logistic regression, discrimenant analysis to predict bank distress in the Sudan i.e applies more advanced methods that add to the literature on Sudan's banking sector failure and can be used for comparison with other similar developing countries. Thus the purpose of this paper is to use the observed situations of banking sector in Sudan to predict banks' failure and build an early warning system. Based on past instances of bank distress it is possible to establish an early warning system for the banking sector in Sudan.

Literature Review

Mayes and Stremmel (2012) examined bank distress within a large quarterly data set of Federal Deposit Insurance Corporation insured US banks from 1992 to 2012. They contrasted two methods, the Logit technique and discrete survival time analysis, to predict bank failures and draw inferences about the stability of contributing bank characteristics. The models incorporate CAMELS indicators that consider the bank-specific variables and macroeconomic conditions. They contrast risk-based and non-risked-weighted measures of capital adequacy. They found that the non-risk-weighted capital measure, the adjusted leverage ratio, explains bank distress and failures best.

Tatom (2012) used CAMELS rating system and national economic variables to forecast bank failure for the entire commercial banks industry in the United States. The model predicted failure (survival) accurately during both the saving and loan crises and the mortgage failure foreclosure crisis. He showed the insignificance of total assets, real prices of energy, currency ratio and interest rate spread.

Kandrac (2010) investigated the response of banks facing regulatory capital adequacy standards and an imperfect market for equity to monetary policy shocks. The results indicated that the smallest ninety percent of banks exhibit behavior consistent with the so-called bank capital channel of monetary policy. This study highlighted the link between the stabilization and regulatory functions of the Federal Reserve. The results have important implications for the effect of recent regulatory proposals on the transmission of monetary policy.

Liu (2010) constructed panel data of Taiwanese financial industry by applying logistic regression model to explore the merger motivations and the impacts of variables on merger. Among variables used are capital adequacy, asset quality, liquidity, and management abilities. Further by using factor analysis he discussed the difference of performance between holding company banks and ordinary banks after merger. The empirical results show that according to the performance scores there are six banks of holding company on the top ten lists. This reveals that the merger between financial institutions have improved merger synergy.

Hays (2009) described the use of a financial autopsy to discover the root causes of bank failure. The causes of failure in the present environment are frequently associated with catastrophic events related to credit quality problems linked with residential and commercial real estate lending activities. Sometimes this is related to declining home prices. This may be aggravated by deterioration of the economy as a whole and rising unemployment. At other times the culprit lies within real estate development loans that default when builders are no longer able to sell their properties. Other failures may be associated with commercial and industrial loan borrowers or small business borrowers adversely affected by the economic decline. Recently banks have begun to experience losses from credit card, student loan and consumer loan defaults.

Poghosyan and Cihak (2008) presented a unique database of individual bank distress across the European Union from mid-1990s to 2008. Using this data set, they analyzed the causes of banking distress in Europe and identified a set of indicators and thresholds that can help to distinguish sound banks from those vulnerable to financial distress. Nimalathasan B (2008) initiated a comparative study of financial performance of banking sector in Bangladesh using CAMELS rating system with 6562 Branches of 48 Banks in Bangladesh from Financial year 1999-2006. CAMELS rating system is widely used for measuring performance of banks in Bangladesh.

Zuabi (2008) assessed the framework of the sufficiency of capital according to the Basel Agreement and the possibility of applying it to the Islamic banks, especially under the international banking demands for the implementation of the items of the new Basel agreement. She delineated a suggested framework to measure the sufficiency of capital that is consistent with the functional nature of Islamic banks and the risks Islamic banks face within the banking crucible. She determined an accounting framework that can measure the solvency of the Islamic banking in a way that may increase and reinforce the efficiency and effectiveness of the control system in those banks, thereby increasing credibility of their function and endorsing their process and role in society. The proposed capital adequacy measure is composed of three elements that is Islamic bank capital, credit, market, and operations risks facing the bank, and the capital adequacy ratio capital over risks. The suggested pattern has been tested according to an applied study relying on the data of the financial lists of some Islamic banks operating in Palestine. Finally, many important recommendations have been presented to support the implementation of the suggested pattern and universalize it on different Islamic banks.

