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Prediction of Financial Distress for Commercial Banks in Kuwait

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The main objective of this article was to find the most accurate model for financial distress prediction. As it is known, predicting bank financial distress reduces the incurred loss and helps avoiding misallocation of Bank's financial resources. A total of six Kuwaiti commercial banks were financially analyzed using data compiled for nine consecutive years from 2001 to 2009. Data has been collected from the annual financial report represented in the balance sheet and income statement for Kuwaiti Commercial Banks. Logistic regression, which can be used as a part of an "early warning" system with respect to the financial distress of the commercial banks, was then undertaken to form a prediction model for time periods in which the banks were going into financial distress. Results *have shown that during the operation of the banks; 41.7% of time periods the banks were expected to go into financial distress, whereas 83.8% of time periods the banks were expected to be in a good financial situation. Out of the eleven ratios that have been included in the study, only three ratios are statistically significant in predicting financial distress of the banks. The 1st ratio is (Investment in Securities to Total Assets), the 2nd ratio is (Loans to Total Assets) and the 3rd ratio is (Loans to Deposits). These ratios are considered to be the best predictors of financial distress for the banks under this study.*

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1. Introduction

Banking crises have a negative influence to the economy as a whole and particularly the financial sectors. The fiscal burden underpins such crises is only a redistribution of resources within the economy. However, the real cost of a banking crisis is the deadweight loss and the consequent diversion in macroeconomic policy forced by the crisis. In the context of Kuwaiti commercial banks, such issue acquires significance as it can potentially inflict reputation damage to the nascent industry. This would slowdown the progress towards interest-free alternatives, and consequent loss in the form of non-realization of the potential benefits of Kuwaiti commercial banks finance to the economy**.**

In literature, it has been indicated that the threat of a milder level crisis has some longitudinal advantages too, as it may improve the efficiency of the banking sector by eliminating the inefficient banks. Keeping the banking industry vigilant and alert, would force the practitioners and researchers to come up with better tactics to run the financial

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system. Although, that might be costly in the short-run, its benefits can be seen in longer-run in averting a bigger and more costly crisis. As well as, motivating the progress and improvement of the financial sector.

The literature on banking crises has identified that the structure of the conventional banks are inherently unstable and itself can contribute to the occurrence of crisis Bryant (1980). Being a deposit taking institution, the liabilities of a bank, at any given point in time, are fixed with a fixed interest guaranteed. Whereas, its assets are in the form of loans earning variable interest and subject to credit risk. Similarly, its demand deposits by nature are of shorter maturity while its loans are for longer duration. Therefore, the risk of maturity mismatch always exists. These features of the assets and liabilities render the banking sector prone to crisis in wake of any mistrust or decreased confidence of the depositors.

On the contrary, the theoretical literature shows how the commercial banks can be more stable. Accordingly, the endogenous linking of returns on deposits with returns on assets of a commercial bank serves as a disciplinary device and increases the efficiency of the bank and the financial system Diamond & Rajan (2000). It also serves as a stabilization device saving the banks from deposit runs in crisis situation. When the value of assets of a bank declines due to some shock, the liability of the bank also decreases correspondingly by the profit sharing nature of the deposit contracts. This preserves the net-worth of the bank. The profit sharing feature on the asset and liability sides adds to the stability of individual banks, and by avoiding a domino effect, it also adds to the stability of the financial system as a whole. As mentioned above regarding the instability of banking structures and its vulnerability to crisis, financial ratios are used to analyze the banks performance in order to assets and benchmark the banks level of solvency and liquidity. The aim of this article was to determine the most important financial ratios that can be used as a good predictor of financial distress for Kuwaiti commercial banks. The reason behind this study is that banks in Kuwait are facing many challenges to operate within ~~a~~ more competitive environment.

