“Prediction of financial strength ratings using machine learning and conventional techniques”

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PREDICTION OF FINANCIAL STRENGTH RATINGS USING MACHINE LEARNING AND CONVENTIONAL TECHNIQUES

Abstract

Financial strength ratings (FSRs) have become more significant particularly since the recent financial crisis of 2007–2009 where rating agencies failed to forecast defaults and the downgrade of some banks. The aim of this paper is to predict Capital Intelligence banks' financial strength ratings (FSRs) group membership using machine learning and conventional techniques. Here the authors use five different statistical techniques, namely CHAID, CART, multilayer-perceptron neural networks, discriminant analysis and logistic regression. They also use three different evaluation criteria namely average correct classification rate, misclassification cost and gains charts. The data are collected from Bankscope database for the Middle Eastern commercial banks by reference to the first decade of the 21st century. The findings show that when predicting bank FSRs during the period 2007–2009, discriminant analysis is surprisingly superior to all other techniques used in this paper. When only machine learning techniques are used, CHAID outperform other techniques. In addition, the findings highlight that when a random sample is used to predict bank FSRs, CART outperform all other techniques. The evaluation criteria have confirmed the findings and both CART and discriminant analysis are superior to other techniques in predicting bank FSRs. This has implications for Middle Eastern banks, as the authors would suggest that improving their bank FSR can improve their presence in the market.

Keywords FSR group membership, Capital Intelligence, machine learning techniques, conventional techniques, Middle East

JEL Classification G21, G24, C14, C38

INTRODUCTION

A bank's financial strength, its risk profile, soundness and financial stability are assessed by Capital Intelligence (CI) banks' financial strength ratings (FSRs). This incorporates factors within its internal and external environment. CI implements a specialized approach, including some qualitative and quantitative factors, in assessing a bank's stability and thus assigning the appropriate banks' FSR. This is achieved by grouping factors into the following six broad categories: ownership and governance; operating environment; management and strategies; franchise value; risk profile and financial profile. Internally, CI assesses a bank's governance and specifically the extent to which there is a division between ownership and the management of its operations. Bridging the gap between a bank's internal and external environment, CI examines a bank's domestic market share as reflected in its assets and its potential future earnings (see, for example, Abdallah, 2013). As such, CI assesses these factors and generates a bank's FSRs.

In the Middle East region, financial stability and soundness are entirely affected by the host country's banking system. This is mainly due to the absence of the capital markets' role in resource allocation and thus FSR is

seen as an important indicator of the banking systems soundness and stability. As such, a bank's FSR is considered as an important indicator for various stakeholders in assessing the bank's FSRs. This is particularly important due to deficiencies in legal and regulatory systems and lack of transparency within banking sectors and financial markets (Abdallah, 2013). The difficulty in developing accurate rating systems for banks as opposed to countries is reflected in the relative inability of rating agencies to agree a universal rating system. A strong bank FSR assists a bank in accessing capital markets with more favorable conditions, as well as positively affecting its operations and performance (Hammer et al., 2012). In addition, these rating agencies have been accused of being liable for the 'housing bubble' and consequently financial crash of 2007–2008 (Diomande et al., 2009).

In the literature, less attention is paid to the Middle East region due to a number of factors that appear to be influential in this respect. First, governments are the main source for Middle Eastern banks' equity financing. Second, the need to assess a bank's creditworthiness is reduced where the bank is government-owned, because the government uses their banks to finance economic activities. This may cause a disconnect between the bank's FSRs and its capital structure. Third, the underdeveloped legal and regulatory system has resulted in a weak system to monitor capital risk in Middle Eastern countries (see of commercial banks in the Middle East that is 64 out of 135, as per Bankscope database 2011, are rated. The development of stock markets in the Middle East has encouraged the operation of foreign rated banks within the region and this, in turn, has resulted in improving the competitiveness and performance of non-rated banks. This raises banks' interests in obtaining adequate FSRs.

The motivation of our investigation is to evaluate and rank the predictive capabilities of machine learning and conventional techniques using different decision criterion namely error rates, misclassification costs and gains charts for different sample sizes. Due to scarcity of studies related to banks' FSR under Capital Intelligence (CI), the objective of this paper is to determine whether Middle Eastern bank's financial and non-financial indicators can be used to predict their FSR group membership. The novelty of this paper is to apply machine learning and conventional techniques to predict a bank's CI FSR by distinguishing high ratings from low rating using financial and non-financial indicators. We use banks' FSRs issued by CI rating agency for Middle Eastern commercial banks[1] in the first decade of the 21st century[2], which is ignored in the literature. There is no empirical study, which, to the best of our knowledge, uses non-financial indicators to capture the effect of country specific differences, with other firm level characteristics, to determine whether they are able to distinguish high from low CI FRSs. The remainder of this paper is organized as follows: section 1 reviews literature; section 2 outlines the research methodology and data collection; section 3 provides a discussion of the empirical findings and compares results of different bank FSR group membership models; and the last section concludes the paper and highlights areas for future research.

1. REVIEW OF RELEVANT LITERATURE

As early as the 1960s, there were studies that focused on forecasting business events and classifying companies into two or more separate groups. Many researchers have applied different conventional and advanced statistical techniques to build classification models to overcome problems such as financial failure; bankruptcies; financial information and stock price manipulation; and predicting bond and credit ratings. The launch of Moody's bank financial strength rating (BFSRs) in 1995 is followed by Poon et al.'s. (1999) logistic regression model to predict Moody's BFSRs. Many researchers have paid attention to the determination and prediction of bank

1 CI is more specialized in rating banks in the Middle East region than Fitch and Moody's. According to Bankscope database as at January 2011, CI assigns bank FSRs for 64 commercial banks in the Middle East region compared to Fitch and Moody's who assign bank ratings for only 50 and 48 commercial banks, respectively. S&Ps has no publically available equivalent individual bank ratings in the period 2001–2009.

2 The reason to choose the first decade of the 21st century is to avoid any potential effect of the Arab spring which commenced in 2010 and the huge missing data due to this phenomenon. However, it is part of our future research plan to investigate the effect of the Arab spring on bank ratings in the Middle East.

ratings for developed economies (see, for example, Poon et al., 1999; Poon & Firth, 2005; Hammer et al., 2012; Beisland et al., 2014), but not the relationship between financial/non-financial factors and bank ratings. Unsurprisingly, less attention has been paid to developing economies and in particular to the Middle East region.

Various statistical machine learning techniques are used in predicting bank rating (see for example, Chen, 2012; Chen & Cheng, 2013). CART algorithms has been employed in a number of situations. For example, to predict bankruptcy (Chandra et al., 2009; Li et al., 2010); to develop credit scoring models for assessing the credit risk of bank customers (Lee et al., 2006; Kao et al., 2012); to develop early warning models to assess the soundness of individual banks (Loannidis et al., 2010); and to predict bank performance (Ravi et al., 2008). Many studies into early warning system models for financial risk (Koyuncugil & Ozgulbas, 2012) and for developing credit scoring models for assessing bank customers credit risk (Thomas et al., 2002; Bijak & Thomas, 2012) have utilized CHAID algorithms. To the best of our knowledge, this is the first paper that uses both CART and CHAID algorithms to predict Middle Eastern commercial banks' FSRs.

Based on human brains, neural networks are non-parametric techniques and computational methods that are used to identify significant patterns or structures in data which are then used to predict future phenomena. Neural networks have been applied in various financial studies such as: to predict bankruptcy of banks (Kumar & Ravi, 2007; Ravi & Pramodh, 2008; Zhao et al., 2009; Loannidis et al., 2010); to predict bankruptcy of firms (Chandra et al., 2009; Falavigna, 2012); to evaluate banks' creditworthiness (see, for example, Huang et al., 2004), and to predict banks' financial strength rating (Poon et al., 1999; Pasiouras et al., 2007; Hammer et al., 2012).