Alhussain (2006) aimed to identify theoretical and practical challenges and obstacle facing Islamic banks in Sudan which applying international measures, how they deal with operations risk and to what extent these banks make use of Basle committee recommendations. In addition, he identified the central banks efforts in dealing with operations risks.

Olaniya (2006) measured the bankruptcy status of Nigerian banks using secondary data over a period of five years ended 2002, while the analysis was carried out through the use of multiple discriminant analysis. He concluded that the bank has high potential failure evidenced by poor operational performance, and low zeta score.

Baral (Dec 2005) examined the financial health of joint venture banks in the CAMEL framework. The health check up conducted on the basis of publicly available financial data concluded that the health of joint venture banks is better than that of the other commercial banks. In addition, the perusal of indicators of different components of CAMEL indicated that the financial health of joint venture banks is not so strong to manage the possible large scale shocks to their balance sheet and their health is fair. Accordingly CAMELS rating system shows that 3 banks were 1 or Strong, 31 banks were rated 2 or satisfactory, rating of 7 banks were 3 or Fair, 5 banks were rated 4 or Marginal and 2 banks got 5 or unsatisfactorily rating. 1 Nipalese Commercial Bank had unsatisfactorily rating and other 3 banks had marginal rating.

Deviz & Podepiera (2004) investigated the determinants of the movements in the long-term Standard & Poor's and CAMELS bank ratings in the Czech Republic during the period when the three biggest banks, representing approximately 60% of the Czech banking sector's total assets, were privatized (i.e., the time span 1998–2001). The same list of explanatory variables corresponding to the CAMELS rating inputs employed by the Czech National Bank's banking sector regulators was examined for both ratings in order to select significant predictors among them. They employed an ordered response Logit model to analyze the monthly long-run S&P rating and a panel data framework for the analysis of the quarterly CAMELS rating. The predictors for which they found significant explanatory power are: Capital Adequacy, Credit Spread, the ratio of Total Loans to Total Assets, and the Total Asset Value at Risk. Models based on these predictors exhibited a predictive accuracy of 70%. Additionally, they found that the verified variables satisfactorily predict the S&P rating one month ahead.

Shen and Hseih (2004) combined micro and macro approaches devising a modified early warning system to monitor individual bank distress of five severely crisis-hit Asian countries, namely, Indonesia, Malaysia, Thailand, Korea, and the Philippines. They found that the ownership structure considered with the state-owned banks being expected to have higher tendency to default, and connected and independent banks are differentiated to identify the moral hazard.

Hassan and Bashir (2002) analyzed the determinants of Islamic bank profitability. They analyzed the performance measures starting with asset quality, capital adequacy ratios, operation ratios, and liquidity ratios. Their findings confirm previous findings.

The above displayed studies focused on incorporating CAMELS indicators that consider the bank-specific variables and macroeconomic conditions on one hand, and devising an early warning system combining micro and macro approaches on the other hand, this study will focus as well on CAEL indicators since the Central Bank of Sudan is applying them at this stage and will differ by using the estimed discrimenant function to specify the position of newly entering bank by forecasting CAEL rating and reproduce them.

Methodology and Data

Variable Explanations

Capital adequacy (Equity/total loans) is a ratio of solvency. Minimum capital adequacy ratios have been designed to ensure banks can absorb a reasonable level of losses before becoming insolvent. The higher the capital adequacy ratios a bank has, the greater the level of unexpected losses it can absorb before becoming insolvent (Said & Saucier 2003).