The scope of investment for Kuwaiti banks is limited to a real estate, trade, and stock market. Those investment opportunities are more likely affected by the global financial crises. And consequently, threaten the financial performance of Kuwaiti banks. Therefore, estimation of financial distress will provide invaluable information for investors and shareholders in aid of their financial decisions to prevent possible loses. Also, gives the bankers a warning signal of possible bankrupt.

One of the major motivation for this study was the non-existence of research in estimation of financial distress cycle for Kuwaiti commercial banks during the global financial crises period (2007-2009) in the GCC region .The extensive research on financial ratios reveals their importance as financial indicators used to predict the financial distress of the banks. In the context of Kuwait region, no comprehensive financial distress prediction analysis has been done so far. However, Tarawneh (2006) studied the impact of financial comparison based on certain selected ratios: return on assets, return on equity, and return on deposits with other financial banking activities to determine the financial performance of Omani commercial banks. The most relevant study was carried out by Zaki, Bah & Rao (2011), who estimated a probability model for commercial and Islamic banks in U.A.E. They used a binary response models for panel data to construct the probability model.

Our study was attempt to determine the financial distress cycle for banks by predicting the proportion of time in which the banks are going into financial distress during the period of operation using a logit regression models. Thus, this study is structured as follows: the next section following the introduction discusses the relevant literature. The third section is the study methodology, a model for estimation the financial distress is specified in this section along with data and sample selection. The fourth section presents the empirical results. The fifth section is the conclusion.

2. Literature Review

Prediction of corporate financial distress and bankruptcy has gained a great deal of interest by researchers in finance starting in the late 1960s. The first step in the evolution of the quantitative firm failure prediction model was taken by Beaver (1966), who developed a dichotomous classification test based on a simple *t*-test in a univariate framework. He used individual financial ratios from 79 failed and non-failed companies that were matched by industry and assets size in 1954 to 1964 and identified a single financial ratio; Cash flow/Total Debt as the best predictor of corporate bankruptcy.

Beaver's study (1966) was then followed by Altman (1968), who suggested a multivariate technique; known as Multivariate Discriminant Analysis (**MDA**). By using 33 bankrupt companies and 33 non-bankrupt companies over the period of 1946 – 1964, five variables were selected to be most relevant in predicting bankruptcy. These variables were: Working Capital to Total Assets, Retained Earnings to Total Assets, Earnings before Interest and Taxes to Total Assets, Market Value of Equity to Book Value of Total Debt and Sales to Total Assets. Z-Score was determined and those companies with a score greater than 2.99 fell into the non-bankrupt group, while those companies having a Z-Score below 1.81 were in the bankrupt group. The area between 1.81 and 2.99 was defined as the zone of ignorance or the gray area. The MDA model was able to provide a high predictive accuracy of 95% one year prior to failure. For that reason, MDA model had been used extensively by researchers in bankruptcy research.

On the other hand, Ohlson (1980) found that there were some inadequacies in MDA with respect to the assumptions of normality and group dispersion. The assumptions were often violated in MDA and this might have biased the test of significance and estimated error rates. Logit analysis, which did not have the same assumptions as MDA, was made popular in the financial distress prediction problem by Ohlson (1980), who used 105 bankrupt companies and 2058 non-bankrupt companies from 1970 to 1976. The results showed that size, financial structure (Total Liabilities to Total Assets), performance, and current liquidity were important determinants of bankruptcy. In the logistic analysis, average data is normally used and it is considered as a single period model. Hence, for each non-distressed and distressed company, there is only one company-year observation. The dependent variable is categorized into one of two categories; distressed or non-distressed.