Altman (1971) introduced DA z-score model that discriminates bankrupt from non-bankrupt firms. In finance literature Altman and Sametz (1977), Canbas et al. (2005), Li et al. (2010) apply many forms of the DA to predict corporate and bank failure and assessing financial distresses. In addition, DA has been employed by Lee et al. (2006), Abdou et al. (2008), Abdou (2009a), Akkoc (2012) in building credit scoring models. In the field of banking DA and hybrid techniques are used in rating predictions (see, for example, Chen, 2012; Chen & Cheng, 2013).

In the literature on finance, LR is a widely-used technique among practitioners in predicting corporate and bank failure (Kolari et al., 2002; Canbas et al., 2005; Zhao et al., 2009; Li et al., 2010; Abdou et al., 2016); in predicting credit ratings (Oelerich & Poddig, 2006; Kim & Ahn, 2012); as well as in building credit scoring models (Lee et al., 2006; Abdou et al., 2008; Abdou, 2009a; Akkoc, 2012; Abdou et al., 2016). Finally, the LR model is employed by Poon et al. (1999), Hammer et al. (2012) to predict bank financial strength rating. Predicting both Moody's BFSRs (see Poon et al., 1999) and Fitch FBRs (Pasiouras et al., 2007; Hammer et al., 2012) have been the focus of the majority of previous studies. It is notable that there is no previous study focused upon CI FSRs (see, for example, Abdallah, 2013). Consequently, the focus of our investigation is to bridge this gap by using both machine learning and conventional techniques to predict banks' CI FSRs group membership in Middle Eastern commercial banks.

2. RESEARCH METHODOLOGY

Using PASW® Modeler 14, initially auto-classifier node is applied to automatically create and compare a number of different statistical predictive techniques. Auto-classifier node uses specific criteria to generate, compare and rank a set of candidate predictive statistical techniques to identify the optimal performing techniques. In our paper, the 'overall accuracy percentage' is used to rank the predictive accuracy of different statistical techniques. This is achieved by identifying the correctly classified percentage of observations for each technique relative to the total number of observations. Moreover, auto-classifier node provides an evaluation chart to visually enable the performance of each predictive statistical technique to be assessed and compared. The software automatically chooses the best five statistical techniques namely CHAID, CART, MLP NN, DA and LR to predict banks' FSRs. Figure 1 provides a graphical visualization of the chosen five predictive statistical techniques in terms of differences in their overall accuracy (SPSSInc, 2012).

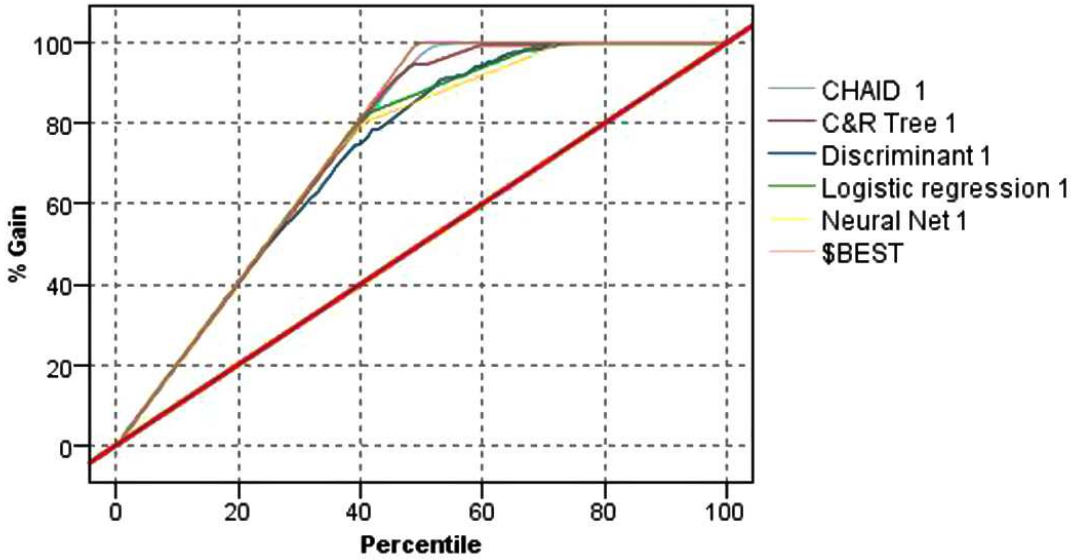


Figure 1. An evaluation chart for the five predictive statistical modelling techniques

From Figure 1, it can be observed that the auto-classifier node ranks the two decision trees techniques namely CHAID, with an overall accuracy of 96.30%, and CART, with an overall accuracy of 95.44%, as first and second. These two techniques are followed by MLP NN with an overall accuracy of 94.02%. In addition, there is a role for DA as one of the conventional techniques with an overall accuracy of 93.16%, which is comparable with the machine learning techniques. However, the auto-classifier node ranks LR far below the other four techniques with an overall accuracy of only 73.5%. Therefore, it can be suggested that CHAID, CART, MLP NN and DA could perform better compared to LR in predicting Middle Eastern commercial banks' FSRs. Finally, four different evaluation criteria namely average correct classification (ACC) rate, error rates, estimated misclassification cost (EMC) and gains charts are used to evaluate the predictive capabilities of these statistical modeling techniques.

2.1. Statistical modelling techniques

2.1.1. Bank FSR machine learning techniques

CHAID

The Chi-squared Automatic Interaction Detector (CHAID) is a statistical technique used to assess the relationship between a target variable and a series of predictor variables (see, for example, Koyuncugil & Ozgulbas, 2012; Abdallah, 2013). A CHAID model divides the data into mutually exclusive and exhaustive sub-sets that best describe the target variable and predict the interaction between predictor variables (Bijak & Thomas, 2012; Abdallah, 2013). For categorical dependent variables, Chi-squared is used as a measurement level, whilst for continuous dependent variables the F-test is used instead (SPSSInc, 2012). In building our CHAID models, we use Pearson Chi-squared statistics which are calculated using both observed expected cell frequencies with the *p*-value being based on the calculated statistics.

The Pearson Chi-squared statistic is calculated as follows (see, for example, PASW, 2012, p. 77; Abdallah, 2013, modified):

$$X^2 = \sum_{j=1}^{J}\sum_{i=1}^{I}\frac{\left(n_{ij}-\hat{v}_{ij}\right)^2}{\hat{v}_{ij}}, \qquad (1)$$

where $n_{ij} = \sum f_n \cdot I \cdot \left(x_n = i \wedge y_n = j\right)$ refers to the actual cell frequency; $\hat{v}_{ij}$ refers to the expected cell frequency for cell $(x_n = i, y_n = j)$ from the independence model; $b = \mathrm{br} \cdot (x_d^2 > X^2)$ refers to the calculation of the corresponding p-value, where x_d^2 follows a Chi-squared distribution with $d = \left(J-1\right)\cdot\left(I-1\right)df$.