Assets quality (Loan loss provisions/total loans) is a ratio evaluates the proportion of bad loans over total loans. A high ratio is supposed to mean a bad quality of assets, but in fact it depends on whether information on ‘bad loans’ is correctly revealed. The Japanese case tends to show that systematic underestimation of ‘bad loans’ has been used by distressed banks as a strategy to avoid loss of confidence. Consequently the ratio may be blurred or underestimated (Said & Saucier 2003). Earnings ability (Pre-tax profit/total assets) is ratio measures profitability. Profits are dependent on all other variables (Said & Saucier 2003). Liquidity position (Deposits/total assets): Perfect liquidity implies that liabilities ranked by maturity be matched by corresponding assets. The size of deposits (short term liabilities) over total assets gives a rough estimate of liquidity risk, associated with deposit withdrawal (Said & Saucier 2003).

Table1: Bank Rating

	Capital	Asset quality	Earning	Liquidity
Rating	Cap/Rwa	NPL/Capital	Return on Asset	Financing/ Deposit Ratio
Strong = 1	9% and above	10% and Below	1.25% and above	55% and above
Satisfactory = 2	8% and above	11% -20%	0.75% and	60% and above

			above	
Fair = 3	7% and above	21% -30%	0.40% and above	65% and above
Marginal = 4	5% and above	31% - 40%	0.00% and above	70% and above
Unsatisfactory= 5	Below 5%	41% -and higher	Less	71% and above

Table 2: Bank Classification

Total ratio (mean)	Bank Classification
1 – 1.4	Strong
1.5 - 2.4	Satisfactory
2.5 - 3.4	Fair
3.5 - 4.4	Marginal
4.5 - 5	Unsatisfactory

Data

The period of this study ranges from the third quarter of 2002 to the fourth quarter of 2009. The subject of study includes 45 banks. Secondary data is compiled from the Central Bank of Sudan. Bank ratings of fair, marginal, satisfactory, strong, and unsatisfactory are 262, 205, 202, 4, and 80 respectively.

Estimation Methodology

The binary models apply linear regression technique to estimate the probability that a particular outcome such as a bank failure occurs, the dependent variable takes on only two values its main variants are Logit and Probit. Logit uses non-normal distribution to the probability of an event occurring, whereas the Probit assumes standardized normal distribution. Results show the estimates of the coefficients, standard error of the coefficients, z-values, and p-values. The use the Logit link function gives the odds ratio and a 95% confidence interval for the odds ratio. The coefficient for each predictor is the estimated change in the link function with a one unit change in the predictor, assuming that all other factors and covariates are the same. G tests the null hypothesis that all the coefficients associated with predictors equal zero versus these coefficients not all being equal to zero. If the p-value is less than your accepted a level, the test would indicate sufficient evidence for a conclusion of an inadequate fit. The probability of observing a value of one that is f_i=1, if the rating is above 3 is as follows:

$$Prob(f_i = 1|x_i; \beta) = 1 - F(-\acute{x}_i\, \beta)$$

Choosing F to be standard normal yields one attractive possibility, the Probit model

$$Prob(f_i = 1) = \emptyset(X_i\beta) = \int_{-\infty}^{X_i\beta} \frac{1}{\sqrt{2\pi}} exp\left(\frac{-z^2}{2}\right) dz$$

The standard normal transformation constrains the probability to lie between 0, and 1.the development of Logit is identical to that of the Probit

$$Prob(f_i = 1) = \Lambda(X_i\beta) = \frac{exp(X_i\beta)}{1 + exp(X_i\beta)}$$

Like the Probit the formulation of the model ensures that the predicted probabilities lie between 0 and 1 (Johnston & DiNardo 2003).