In 2005**,** Altman & Sabato (2005) probit model was first applied to the firm failure prediction. However, this type of binary econometric model was less intensely used in this field. Some studies that implied the use of logistic and probit models for the distress prediction problem were made by Lennox (1999). In 2005, some econometric problems with a single period logit model were discussed by Chiang (2005). The first problem was the sample selection bias that arises from using only one, non-randomly selected observation for each bankrupt company. The second problem was the model failure to include time varying changes that reflect the underlying risk of bankruptcy. Being based on a 6 dichotomous classification, the traditional static model is not suited to handle the temporal concept. The dichotomous approach treats all firms that belong to each group as the same and there will be no recognition of default timing, whether it falls within the window or not. The failure process must be fairly stable over a considerable period of time for this specification to work properly. Shumway (2001) demonstrated that these problems could result in biased, inefficient, and inconsistent coefficient estimates. To overcome such econometric problems, he proposed the hazard model for predicting bankruptcy. Hazard model was superior to the logit and the MDA models. This particular model is actually a multi-period logit model because the likelihood functions of the two models are identical. For this reason, the discrete-time hazard model with time-varying covariates can be estimated by using the existing computer packages for the analysis of binary dependent variables. The main particularities of the hazard model consist in the facts that firm specific covariates must be allowed to vary with time for the estimator to be more efficient and a baseline hazard function is also required, which can be estimated directly with macroeconomic variables to reflect the radical changes in the environment.

Further on, Nam et al. (2008) extended the work of Shumway (2001) and developed a duration model with time varying covariates and a baseline hazard function incorporating macroeconomic variables, such as exchange rate volatility and interest rate. Using the proposed model, they investigated how the hazard rates of listed companies in the Korea Stock Exchange (KSE) are affected by changes in the macroeconomic environment and by time varying covariate vectors that show unique financial characteristics of each company. By investigating the out-of-sample forecasting performances of their model compared to the results of both a traditional dichotomous static model and also a logit model with time-varying covariates, but no baseline hazard function, they demonstrated the improvements produced when allowing temporal and macroeconomic dependencies. In another study, Abdullah et al. (2008) compared three methodologies of identifying financially distressed companies in Malaysia that are: multiple discriminant analysis (MDA), logistic regression, and hazard model. In a sample of 52 distressed and non-distressed companies with a holdout sample of 20 companies, the predictions of hazard model were accurate in 94.9% of the cases examined. This was a higher accuracy rate than generated by the other two methodologies. However, when the holdout sample was included in the sample analyzed, MDA had the highest accuracy rate of 85%. Among the ten determinants of corporate performance examined, the Ratio of Debt to Total Assets was a significant predictor of corporate distress regardless of the methodology used. In addition, Net Income Growth was another significant predictor in MDA, whereas the return on Assets was an important predictor when the logistic regression and hazard model methodologies were used. Their analysis was similar to the studies of Low, Nor & Yatim (2001) and Sulaiman, Jili & Sanda (2001).

In recent years, many types of heuristic algorithms, such as neural networks and decision trees have also been applied to the bankruptcy prediction problem and several improvements in the financial distress prediction were noticed. For example, the studies made by Tam & Kiang (1992), Salchenberger, Cinar, and Lash. (1992) provided evidence to suggest that neural networks outperform conventional statistical models such as discriminant analysis, logit models in financial applications involving classification and prediction. Soon after that, hybrid Artificial Neural Network methods were proposed in some financial distress prediction studies. For example, Yim &