CART

The Classification and Regression Trees (CART) is a classification non-parametric statistical model, which can use a binary decision tree-based procedure. It can be simultaneously applied to both categorical and continuous data based on a set of 'if-then' rules. It automatically separates complex databases for separating significant patterns and relationships (Ravi et al., 2008; Chandra et al., 2009; Abdallah, 2013). CART methodology can be divided into three phases: first, the construction of a maximum tree (tree-growing process); second, the selection of the right-sized tree (pruning process); third, the classification of the new data using the constructed tree. Gini index is used as part of the process, and the model repeats the splitting process until either the homogeneity criterion is reached or other stopping criteria are fulfilled. The Gini index uses the following impurity function $g(t)$ at a node t in CART tree (PASW, 2012, p. 63; Abdallah, 2013; Abdou et al., 2016, modified):

$$G(r)=\sum_{j\neq i} b(j|r)\cdot b(i|r), \tag{2}$$

where i and j are categories of the independent predictor variable, and

$$b(j|r)=\frac{b(j,r)}{b(r)}, \tag{3}$$

$$b(j|r)=\frac{\pi(j)\cdot N_j(r)}{N_j}, \tag{4}$$

$$b(r)=\sum_j b(j,r), \tag{5}$$

where $\pi(j)$ refers to the prior probability value for category j; $N_j(r)$ refers to the number of records in category j of node r, and N_j refers to the number of records of category j in the root node. The Gini index enhances splitting during tree growth process. As such, $N_j(r)$ and N_j are only calculated, respectively, from the records on node r and the root node with valid values for the split-predictor.

Then, 'the pruning process' improves generalization to avoid over-fitting by applying two pruning algorithms. First is the optimization by number of points in each node pruning algorithm which implies that the splitting is stopped when the number of observation in the node is the pre-defined required minimum number of observations. Second is the cross-validation pruning algorithm, which establishes an optimal proportion between the misclassification error and the complexity of the tree. As such, the focus of the cross-validation pruning algorithm process is to use the minimal cost-complexity function to minimize both misclassification risk and the complexity of the tree in order to obtain an optimal tree as follows (see, for example, PASW, 2012, p. 67; Abdallah, 2013):

$$R_\alpha(C)=R(C)+\alpha\left|\tilde{C}\right|, \tag{6}$$

where $R(C)$ refers to the misclassification risk of tree C; $\left|\tilde{C}\right|$ refers to the number of terminal nodes for tree C; and α refers to the complexity cost per terminal node for the tree. Finally, following the construction of right-size tree with the lowest cross-validated rate, the outcome of the third phase process is to classify the new data. As such, based on a set of rules, each new observation is assigned to a class or response value that fits with one of the terminal nodes of the tree.

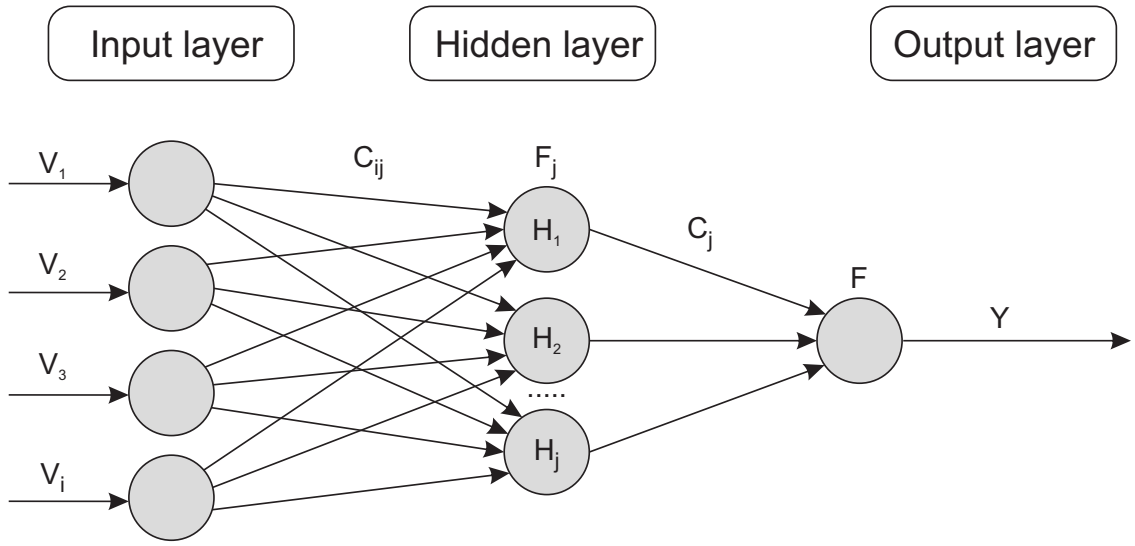
Multilayer-Perceptron Neural Networks

Multilayer-Perceptron Neural Network (MLP NN) enables the analysis of complex relationships between different variables and consists of layers of interconnected nodes between the input layer and the output layer. As part of the network nomenclature, predicted outputs are generated and compared with actual outputs in order to calculate an error function. The network repeats the process until the either of the number of iterations is reached or the error function is almost zero.

An architecture of MLP NN is shown in Figure 2. This consists of an input layer with a number of neurons with their dendrites for input predictor variables $(V_1, V_2 \ldots V_i)$; the hidden layer with a number of neurons (L); and the output layer Y. The statistical formula of MLP NN with one hidden layer is as follows (Abdallah, 2013, modified):

$$Y=F\left[\sum_{j=1}^{J} C_j\cdot F_j\cdot\left(\sum_{i=1}^{i} C_{ij}\cdot V_i\right)\right], \tag{7}$$

where Y refers to the network output; F refers to the transfer function; C_j refers to the connec-



Notes: Figure 2 shows architecture of 'n' independent predictor indicators for MLP NN in the input layer; the hidden layer consists of a number of nodes; and the output layer (see, for example, Abdallah, 2013; Brown & Mues, 2012; Abdou, 2009a, modified).

Figure 2. MLP feed-forward NN architecture (one hidden layer)

tion weights from L to Y, F_j refers to the transfer function for L, C_{ij} refers to the connection weights from $(V_1, V_2 \ldots V_i)$ to L, and V_i refers to the input predictor variable (see for example, Abdou, et al., 2014; Abdallah, 2013; Brown & Mues, 2012, modified).

2.1.2. *Conventional techniques*

Discriminant analysis

Discriminant analysis (DA) is a classification technique widely used to develop a Z-score model to discriminate between two or more groups of observations (Abdou et al., 2008). DA predicts and classifies problems where the nature of the dependent variable is binary, for example, high versus low risk, high versus low FSRs etc. The formula used in DA is as follows:

$$Z = \alpha + a_1 \cdot V_1 + a_2 \cdot V_2 + \ \ldots \ + a_n \cdot V_n, \qquad (8)$$

where Z refers to the discriminant outcome score which reflects group differences; α refers to the intercept; $a_1, a_2, ..., a_n$ are the discriminant coefficients; and $V_1, V_2 \ldots V_n$ refer to the independent variables (see, for example, Abdou et al., 2008; Abdallah, 2013).

Logistic regression

Logistic regression (LR) is a multivariate statistical technique used for prediction purposes in cases where the dependent variable is dichotomous. Binomial probability is used to develop a logit function from conventional linear regression. LR formula is as follows (see, for example, Abdallah, 2013; Abdou et al., 2016):

$$Log\left(\frac{b}{1-b}\right) = \alpha + \beta_1 \cdot V_1 + \beta_2 \cdot V_2 + \ldots + \beta_n \cdot V_n, \quad (9)$$

where b refers to the output probability; α refers to the intercept of the equation; and β_1, β_2 ... β_n refer to the coefficients in the linear combination of the independent variables $V_1, V_2 \ldots V_n$.