Several models has been used to predict bank failure, they include artificial neutral networks, discriminant analysis, support vector machine, hazard model, Data envelopment analysis (DEA), and binary models. Artificial neutral networks are use in variety of fields including agriculture, business, and manufacturing. Their primary drawback is their adaptation to given inputs in order to employ them in the real world. DEA aims at determining production efficiency by transforming a given input factor into given output factors by linear programming techniques. Due to the nonparametric approach, there is no equation that describes the relationship between the input and output factors. DEA is often used for banking benchmarking purposes and only rarely to predict banking failures. Support vector machine has been used for machine learning ie learning structure from data. In case of existing L training points, where each input x_i has D attributes (i.e. is of dimensionality D) and is in one of two classes yi = -1 or +1,it is assumed that the data is linearly separable, meaning that we can draw a line on a graph of x_1 vs. x_2 separating the two classes when D = 2 and a hyperplane on graphs of x_1; x_2 : : : xD for when D > 2. This hyperplane can be described by w _ x + b = 0 where: w is normal to the hyperplane; and $\frac{b}{\|w\|}$ is the perpendicular distance from the hyperplane to the origin. Support Vectors are the examples closest to the separating hyperplane and the aim of Support Vector Machines (SVM) is to orientate this hyperplane in such a way as to be as far as possible from the closest members of both classes (Fletcher 2009). It has been found that it is able to predict accurately (Mayes & Semmeler 2012). The Cox proportional hazard model has been found to predict failure well in advance (Tatom 2012). Linear probability model has intrinsic defects for some applications. It dose not ensure that the predicted probabilities lie between 0 and 1, and the error term is heteroscadistic (Johnston & DiNardo 2003).

Discriminant analysis is used in situations where the clusters are known a priori. The aim of discriminant analysis is to classify an observation, or several observations, into these known groups (Hardle, Simar 2003). Discriminant analysis can also used to investigate how variables contribute to group separation. Discriminant analysis can be broken into linear, quadratic and multivariate. The latter is popular in corporate finance and marketing, its main drawbacks are: the possibility of inaccurate assumption of normal distribution, and equal variance-covariance between groups. Minitab offers both linear and quadratic discriminant analysis. With linear discriminant analysis, all groups are assumed to have the same covariance matrix. Quadratic discrimination does not make this assumption but its properties are not as well understood. Observations are assigned to the group with the highest posterior probability. In the case of classifying new observations into one of two categories, logistic regression may be superior to discriminant analysis (Fienberg 1987).

Results and Interpretations

Results are composed of two types the binary regression output (Logit) and discriminant analysis. Results of logistic regression displayed in annex (1) show that the Central Bank of Sudan applies only four rating measures at this stage, the two missing ratings are management and sensitivity to risk. The most influential CAEL rating is the earning, followed by asset quality, liquidity and finally capital adequacy. Results show that the estimated change in the link function with a one unit change in the CAEL measures (predictor), assuming that all other factors and covariates are the same can be ordered earning, asset quality, liquidity, and capital adequacy. The likelihood ratio (LR) with four degrees of freedom rejects the null hypothesis that all coefficients are zero except the constant. Mc Fadden R squared is 0.966. Discrimenant analysis and logistic results are similar. The estimate model can be summarized in the following equation:

F = 1-@LOGIT(-(7.09*C + 7.44*A + 7.89*E + 7.19*L - 92.298))

Where F stands for cumulative probability, and L stands for liquidity posion, E for earning ability, A for asset quality, and C is the capital adequacy.

Discriminant analysis output gives a classification results presented below obtained based on a linear discriminant analysis with the coefficients of each parametric representation as independent variables.

Fair = -23.8859+2.4561*L+5.6353*E+4.101*A+3.2173*Q

Marginal = -39.5361+3.9951*L+6.5697*E+5.1648*A+4.4409*Q

Satisfactory = -10.1697+1.825*L+3.244*E+2.9096*A+2.2585*Q

Strong = -4.83089+1.09623*L+2.45374*E+1.89011*A+1.52709*Q

Unsatisfactory = -51.0748+5.0823*L+6.6012*E+6.1715*A+5.2453*Q

The above results are for commercial banks including four specialized public banks. It has been noticed that all constants are negative, strong and satisfactory ratings have the smallest estimated coefficients whereas marginal and unsatisfactory are the biggest. Concerning the individual rating, earning measures are the most influential ones. The magnitudes of the constants and the negative signs suggest that economic policies concerning banking sector, the newly entraining bank is most probably rated as unsatisfactory, followed by marginal, fair, satisfactory and the least probable is the strong rating.