Mitchell (2005) tested the ability of a new technique, hybrid ANN's to predict corporate distress in Brazil.The models used in their study were compared with the traditional statistical techniques and conventional ANN models. The results indicated that the most relevant financial ratios for predicting Brazilian firm failure are Return on Capital Employed, Return on Total Assets, Net Assets Turnover, Solvency, and Gearing. The first ratio tells how much the firm is earning on shareholder investment, being a measure of overall efficiency and a reflection on financial as well as operational management. ROA measures the efficient utilization of the company's assets in generating profits. As expected, low profitability ratio is associated with high probability of failure. The solvency ratio is the total of shareholders' funds per total assets. Failed firms had a low solvency ratio because it implies that these firms are predominantly financed with debt. The lower the level of solvency is, the lower the chances of the firm to meet its obligations are. The asset management ratio is the net asset turnover. This measures the company's effectiveness in using its total assets and is calculated by dividing total assets into sales. This ratio shows how many dollars of sales have been generated for every one dollar of asset employed. Low activity ratio is associated with high probability of failure. Last, the gearing ratio is defined as the debt per equity and indicates how much of the company's financial structure is debt and how much is equity. A high ratio indicates greater leverage. The results of the study also suggested that hybrid neural networks outperform all other models in predicting firms in financial distress one year prior to the event, concluding that hybrid ANN is a very useful tool in early warning systems for predicting firm failure. However, the main disadvantages are: the difficulty of building up a neural network model, the required time to accomplish iterative process, and the difficulty of model interpretation. Compared to neural networks, decision tree is not only a nonlinear architecture, which is able to discriminate patterns that are not linearly separable and allow data to follow any specific probability distribution, but also plain to interpret its results, require little preparation of the initial data and perform well with large data in a short time.

Zheng & Yanhui (2007) used decision tree methodologies for corporate financial distress prediction in their study. The authors presented the advantages of using CHAID decision trees in comparison to a neural network model, which is complicated to build up and to interpret or to a statistic model such as multivariate discriminate regression and logistic regression, where the patterns need to be linearly separable and samples are assumed to follow a multivariate normal distribution. Their study focused on 48 failed and continuing listed Chinese companies in the period 2003–2005. The following variables embodied most information for predicting financial distress: Net Cash Flow from Operating Activity as a percentage of Current Liabilities, Return Rate on Total Assets, Growth rate of Total Assets, and Rate on Accounts Receivable Turnover. They also noticed that it is not appropriate to use financial information to predict financial distress ahead of four years. However, the results supported by the test study showed that decision trees was a valid model to predict listed firms financial distress in China, with a 80% probability of correct prediction.

Another similar study based on CHAID decision tree models for distress prediction problem was made by Koyuncugil and Ozgulbas (2007). They identified Return on Equity (ROE) to be the best financial early warning signal for detecting financial distress of the Small and Medium-sized Enterprises listed in Istanbul Stock Exchange for the period 2000-2005. As noticing from the literature review presented above, the bankruptcy and distress prediction issues were intensively studied starting with the late 1960s and still remain an opened challenge, especially in the times when the financial crisis tests each company's surviving skills even more. In this context, early warning signals could be of great help in preventing financial distress or even bankruptcy.

3. Methodology

The most widely used statistical models to predict corporate or bank bankruptcy or distress are discriminant analysis and logistic regression was first proposed by Shumway (2001). Logistic-like regressions fit a relationship between the bank's financial distress and its accounting and market based variables, in an attempt to estimate its distress probability. Our analysis is based on a logistic regression fitted to a recent sample of Kuwaiti commercial banks. In practice many researchers choose logit model because of its comparative mathematical simplicity Gujarati (2004). Comparing to quantitative explanatory variables in normal regression, dependent variables in logistic regression are normally qualitative (or dummy). Martin (1977) first intended to build an early warning model for predicting future bank failure based on current period's balance sheet and income statement by using logistic regression.

In this paper, Logistic Regression was used to find models and make extant predictions in order to determine the banks which were financially in bad condition. Despite the existence of other multivariate statistical models that could be used in modeling and prediction, Logistic Regression model was preferred because of its statistical advantages. Logistic Regression does not face the strict assumptions such as multivariate normality and equal variance-covariance matrices across groups.

In evaluating bank's performance, we need tools that can be used to measure the performance and one of the most popular tools is the financial ratio analysis. Therefore, it is hypothesized that there is financial ratios, which are statistically significant indicators to predict the financial distress for commercial banks in Kuwait. It is also hypothesized that such ratios exert significant influence on dependent variable when using logit regression models.

This paper will explore the use of logistic technique to identify the most important financial ratios that can be considered as indicators of the banks financial position, which give the bank's management an early warning of bank situation.