2.2. Data collection, variables and sampling

2.2.1. *Data collection*

In order to develop the proposed bank FSR group membership models, we use 64 commercial banks rated by Capital Intelligence (CI) out of a total number of 135 Middle Eastern banks in our original sample. As the vast majority of

Table 1. Descriptive statistics for banks, by country and whether rated by CI based on size (*ln* total assets)

Country	No. of commercial active banks	No. of banks with CI's FSR	% of banks rated by CI, %	Mean size	Standard deviation
Egypt	24	6	25	8.809	0.855
Bahrain	10	4	40	9.422	0.819
Kuwait	6	6	100	9.231	0.598
Jordan	11	7	63.6	7.433	1.296
Qatar	8	4	50	8.547	1.146
Lebanon	38	6	15.7	8.688	0.708
Saudi Arabia	9	9	100	9.672	0.815
United Arab Emirates	18	15	83.3	8.248	1.316
Oman	6	5	83.3	7.810	0.708
Yemen	5	2	40	5.832	0.554
Total	135	64	47.4	8.521	1.308

Note: Size is measured by ln total assets. The initial sample consists of 135 active commercial banks (of which 64 are rated by CI) covering 10 countries from the Middle East region: Egypt, Bahrain, Kuwait, Jordan, Qatar, Lebanon, Saudi Arabia, United Arab Emirates, Oman and Yemen. The data are extracted from Bankscope for 9 years from 2001 to 2009 inclusive.

banks in the Middle Eastern region are commercial banks, we then focus on this group of banks to avoid any potential comparison problems between different types of banks and for homogeneity across different countries included in our final sample. We use data from 10 Middle Eastern countries[3], as shown in Table 1. Our data are collected from Bankscope database by reference to the first decade of the 21st century, i.e., 2001–2009.

Descriptive statistics for each of the 10 countries' banks based on their natural log of total assets ($) are shown in Table 1. Clearly, banks in Bahrain, Kuwait and Saudi Arabia are larger in size than other countries in our final sample. By contract,

3 Israel, Palestinian Territory, Iraq and Syrian Arab Republic are excluded from the sample, because they do not have commercial banks rated by CI. Iran is also excluded from the sample as all Iranian banks are classified as Islamic banks.

Table 2. A synopsis of CI bank FSRs numerical ratings and rating categories

CI's bank FSR	Numerical	Quartiles
AAA	20	**High-FSR**
AA+	19	
AA	18	
AA−	17	
A+	16	
A	15	
A−	14	**Near-high-FSR**
BBB+	13	
BBB	12	**Near-low-FSR**
BBB−	11	**Low-FSR**
BB+	10	
BB	9	
BB−	8	
B+	7	
B	6	
B−	5	
C+	4	
C	3	
C−	2	
D	1	

Notes: This table explains how various FSRs are translated to numbers. We use a simple weighted average to create four quartiles as shown above.

banks in Yemen tend to be smaller in size when compared to other banks in other countries in the sample. In addition, banks in Egypt, Qatar, Lebanon and United Arab Emirates have a similar average size, as do banks in Jordan and Oman.

2.2.2. *Dependent variable*

As shown in Table 2, we rank CI banks' FSR using a scale from 1 up to 20; where 1 refers to the lowest FSR rating category (D) and 20 refers to the highest FSR rating category (AAA) (see, for example, Poon et al., 2009). As also shown in Table 2, the highest FSR rating category for banks in the Middle East region in our sample is AA^- (17) and the lowest FSR rating category is B (6). We use a simple weighted average to divide the data into four quartiles. Then, we use the highest quartile (15 to 17) versus the lowest quartile (6 to 11) as our dependent categorical variable[4].

2.2.3. *Independent variable*

Selected independent variables for the proposed models are reduced to 17 financial and non-financial variables[5].

Financial variables

We use different financial ratios under the following categories: asset quality, capital adequacy, profitability, credit risk and liquidity, following CI rating agency, to predict Middle Eastern banks' FSR group membership, as shown in the Appendix.

Non-financial variables

In this paper, authors examine non-financial variables that may improve a models predictive capability in terms of a bank's FSR group membership. The following three non-financial variables are used: first, we use size as a dummy variable which is measured by *ln* total assets. To reflect qualitative characteristics such as product diversification and geographic location, we classify banks' size into small, medium and large. Second, we use a dummy variable for the effect of time. Third, we use CI's country sovereign risk ratings (SR) to reflect differences in the implemented regulatory systems across countries. In calculating SR, the following macroeconomic factors are considered: inflation, taxation, exchange rates, infra-structure, employment rate, size and the growth of economy and regulations. Sovereign ratings reflects the probability that a government may default in meeting their obligations (see, for example, Abdallah, 2013; Laere et al., 2012). Correlation between our finally selected variables indicates no serious correlation (i.e., > 0.60) found amongst these variables, as shown in the following section.

We divided the data-set into two samples. $Sample_1$ (we use 2001–2006 observations as a training $sub\text{-}sample_1$, 235 observations; and 2007–2009 observations as a hold-out $sub\text{-}sample_1$, 116 observations). $Sample_2$ (67% training $sub\text{-}sample_2$, 235 observations; and 33% hold-out $sub\text{-}sample_2$, 116 observations), which are randomly selected by the PASW@ Modeler 14 software.

3. EMPIRICAL FINDINGS

PASW® Modeler 14, Scorto and IBM SPSS 22 software are used in this paper to build the proposed models. The descriptive statistics and detailed bank FSR group membership results for the chosen statistical techniques are summarized below.

3.1. Descriptive statistics

Correlation results between our predictor indicators including the dependent variable (high-FSR versus low-FSR), are shown in Table 3. All correlations between predictor indicators are within an acceptable range, i.e., < 0.60. Table 3 highlights that the highest correlation coefficient of 0.588 is between LLPTL and NIEAA. We argue that there is no multicollinearity problem between them as only correlations over 0.80 cause a serious problem (see, for example, Abdou et al., 2016).

3.1.1. *Financial indicators*

Descriptive statistics for the 14 financial predictor indicators finally used in our analysis are shown in Table 4. Clearly EM has the highest mean value of

4 Low-FSR banks are 179 observations while high-FSR banks are 172 observations.

5 The issue of multicollinearity is addressed by examining the Variance Inflation Factor (VIF) scores. The regression analysis is run for number of times to trace the variables associated with VIF scores > 5 (Abdallah, 2013).

Table 3. Correlation matrix for predictor variables

	LLPNIR	LLRIL	ILGL	TCR	CS	ENL	EM	NIM	NIEAA	REP	AU	TME	LLPTL	LADSTF	Time	SR	Size	CAT
LLPNIR	1	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–
LLRIL	–.179**	1	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–
ILGL	.306**	–.461**	1	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–
TCR	–.144*	–.003	.177**	1	–	–	–	–	–	–	–	–	–	–	–	–	–	–
CS	–.218**	.141*	–.445**	.169**	1	–	–	–	–	–	–	–	–	–	–	–	–	–
ENL	–.052	–.100	.195**	.581**	.247**	1	–	–	–	–	–	–	–	–	–	–	–	–
EM	.353**	–.130*	.153**	–.254**	–.447**	–.118*	1	–	–	–	–	–	–	–	–	–	–	–
NIM	–.270**	–.058	.097	.178**	.264**	–.006	–.168**	1	–	–	–	–	–	–	–	–	–	–
NIEAA	.511**	–.298**	.479**	–.108	–.207**	–.154**	.284**	.227**	1	–	–	–	–	–	–	–	–	–
REP	.180**	.239**	–.193**	.125*	.411**	.001	–.207**	.533**	.077	1	–	–	–	–	–	–	–	–
AU	.391**	–.090	.349**	.225**	–.216**	–.004	.155**	.290**	.518**	.424**	1	–	–	–	–	–	–	–
TME	–.039	.141*	–.177**	.058	.147**	–.001	–.135*	.001	–.157**	.111*	–.118*	1	–	–	–	–	–	–
LLPTL	.548**	–.236**	.500**	.259**	–.274**	.334**	.364**	.081	.588**	.225**	.469**	–.126*	1	–	–	–	–	–
LADSTF	.040	–.255**	.360**	.330**	.001	.436**	.007	–.095	.029	–.182**	–.015	–.150**	.204**	1	–	–	–	–
Time	–.002	.132*	–.202**	–.161**	.003	–.042	.020	–.056	–.108*	.040	.097	.077	–.030	–.271**	1	–	–	–
SR	–.066	.403**	–.536**	–.252**	.457**	–.353**	–.256**	–.020	–.208**	.324**	–.337**	.212**	–.354**	–.346**	.103	1	–	–
Size	–.011	.415**	–.505**	–.345**	–.107*	–.274**	.051	–.267**	–.336**	.004	–.256**	.144**	–.232**	–.385**	.405**	.453**	1	–
CAT	–.153**	.467**	–.572**	–.209**	.074	–.317**	–.119*	–.076	–.350**	.160**	–.391**	.177**	–.297**	–.374**	.096	.432**	.523**	1

Notes: The overall sample consists of 135 active commercial banks (of which 64 banks rated by CI) covering 10 countries from Middle East region: Egypt, Bahrain, Kuwait, Jordan, Qatar, Lebanon, Saudi Arabia, United Arab Emirates, Oman and Yemen. The data are extracted from Bankscope for the years 2001–2009 inclusive.