Annex 2 gives the correct classification scores of the discriminant analysis for the different parametric representations. Proportions given for the distinction among fair, marginal, satisfactory, strong, and unsatisfactory put in true group are 0.941, 0.872, 0.764, 1.00, and 0.961 respectively and 633 of 721 cases are correct cases, the overall performance is 0.878.

Annex 3 gives summary of classification with cross-validation. Cross-validation is one technique that is used to compensate for an optimistic apparent error rate. The apparent error rate is the percent of misclassified observations. This number tends to be optimistic because the data being classified are the same data used to build the classification function. The proportion of misclassified observations is 0.756 that is 569 out of 721. It is obvious that cross validation is inferior the estimation of discrimenant function. Reproducing CAEL rating for a sample of the information available the outcome was very encrouging since most rating were being reproduced, the failed ones has a similar characteristic that is either an preceding upper rating or a subsequent lower rating (annex 5).

To identify newly-established bank, we could compute the estimated linear discriminant functions associated with its five ratings based on CAEL forecasts, and identify the new bank as being of a particular rating depending upon which discriminant function value is higher.

Discussion

The central bank of Sudan (BS) imposes on-site and off-site supervision on financial institutions. During the period 1994-97 BS formulated many policies, and issued technical, financial, legal, and administrative reforms of the financial institutions in Sudan to reduce operations risks. The main concern of the BS during the period 2000-2002 was to reform the banking sector in particular aiming to create large banks capable of raising their capital and financial adequacy, and providing banking services efficiently accompanied by introduction of new technology and highly trained human capital. As well as inducing competition and reducing the ratio of operations risks which come mainly from bad debts to make it compatible with the international one, and improving the legal ground. The pace of reforms was very slow compared to Egypt, Jordon, and Saudi Arabia in ten years only 58% of banks has been reformed (BS 2006). The banking sector has been facing many obstacles of which are: weak financial basis, inappropriate spread of bank branches causing losses, weak administrative and supervision apparateous, slim reserves, large fixed assets and investment that can not be liquiditated easily, international competition, old fashion technology, and respective rule which impede the financial flow. Basically the application of Basle accord resulted in raising banks' capital which was reflected positively on capital adequacy, encouragement bank merger, and has been advantageous in the following: (1) it provided a quantitative institutional framework which can be used to measure banking adequacy. This led to stabilization of the banking sector and removed differences in banks' abilities to compete since their capitals are being determined according to CAEL measures. In turn this eased the comparison between banks, (2) the measures contributed in organizing supervision process on capital adequacy and make it more related to operations risks facing banks' assets, (3) owners responsibility of supervision on banks operations has been increasing. Basle accord geared increase of capital to an increase its risky assets. As well as investors became more aware of choosing board members in fear of an increase of operations risks which from mismanagement, (4) rasing the bank efficiency in utilizing its resources. Banks became more inclined to invest in asset with less risk weight. In 2005 BS ordered all banks to establish an administration for risk management to responsible directly to the top management. The central banks assisted the banks in the training and habilitation of their personnel on the application of capital adequacy measure and guidance to the operations risk department.

Conclusion

The central bank of Sudan adopted many policies and measures to reform the banking system in the Sudan. Recently the reform program was pursued in three phases, the first was during 1994-1997, the second in 2002, and the third in 2005. Since late 2002 the BS has been applying CAEL on the banking sectors measures firmly the matter that raised capital adequacy, and lowered operations costs. An early warning system was the aim of this paper and has been built successfully. It could identify any new bank by calculating the discriminant function of the five rating and choose the higher to be the specified rating.