3.1 Data Set

All Kuwaiti commercial banks were included in the study they were 6 banks as follows:

1) National Bank of Kuwait.
2) Gulf Bank.
3) Kuwait Commercial Bank.
4) AL-Ahli Kuwaiti Bank.
5) Burgan Bank.
6) Bank of Kuwait and middle east (BKME).

The data were collected from the balance and the Income sheet of the annual report for the banks during the period of nine years started from 2001 till 2009. Financial ratios of six banks are calculated from the original data based on the formulas shown in appendix one. The values of the financial ratios were calculated, using Spss software,

are shown in appendix two. Also Spss Statistical software was used in the analysis of data and modeling Logistic Regression.

We have 11 independent variables and 6 banks, in this case the number of variables exceeds the number of cases as a result of this the estimated standard errors become large and the model will more depend on the observed data, therefore, the model will be over fit. Also large standard errors of the estimated coefficients signal the possibility of multicollinearity Gujarati (2004). In order to overcome this problem of over fit model we have considered the periods of years as subjects which exceeds the number of the independent variables. Therefore, our approach will be modeling a logit function to predict the proportion of time that banks are going into financial distress during their operation time. Only 11 ratios have been analyzed. They were coded as follows:

$$X_1 = R_1, X_2 = R_2, X_3 = R_3, X_4 = R_4, X_5 = R_5, X_6 = R_6, X_7 = R_7, X_8 = R_8, X_9 = R_9, X_{10} = R_{10}, X_{11} = R_{11}$$

In this study 11 ratios were chosen among the many that has been used in previous studies. These 11 ratios were chosen to assess: profitability, efficiency, liquidity, and solvency. The choice of ratios used was based on two main criteria, namely their popularity as evidenced by their frequent usage in the finance and accounting literature and that the ratios have been shown to perform well in previous studies. The ratios are shown in the following table.

Table 1: Ratios included in the analysis

SI. No.	Selected Ratios	Abbreviation	Measure
X_1	Net Profit to Assets	NPTA	Profitability
X_2	Banking Income to Assets	BITA	Profitability
X_3	Investments in securities to Assets	ISTA	Profitability
X_4	Liquidity Assets to Assets	LATA	Liquidity
X_5	Equity to Assets	ETA	Structural
X_6	Profitable Assets to Assets	PATA	Profitability
X_7	Fixed and Other Assets to Assets	FOTA	Structural
X_8	Loans to Assets	LTA	Structural
X_9	Dept to Assets	DTA	Structural
X_{10}	Investments and Deposits to Assets	IDTA	Structural
X_{11}	Loans to Deposits	LD	Structural

The dependent variable is the financial distress of the bank or the non-financial distress of the bank, a dummy variable with a binary measure was used where 1 denoted a non-financial distress of the bank and 0 represented a financial distress of the bank.

Before any of the techniques could be applied, the data needed to be tested and checked. A visual inspection of the raw data was the initial approached, then leading to an analysis of frequency tables and descriptive statistics. The data were also checked for the presence of outliers which would affect results leading to incorrect interpretation. Normality and linearity testing were preformed to meet the required assumptions of the statistical techniques. A correlation analysis on the 11 independent variables was also undertaken to avoid the possibility that some ratios are redundant.

3.2 The Model

The construction of a model in general, assumes the following procedure:

- Choice of the proper theoretical model.
- Identification of the explanatory variables.
- Estimation of the parameters and statistical hypothesis testing.

As far as the models under study are concerned, there exist several alternative choices, which include, among others, the following:

- Univariate Analysis.
- Linear and multiple discriminant analysis.
- Logit analysis.

The independent variables often include financial ratios.
Univariate Analysis is the simplest and at the same time the weakest methodology, however, there is evidence that it can produce effective estimates.