Table 4. Descriptive statistics for the 14 financial indicators

	N	Minimum	Maximum	Mean	Std. Deviation	Skewness		Kurtosis	
	Statistic	Statistic	Statistic	Statistic	Statistic	Statistic	Std. Error	Statistic	Std. Error
LLPNIR	340	–0.4375	8.6851	0.251918	0.5918581	9.389	0.132	123.554	0.264
LLRIL	303	0.0953	5.8233	1.176414	0.6819929	2.238	0.140	8.458	0.279
ILGL	304	0.0005	1.0465	0.105629	0.1431808	2.824	0.140	10.676	0.279
TCR	298	0.0070	0.6700	0.195679	0.0832238	2.094	0.141	6.307	0.281
CS	351	–0.3137	0.3677	0.115414	0.0557142	–0.775	0.130	11.848	0.260
ENL	351	–0.5327	1.8767	0.312396	0.2693451	3.086	0.130	12.164	0.260
EM	351	–7.1175	130.1947	10.426138	8.1806933	9.358	0.130	131.515	0.260
NIM	351	–0.0008	0.0618	0.030848	0.0104339	–0.139	0.130	0.590	0.260
NIEAA	351	0.0061	0.1242	0.022534	0.0125309	3.307	0.130	18.584	0.260
REP	351	–0.0097	0.1024	0.025833	0.0132440	1.419	0.130	5.972	0.260
AU	306	0.0259	0.1968	0.067346	0.0190842	1.643	0.139	8.496	0.278
TME	347	–8.5000	1.5833	0.869359	0.6413212	–11.715	0.131	153.833	0.261
LLPTL	341	–0.0171	0.1473	0.013168	0.0214967	2.975	0.132	10.538	0.263
LADSTF	351	0.0086	0.9434	0.369100	0.1839937	0.691	0.130	0.043	0.260

Notes: The overall sample consists of 135 active commercial banks (of which 64 banks rated by CI) covering 10 countries from Middle East region: Egypt, Bahrain, Kuwait, Jordan, Qatar, Lebanon, Saudi Arabia, United Arab Emirates, Oman and Yemen. The data are extracted from Bankscope for the years 2001–2009 inclusive. This table shows descriptive statistics for the 14 financial indicators are finally used in building our five proposed statistical techniques.

Table 5. Group statistics for the 14 financial indicators

	CAT	N	Mean	Std. Deviation	Std. Error Mean
LLPNIR	High-FSR	172	0.162755	0.2880616	0.0219645
	Low-FSR	168	0.343203	0.7807317	0.0602348
LLRIL	High-FSR	164	1.468992	0.7288206	0.0569113
	Low-FSR	139	0.831213	0.4107235	0.0348371
ILGL	High-FSR	165	0.030640	0.0295505	0.0023005
	Low-FSR	139	0.194644	0.1710849	0.0145112
TCR	High-FSR	167	0.180305	0.0540258	0.0041806
	Low-FSR	131	0.215277	0.1067987	0.0093310
CS	High-FSR	172	0.119607	0.0285815	0.0021793
	Low-FSR	179	0.111385	0.0727009	0.0054339
ENL	High-FSR	172	0.225523	0.0640988	0.0048875
	Low-FSR	179	0.395871	0.3527058	0.0263625
EM	High-FSR	172	9.434960	9.4559659	0.7210106
	Low-FSR	179	11.378556	6.6205101	0.4948402
NIM	High-FSR	172	0.030043	0.0065669	0.0005007
	Low-FSR	179	0.031621	0.0130922	0.0009786
NIEAA	High-FSR	172	0.018070	0.0071052	0.0005418
	Low-FSR	179	0.026825	0.0149159	0.0011149
REP	High-FSR	172	0.027992	0.0078521	0.0005987
	Low-FSR	179	0.023759	0.0166384	0.0012436
AU	High-FSR	147	0.059595	0.0122440	0.0010099
	Low-FSR	159	0.074512	0.0213763	0.0016953
TME	High-FSR	172	0.983616	0.0402651	0.0030702
	Low-FSR	175	0.757061	0.8892001	0.0672172
LLPTL	High-FSR	172	0.006839	0.0093660	0.0007142
	Low-FSR	169	0.019610	0.0276255	0.0021250
LADSTF	High-FSR	172	0.298933	0.1620916	0.0123594
	Low-FSR	179	0.436523	0.1788769	0.0133699

Notes: The overall sample consists of 135 active commercial banks (of which 64 banks rated by CI) covering 10 countries from Middle East region: Egypt, Bahrain, Kuwait, Jordan, Qatar, Lebanon, Saudi Arabia, United Arab Emirates, Oman and Yemen. The data are extracted from Bankscope for the years 2001–2009 inclusive. This Table shows group statistics for the 14 financial indicators are finally used in building our five proposed statistical techniques.

10.426 (and the highest standard deviation value of 8.181) and LLPTL has the lowest mean value of 0.013 (NIM has the lowest standard deviation value of 0.010). Table 5 shows group statistics for the 14 financial predictors for both high-FSR and low-FSR. Again EM has the highest high-FSR and low-FSR mean values of 11.379 and 9.435, respectively (EM also has the highest standard deviation values for high-FSR and low-FSR of 9.456 and 6.621, respectively). LLPTL has the lowest high-FSR and low-FSR mean values of 0.007 and 0.019, respectively (NIM has the lowest standard deviation value for high-FSR and low-FSR of 0.007 and 0.013, respectively).