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Annex

Annex 1:

Dependent Variable: Failure				
Method: ML - Binary Logit				
Date: 12/24/12 Time: 07:33				
Sample: 1 750				
Included observations: 720				
Excluded observations: 30				
Convergence achieved after 11 iterations				
Covariance matrix computed using second derivatives				
Variable	Coefficient	Std. Error	z-Statistic	Prob.
Capital	7.090847	1.253229	5.658063	0.00

Asset	7.443646	1.416735	5.254087	0.00
Earning	7.885374	1.501939	5.250129	0.00
Liquidity	7.188627	1.256418	5.721526	0.00
C	-92.2978	16.00449	-5.767	0.00
Mean dependent var	0.448611	S.D. dependent var		0.497698
S.E. of regression	0.054712	Akaike info criterion		0.060631
Sum squared resid	2.14029	Schwarz criterion		0.092431
Log likelihood	-16.827	Hannan-Quinn criter.		0.072907
Restr. log likelihood	-495.257	Avg. log likelihood		-0.02337
LR statistic (4 df)	956.8589	McFadden R-squared		0.966024
Probability(LR stat)	0.00			
Obs with Dep=0	397			
Obs with Dep=1	323	Total obs		720

Annex 2: Linear Discriminant Function with Cross Validation

Discriminant Analysis (banks)

Linear Method for Response: C20

Predictors: C A E L

Group: Fair, Marginal, Satisfactory, Strong, Unsatisfactory

Count: 262, 205, 202, 4, 80

Summary of Classification

Put into ....True Group....

Group	Fair	Marginal	Satisfactory	Strong	Unsatisfactory
Fair	239	2	3	0	2
Marginal	4	171	0	0	1
Satisfactory	11	0	146	0	0
Strong	0	0	42	4	0
Unsatisfactory	0	23	0	0	73
Total N	254	196	191	4	76
N Correct	239	171	146	4	73
Proportion	0.941	0.872	0.764	1.000	0.961

N = 721 N Correct = 633 Proportion Correct = 0.878

Annex 3: Summary of Classification with Cross-validation

Put into ....True Group....

Group	Fair	Marginal	Satisfactory	Strong	Unsatisfactory
Fair	243	2	3	0	2
Marginal	0	171	0	0	1
Satisfactory	11	0	146	1	6
Strong	0	0	42	3	1
Unsatisfactory	0	23	0	0	1
Total N	254	196	186	4	80
N Correct	243	171	146	3	71
Proportion	0.824	0.872	0.764	0.750	0.961

N = 753 N Correct = 569 Proportion Correct = 0.756

Annex 4: Estimated Model

	Fair	Marginal	Satisfactory	Strong	Unsatisfactory
Constant	-23.8859	-39.5361	-10.1697	-4.83089	-51.0748
Liquidity	2.4561	3.9951	1.825	1.09623	5.0823
Earning	5.6353	6.5697	3.244	2.45374	6.6012
Assets quality	4.101	5.1648	2.9096	1.89011	6.1715
Capital	3.2173	4.4409	2.2585	1.52709	5.2453

Annex 5: Reproducing CAEL Rating

	FITS2	XFIT2
Marginal	Marginal	Marginal
Unsatisfactory	Marginal	Marginal
Marginal	Marginal	Marginal
Marginal	Marginal	Marginal
Marginal	Marginal	Marginal
Marginal	Marginal	Marginal
Marginal	Marginal	Marginal
Marginal	Unsatisfactory	Unsatisfactory
Marginal	Unsatisfactory	Unsatisfactory
Marginal	Marginal	Marginal
Marginal	Unsatisfactory	Unsatisfactory
Marginal	Unsatisfactory	Unsatisfactory
Unsatisfactory	Unsatisfactory	Unsatisfactory
Satisfactory	Satisfactory	Satisfactory
Satisfactory	Strong	Strong
Satisfactory	Satisfactory	Satisfactory
Unsatisfactory	Satisfactory	Satisfactory