Discriminant Analysis was introduced by Fisher and was successfully applied in a great number of empirical studies. This methodology leads to determine a "Discriminant Function", based on which a score is estimated for banks. According to this score, banks are categorized in two main groups, the financial healthy ones and those going into financial distress. Discriminant Analysis assumes the validity of certain assumptions, such as:

-The independent variables consist of a multi-normal distribution
-The within-group variance and covariance matrices of each group are equal
-The prior probability for a bank to be healthy is equal to the probability for a bank to go into financial distress.

To the extent that any of the above assumptions don't hold, the method produces inferior results.

3.3 A logistic Regression Model

Logistic regression is a form of regression which is used when the dependent is a dichotomy and the independents are of any type. Continuous variables are not used as dependents in logistic regression. Unlike logit regression, there can be only one dependent variable. Logistic regression can be used to predict a dependent variable on the basis of continuous and/or categorical independents and to determine the percent of variance in the dependent variable explained by the independents; to rank the relative importance of independents; to assess interaction effects; and to understand the impact of covariate control variables. Logistic regression applies maximum likelihood estimation after transforming the dependent into a logit variable (the natural log of the odds of the dependent occurring or not).

In this way, logistic regression estimates the probability of a certain event occurring. Our objective of using a logistic regression model is to determine the financial ratios as explanatory variables in the model that are significantly related to the response variable in the model which reflect the financial distress of the banks within a period of time. Regression methods have become an integral component of any data analysis concerned with describing the relationship between a response variable and one or more explanatory variables .In logistic regression model the outcome variable (response variable) is binary or dichotomous. The specific form of the logistic regression model we use is:

$$\pi(x) = \frac{e^{\beta_\circ + \beta_1 x}}{1 + e^{\beta_\circ + \beta_1 x}} \qquad (1)$$

This model is not linear with respect to $\beta_\circ$ *and* β_1

So we make a transformation of $\pi(x)$ that is central to our study of logistic regression is the logit transformation. This transformation is defined in terms of $\pi(x)$ as:

$$g(x) = \ln\left[\frac{\pi(x)}{1-\pi(x)}\right] = \beta_\circ + \beta_1 x \qquad (2)$$

The importance of this transformation is that $g(x)$ has many of the desirable properties of a linear regression model. The logit, $g(x)$, is a linear in its parameters, may be continuous and may range from $-\infty$ *to* $+\infty$ depending on the range of x .The model should satisfy the following conditions:

1- $\pi(x)$ given in (1) should be bounded between 0 and 1.

2- $\pi(x)$ should have a binomial distribution and will be the statistical distribution upon which the analysis is based.

3- The principles that guide analysis using linear regression will also guide us in logistic regression. Where the general method of estimation that leads to the least square function under the linear regression model is called maximum likelihood. This method will provide the foundation for our approach to estimation with the logistic regression model.

To fit the logistic regression model in equation (1) to our set of data requires that we estimate the values of $\beta_\circ, \beta_1$ the unknown parameters. The general method of estimation that leads to the least square function under the linear regression model, when the error terms are normally distributed, is called maximum likelihood. This method will provide the foundation for our approach to estimation with the logistic regression model. In practice the modeling of a set of data is a more complex process than one of fitting and testing. After estimating the coefficients $\beta_\circ, \beta_1$, our first look at the fitted model commonly concerns an assessment of the significance of the variables in the model. This usually involves formulation and testing of a statistical hypothesis to determine whether the independent variables in the model are significantly related to the outcome variable. The method for performing this test is quite general and differs from one type of model to the next. One approach is to test for the significance of the coefficient ($\beta_\circ$, β_1) of a variable in any model relates to the following question: does the model that includes the variable in question tell us more about the outcome or response variable than a model that does not include that variable ?. This question can be answered by comparing the observed values of the response variable to those predicted by each of two models, the first with and the second without the variable in question.