Table 6. Descriptive statistics for non-financial indicators

Characteristic	Value	Count	Total distribution, %	Goods	Goods distribution, %	Bads	Bads distribution, %	Bad rate	WOE
Time									
2001	1	37	10.54	17	9.88	20	11.17	54.05%	–12.263
2002	2	38	10.83	17	9.88	21	11.73	55.26%	–17.142
2003	3	38	10.83	17	9.88	21	11.73	55.26%	–17.142
2004	4	38	10.83	17	9.88	21	11.73	55.26%	–17.142
2005	5	40	11.40	18	10.47	22	12.29	55.00%	–16.078
2006	6	40	11.40	18	10.47	22	12.29	55.00%	–16.078
2007	7	41	11.68	21	12.21	20	11.17	48.78%	8.868
2008	8	40	11.40	24	13.95	16	8.94	40.00%	44.536
2009	9	39	11.11	23	13.37	16	8.94	41.03%	40.28
IV:0.058									
Sovereign country risk rating (SR)									
C	3	6	1.71	0	0.00	6	3.35	100.00%	–244.502
B⁻	5	27	7.69	0	0.00	27	15.08	100.00%	–394.909
B	6	19	5.41	0	0.00	19	10.61	100.00%	–359.769
B⁺	7	3	0.85	0	0.00	3	1.68	100.00%	–175.187
BB⁻	8	8	2.28	0	0.00	8	4.47	100.00%	–273.27
BB	9	29	8.26	3	1.74	26	14.53	89.66%	–211.959
BB⁺	10	21	5.98	4	2.33	17	9.50	80.95%	–140.703
BBB⁻	11	28	7.98	9	5.23	19	10.61	67.86%	–70.732
BBB	12	10	2.85	2	1.16	8	4.47	80.00%	–134.64
BBB⁺	13	11	3.13	7	4.07	4	2.23	36.36%	59.951
A⁻	14	33	9.40	29	16.86	4	2.23	12.12%	202.089
A	15	43	12.25	33	19.19	10	5.59	23.26%	123.381
A⁺	16	64	18.23	41	23.84	23	12.85	35.94%	61.797
IV:2.712									
Size									
Small	1	136	38.75	8	4.65%	128	71.51	94.12%	–273.27
Medium	2	94	26.78	55	31.98%	39	21.79	41.49%	38.366
Large	3	121	34.47	109	63.37%	12	6.7%	9.92%	224.633
IV:3.139									

Note: Size reflects qualitative characteristics such as product diversification and geographic location and we use *ln* of total assets.

3.1.2. Non-financial indicators

Descriptive statistics for the 3 non-financial predictor indicators are shown in Table 6. As per the information value[6] score, 'Size' is the most influential non-financial predictor with a sore of 3.139. 'Sovereign Country Risk Rating' (SR) with an information value score of 2.712 comes second. Finally, 'Time' shows the lowest importance with information value score of 0.058. The latter value indicates that 'Time' has no effect on our Middle Eastern banks sample from 2001 to 2009 even during the financial crisis, i.e., 2007–2009. This implies that the effect of the financial crisis on Middle Eastern banks during this period was not evident, but it might have an effect in later years.

6 Information value directly relates to a statistical technique called Weight of Evidence (WoE) which identifies the strength of different predictor indicators, as an alternative to Chi2. For more details the reader is referred to Abdou et al. (2016).

Table 7. Classification results for the three machine learning modelling techniques

Actual bank FSR group membership	Predicted bank FSR group membership											
	CHAID				CART				MLP NN			
	High-FSR	Low-FSR	Total	% total	High-FSR	Low-FSR	Total	% total	High-FSR	Low-FSR	Total	% total
Testing sub-sample$_1$												
High-FSR	61	6	67	91	55	12	67	82.1	54	13	67	80.6
Low-FSR	7	42	49	85.7	8	41	49	83.7	9	40	49	81.6
Total	68	48	116	88.8	63	53	116	82.8	63	53	116	81
Testing sub-sample$_2$												
High-FSR	48	10	58	82.2	52	6	58	89.7	53	5	58	91.4
Low-FSR	4	54	58	93.1	3	55	58	94.8	11	47	58	81
Total	52	64	116	87.9	55	61	116	92.2	64	52	116	86.2

Notes: The overall sample consists of 135 active commercial banks (of which 64 banks rated by CI) covering 10 countries from Middle East region: Egypt, Bahrain, Kuwait, Jordan, Qatar, Lebanon, Saudi Arabia, United Arab Emirates, Oman and Yemen. The data are extracted from Bankscope for the years 2001–2009 inclusive. This table shows classification results for the three machine learning statistical techniques namely CHAID, CART and MLP NN. The dependent variable is a categorical variable where high-FSR = 1 and low-FSR = 2. Sub-sample1 uses 2001–2006 to build the models (training sub-sample) and 2007–2009 to test the fitted models (testing sub-sample); subsample2 is randomly chosen by the PASW@ Modeler 14 software.

3.2. Statistical techniques

3.2.1. Machine learning statistical techniques

CHAID

Classification results for bank FSR group membership models using CHAID technique are summarized in Table 7. All the 17 financial and non-financial indicators for sub-sample$_1$ and sub-sample$_2$ are utilized. For the testing/hold-out sub-sample$_1$, the overall average correct classification (ACC) rate is 88.8%. The predictive capabilities for high-FSR and low-FSR are 91% and 85.7%, respectively. Concerning testing sub-sample$_2$, the overall ACC rate is 87.9% and the predictive capability of CHAID in foreseeing low-FSR rate of 93.1% is better than the high-FSR rate of 82.8%. Comparing different testing sub-samples, CHAID model using sub-sample$_1$ predicts 91% high-FSR which is better than the 85.7% low-FSR. By contrast, CHAID model using sub-sample$_2$ predicts 93.1% low-FSR in comparison to only 82.2% high-FSR.

CART

CART is used to explore the anticipated differences between the proposed models in relation to ACC rates using the same 17 financial and non-financial predictor indicators. Table 7 shows the classification for sub-sample$_1$ and sub-sample$_2$ for CART bank FSR group membership models. Concerning testing sub-sample$_1$, the overall ACC rate is 82.8% with 82.1% and 83.7% for high-FSR and low-FSR, respectively. The overall ACC rate is lower than that associated rate under CHAID model (i.e. 88.8%) using the same sample. This significant decline in the ACC rate is a result of the lower predictive power of the CART model (i.e. 82.1% for high-FSR and 83.7% for low-FSR) compared to the CHAID model (i.e. 91% for high-FSR and 85.7% for low-FSR). For the testing sub-sample$_2$, the ACC rate is 92.2% which is higher than that associated rate under CHAID model (i.e. 87.9%). This is a result of the better predictive accuracy rates of 89.7% and 94.8% for high-FSR and low-FSR, respectively using CART compared to 82.8% and 93.1% for high-FSR and low-FSR, respectively using CHAID.

Multilayer-Perceptron Neural Networks

MLP NNs are designed using the same 17 financial and non-financial indicators under sub-sample$_1$ and sub-sample$_2$. The overall ACC rate using testing sub-sample$_1$ is 81% with 80.6% and 81.6% for high-FSR and low-FSR, respectively, as shown in Table 7. As for testing sub-sample$_2$, the classification matrix shows that the overall ACC is 86.2%; in addition, MLP NN model predicts high-FSR (i.e., 91.4%) better than the low-FSR (i.e., 81%). The

Table 8. Classification results for the two conventional modelling techniques

Actual bank FSR group membership	Predicted bank FSR group membership							
	DA				LR			
	High-FSR	Low-FSR	Total	% total	High-FSR	Low-FSR	Total	% total
Testing sub-sample$_1$								
High-FSR	59	8	67	88.1	16	51	67	23.9
Low-FSR	1	48	49	98	19	30	49	61.2
Total	60	56	116	92.2	35	81	116	39.7
Testing sub-sample$_2$								
High-FSR	55	3	58	94.8	53	5	58	91.4
Low-FSR	13	45	58	77.6	12	46	58	79.3
Total	68	48	116	86.2	65	51	116	85.3

Notes: The overall sample consists of 135 active commercial banks (of which 64 banks rated by CI) covering 10 countries from Middle East region: Egypt, Bahrain, Kuwait, Jordan, Qatar, Lebanon, Saudi Arabia, United Arab Emirates, Oman and Yemen. The data are extracted from Bankscope for the years 2001–2009 inclusive. This Table shows classification results for the three machine learning statistical techniques namely CHAID, CART and MLP NN. The dependent variable is a categorical variable where high-FSR = 1 and low-FSR = 2. Sub-sample1 uses 2001–2006 to build the models (training sub-sample) and 2007–2009 to test the fitted models (testing sub-sample); subsample2 is randomly chosen by the PASW@ Modeler 14 software.

increased overall ACC rate is a result of the higher predictive capability rate of 91.4% for high-FSR in testing sub-sample$_2$, compared to a rate of 80.6% in sub-sample$_1$.