The Walid Statistic test is used to accomplish the validity of the model through testing the significance of the coefficients $\beta_\circ$, β_1, and it is obtained by comparing the maximum likelihood estimate of the slope β_1 to an estimate of its standard error. The resulting ratio under the hypothesis that $\beta_\circ$= 0 will follow a standard normal distribution. An important adjunct to test for significance of the model is calculation and interpretation of confidence intervals for parameters of interest $\beta_\circ$, β_1. As the case in linear regression we can obtain these for the slope, intercept and the "line", (i.e., the logit). In some settings it may be of interest to provide interval estimates for the fitted values (i.e., the predicted probabilities).

With respect to model building and model evaluation we used foreword /backward stepwise selection to identify our final models. The final best model have determined on the 9th step by using stepwise procedure based on likelihood ratio test. The 1st step includes a model with all variables (11 variables). Then each variable will be removed from the next step based on its contribution in the magnitude change in 2 log likelihood ratio from one step to next step. The one with the minimum contribution in the magnitude change in 2 log likelihood ratio will be removed first in the next step.

4. Findings

4.1 Descriptive Results

Table 2 illustrates informative descriptive statistics for the financial ratios. Stability has been detected as the standard deviation small for all financial ratios. The following ratios R_1, R_3, R_4, R_7, R_9 exhibit small values. The ratios R_1, R_3 and R_4 are considered as profitability measures and their value indicate that all banks in general are affected by the global financial crises which started from 2007 until 2009. The ratios $R_7, and\, R_9$ are considered as structural measures and they also reflect small values. The ratios that exhibit high values are $R_8, and\, R_{11}$ and these ratios measure the financial structure of the banks. Descriptive are shown in **Table 2**.

Table 2 : Descriptive Statistics

	N	Mean	Std.	Skewness		Kurtosis	
	Statistic	Statistic	Statistic	Statistic	Std. Error	Statistic	Std. Error
R1=Net Profit/Assets	54	.02	.01	1.99	.32	9.42	.64
R2=Banking Income/Assets	54	.06	.02	3.42	.32	14.27	.64
R3=Investments in Securities/Assets	54	.06	.04	1.48	.32	1.78	.64
R4=Liquidity Assets/Assets	54	.29	.09	.10	.32	-.19	.64
R5=Equity/Assets	54	.08	.03	.40	.32	-1.26	.64
R6=Profitable Assets/Assets	54	.83	.08	-.73	.32	.68	.64
R7=Fixed And Other Assets/Asset	54	.02	.01	1.21	.32	1.31	.64
R8=Loans/Assets	54	.56	.10	-.55	.32	2.06	.64
R9=Debt/Assets	54	.89	.07	-3.63	.32	19.96	.64
R10=Investments And deposits/Assets	54	.32	.15	1.29	.32	2.75	.64
R11=Loans/Deposits	54	.63	.13	-.09	.32	.84	.64
Valid N (listwise)	54						

Skewness is a measure of symmetry, or more precisely the lack of symmetry. A distribution or data set is symmetric if it looks the same to the left and right of the center point. Based on the values of skewness, the distributions of the following financial ratios are skewed to the right: $R_1, R_3, R_4, R_5, R_7, R_9, R_{12}$ and the distributions of the following ratios are skewed to the left: $R_8, R_{10}, R_{11}, R_{13}$. Since the values of skewness are relatively small, the shape of the distributions is approximately symmetric. Therefore, the normality is satisfied. Kurtosis is a measure of whether the data are peaked or flat relative to a normal distribution. That is, data sets with high kurtosis tend to have a distinct peak near the mean, decline rather rapidly, and have heavy tails. Data sets with low kurtosis tend to have a flat top near the mean rather than a sharp peak. Based on the values of Kurtosis most of financial ratios has a flat distribution around the mean, only two Ratios has a sharp distribution. In terms of the values of standard deviations for the financial ratios, it was observed that no extreme values or outliers have been detected in the values of the ratios.