3.2.2. Conventional techniques

Discriminant analysis

We run DA models using the same 17 financial and non-financial predictor indicators, and they are statistically significant at the 99% confidence level. As shown in Table 8, the overall ACC rate under testing sub-sample$_1$ is 92.2% which is surprisingly the highest of all the techniques applied in this paper. The ACC rates for high-FSR and low-FSR are 88.1% and 98%, respectively. Clearly DA superiorly predicts low-FSR compared to all other techniques used in this paper. The classification results for testing sub-sample$_2$ revealed that the overall ACC rate is 86.2% with 94.8% and 77.6% ACC rates for high-FSR and low-FSR, respectively, as shown in Table 8.

Logistic regression

We also run LR models using the 17 financial and non-financial predictor indicators, and they are statistically significant at the 99% confidence level. As summarized in Table 8, the ACC rate associated with testing sub-sample$_1$ is 39.7% which is the lowest rate across all statistical techniques employed in our paper. In addition, this model has the lowest predictive power for high-FSR (i.e., 23.9%). Concerning testing sub-sample$_2$, the overall ACC is 85.3% with 91.4% and 79.3% for high-FSR and low-FSR, respectively. Clearly sub-sample$_2$ results show huge improvement compare to sub-sample$_1$ results for this technique.

3.3. Comparison of different models' results

Using testing sub-sample$_1$ (i.e., predicting bank FSR group membership in 2007–2009), the highest ACC rate of 92.2% is associated with DA model; whilst using testing sub-sample$_2$, the same ACC rate of 92.2% is associated with CART. All techniques predict low-FSR better than high-FSR group memberships using sub-sample$_1$, except the CHAID model. However, for sub-sample$_2$ (randomly predicting 33% of the overall sample), results are mixed. Both CHAID and CART predict low-FSR better than high-FSR, whilst the other three techniques namely MLP NN, DA and LR predict high-FSR better than low-FSR group memberships, as show in Tables 7 and 8. In order to compare different models predictive capabilities, estimates misclassification cost (EMC) is used. The following equation (see for example, Abdou (2009b) is applied in calculating the EMC:

Table 9. Error rates, estimated misclassification costs and gain chart ranking for all the five modelling techniques

Bank FSR models	Testing sub-sample$_1$				Testing sub-sample$_2$			
	Error results		EMC	Gain chart rank	Error results		EMC	Gain chart rank
	Type I	Type II			Type I	Type II		
CHAID	0.09	0.143	0.776	Second	0.172	0.069	0.5	Second
CART	0.179	0.163	0.931	Third	0.103	0.052	0.362	Fisrt
MLP NN	0.194	0.184	1.04	Fourth	0.086	0.19	1.181	Third
DA	0.119	0.02	0.172	First	0.052	0.224	1.37	Fifth
LR	0.761	0.388	2.405	Fifth	0.086	0.207	1.284	Fourth

Notes: The overall sample consists of 135 active commercial banks (of which 64 banks rated by CI) covering 10 countries from Middle East region: Egypt, Bahrain, Kuwait, Jordan, Qatar, Lebanon, Saudi Arabia, United Arab Emirates, Oman and Yemen. The data are extracted from Bankscope for the years 2001-2009 inclusive. This Table shows classification results for the three machine learning statistical techniques namely CHAID, CART and MLP NN. The dependent variable is a categorical variable where high-FSR = 1 and low-FSR = 2. Sub-sample1 uses 2001–2006 to build the models (training sub-sample) and 2007–2009 to test the fitted models (testing sub-sample); Subsample2 is randomly chosen by the PASW@ Modeler 14 software.

$$EMC = E\frac{L}{H}\cdot b\frac{L}{H}\cdot \pi_2 + E\frac{H}{L}\cdot b\frac{H}{L}\cdot \pi_1, \qquad (10)$$

where, E (predicted low-FSR/actually high-FSR) and E (predicted high-FSR/actually low-FSR) refers to the corresponding EMC of Type I error and Type II errors; b (predicted low-FSR/actually high-FSR) and b (predicted high-FSR/actually low-FSR) refers to the probabilities of Type I error and Type II errors; and π_2 and π_1 are prior probabilities of low-FSR and high-FSR, respectively. We use a ratio of 5:1 to present the EMC associated with Type II and Type I errors following, for example, Abdou et al. (2008) and Abdou (2009b). Table 9 summarizes the error rates namely Type I[7]and Type II[8] errors and the EMC results for all techniques under the samples namely sub-sample$_1$ and sub-sample$_2$.

For testing sub-sample$_1$, CHAID's Type I error rate is lower than Type II error rate achieving a EMC of 0.776. In contrast, for other statistical techniques namely CART, MLP NN, DA and LR, the lowest misclassification cost of 0.172 is surprisingly associated with DA. It is believed that this is due to the significantly low Type II error associated with DA model, as shown in Table 9. Indeed, this result agrees with our previous findings using ACC rate where the DA model provides the highest ACC rate of 92.2%, as shown in Tables 7 and 8. Concerning testing sub-sample$_2$, the lowest EMC of 0.362 is associated with CART model. This result also is confirmed using the ACC rate criterion where CART has the highest ACC rate of 92.2%, as discussed above, as shown in Table 7.

For more details relating to testing sub-sample$_1$ (predicting 2007–2009) and testing sub-sample$_2$ (randomly predicting 33% of the overall sample), the reader is referred to Figure 3 and Figure 4; this illustrates our third criterion namely the gain chart using the machine leaning and conventional techniques applied in this paper, respectively. The gains chart is a valuable method of visualizing how good a predictive model is, as it plots the values in the Gain (%) column from the gains table. Gains refer to the increment number of hits divided by the overall number of hits multiplied by one hundred. If the models are not used, the 'diagonal line' plots the expected response in the testing sub-samples. The higher percentiles of gains, reflected in the curve line, represent how much the model can be improved with steeper curves representing higher gains. Visual gain charts analysis has indeed confirmed our results for both sub-sample$_1$ and sub-sample$_2$ using other criteria, namely ACC rate and EMC.

7 High-FSR is misclassified as low-FSR.

8 Low-FSR is misclassified as high-FSR.

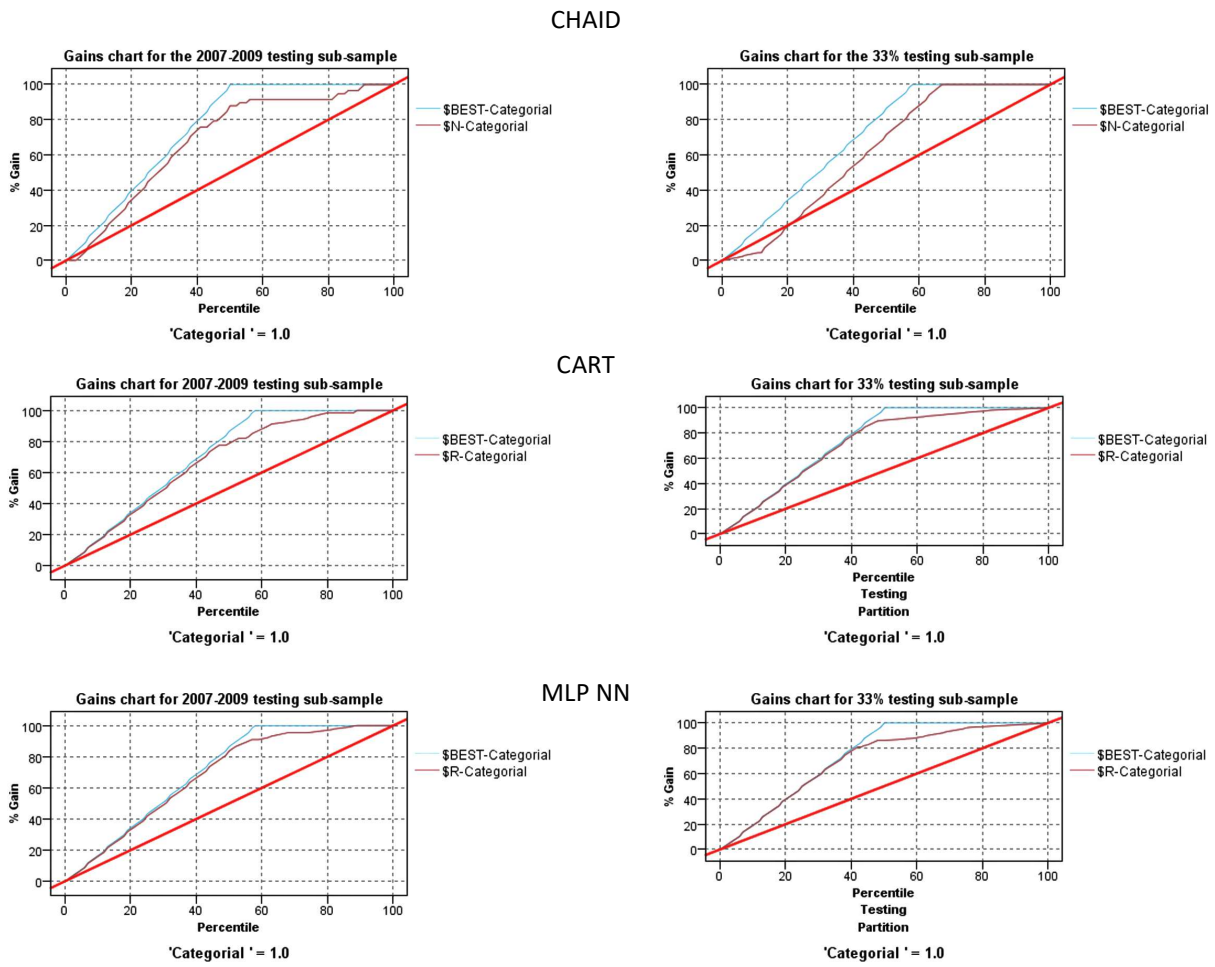


Figure 3. Gain charts for machine learning techniques using 2007–2009 testing sub-sample$_1$ and 33% testing sub-sample$_2$

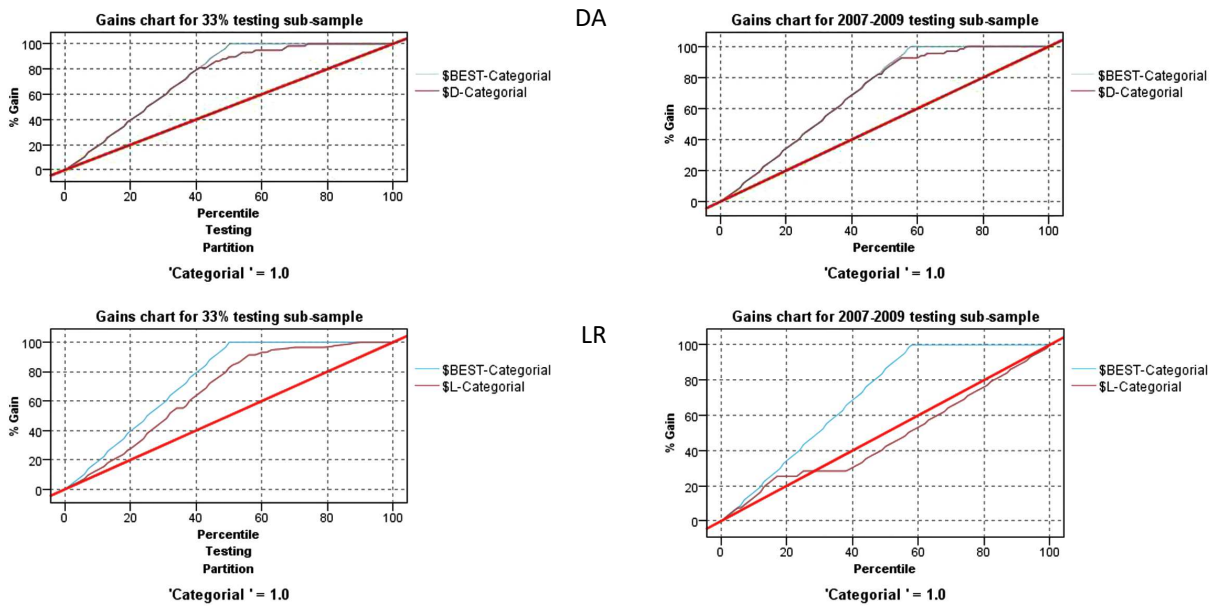


Figure 4. Gain charts for conventional techniques using 2007–2009 testing sub-sample$_1$ and 33% testing sub-sample$_2$

CONCLUSION AND AREAS FOR FUTURE RESEARCH

The assessment of the creditworthiness of banks and other financial institutions has become very challenging due to structural changes in the global banking sector and the variability of creditworthiness within this sector. In addition, the financial crisis of 2007–2009 highlighted that banking systems are facing severe problems across different regions and that predicting 'correct' banks' FSR group membership seems more important than ever. This paper presents how Middle Eastern banks can use machine learning techniques, namely CHAID, CART and MLP NN as well as conventional techniques, namely DA and LR to utilise financial and non-financial indicators to predict a bank's FSR group membership.

Our results show that using testing/hold-out sub-sample1, DA model has the highest ACC rate of 92.2% and the lowest EMC of 0.172. This can be explained due to the minimal type II error rate. As for testing sub-sample$_2$, CART has the highest ACC rate of 92.2% and lowest EMC of 0.362. Our gain chart results for both sub-samples do support the findings under the previous criteria, namely ACC rate and EMCs. In general, it can be concluded that DA as a conventional technique and CART as a machine learning technique are superior to all other techniques in predicting 'correct' bank's FSR group membership in the Middle East region using data for the period 2007–2009 and for randomly selected sub-sample, respectively. Our future research can be extended in a number of ways. First, to investigate the prediction of high-FSR (and near high-FSR) versus low-FSR (and near low-FSR) during the Arab Spring commencing 2010. Second, to compare rated and non-rated banks to identify what non-rated banks need to achieve in order to secure higher rates. Third, apply other statistical modelling techniques such as SVM and genetic algorithms. Finally, use cross-validation technique to reduce any possible inconsistencies in results.

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APPENDIX

Table A1. List of bank financial variables used in building the proposed bank FSR group membership models

Financial indicators	Variables
Asset quality	The ratio of loan loss provision to net interest revenue (LLPNIR)
	The ratio of loan loss reserve to impaired loans (LLRIL)
	The ratio of impaired loans to gross loans (ILGL)
Capital adequacy	The total capital ratio (TCR)
	The ratio of equity to total assets (CS)
	The ratio of equity to net loans (ENL)
	The equity multiplier (EM)
Profitability	The net interest margin (NIM)
	The ratio of non interest expense to total average assets (NIEAA)
	The recurring earning power ratio (REP)
	The asset utilization ratio (AU)
	The tax management efficiency ratio (TME)
Credit risk	The ratio of loan loss provisions to total loans (LLPTL)
Liquidity	The ratio of liquid assets to deposit and short term funding (LADSTF)*

Note: * liquid assets are short-term assets that can be easily converted into cash, such as cash itself and deposits with the central bank, treasury bills, other government securities and interbank deposits.