4.2 A logistic Regression Analysis

Similar to linear regression, logistic regression also gives estimation for the coefficient of each parameter and its relevant significance (based on t-ratios) to the dependent variable. On the other hand, the interpretation of logit regression is different, since it assumes a non-linear relationship between probability and the independent variables. After taking the antilog of the estimated logit function, we get the odds ratios. Therefore, instead of looking at parameter which is used to explain the ln (odds of financial distress), Exp (P) should be considered the equivalent value when interpreting odds of distress directly, where p represent the probability of distress**.**

4.3 Selection of Predictor Variables

Stepwise method, which is based on the likelihood ratio tests, has been implemented to determine the important variables with respect to their contributions on explaining the response variable. In stepwise procedure, the probability used as a criterion to include the variable into the model is equal to 0.15, while the probability used to exclude the variable from the model is equal to 0.20, and the cutoff point was set to be equal to 0.5.

The stepwise procedure using the likelihood tests was run in 9 steps as follows:
The zero step is including a model with only constant term. The model is: $y = B_{\circ} = 0.233$.

The coefficient is not significant as the p-value associated with Wald test statistics exceeds the value of α = 0.05, where α is the significance level of the test.

The 1st step is including a model with all variables (11 variables). Then each variable will be removed from the next step based on its contribution in the magnitude change in 2 log likelihood ratio from one step to next step. The one with the minimum contribution in the magnitude change in 2 log likelihood ratio will be removed first in the next step. The last step has the final important variable in the model. The following variables were included in the 9th step : X_3, X_8, X_{11} based on the likelihood test for stepwise procedure as shown in **Table 3.**

Table 3 : Likelihood Ratio Test for Stepwise Procedure

Variable		Model Log Likelihood	Change in -2 Log Likelihood	df	Sig. of the Change
Step 9	X3	-36.228	4.637	1	.031
	X8	-35.080	2.343	1	.126
	X11	-35.191	2.565	1	.109

It is clear from **Table 3** that the change in -2 log likelihood is significant for each variable as P-value does not exceed the value of $\alpha = 0.05$.Therefore, the variables $X_3, X_{8,}$ and X_{11} are included in the model. Also based on score test, the variables were removed from the model in the 9th step are $X_1, X_2, X_4, X_5, X_6, X_7, X_9,$ and X_{10} as shown in the **Table 4**.

Table 4 : Variables not in the Equation

			Score	df	P-Value
Step 9	Variables	X1	.002	1	.963
		X2	.765	1	.382
		X4	.002	1	.969
		X5	.058	1	.809
		X6	.140	1	.708
		X7	.045	1	.831
		X9	.030	1	.863
		X10	.169	1	.681
	Overall Statistics		2.317	8	.970

It is clear from **Table 4** that all variables will be removed from the model in the 9th step due to the fact that the score statistics for all variables are not significant. At $\alpha = 0.05$ level of significance and based on the results of likelihood ratio test and the score test, there is a sufficient evidence that only the following variables X_3, X_8, X_{11} are very important in explaining the response variable. Omnibus test of model coefficients indicates the significance of the coefficients for the model included the variables X_3, X_8, X_{11} as shown in **Table 5.**

Table 5 : Omnibus Tests of Model Coefficients

		Chi-square	df	Sig.
Step 1	Step	9.066	11	.616
	Block	9.066	11	.616
	Model	9.066	11	.616
Step 2[a]	Step	-.006	1	.940
	Block	9.061	10	.526
	Model	9.061	10	.526
Step 3[a]	Step	-.012	1	.914
	Block	9.049	9	.433
	Model	9.049	9	.433
Step 4[a]	Step	-.050	1	.822
	Block	8.999	8	.342
	Model	8.999	8	.342
Step 5[a]	Step	-.094	1	.760
	Block	8.905	7	.260
	Model	8.905	7	.260
Step 6[a]	Step	-.125	1	.724
	Block	8.780	6	.186
	Model	8.780	6	.186
Step 7[a]	Step	-1.214	1	.270
	Block	7.566	5	.182
	Model	7.566	5	.182
Step 8[a]	Step	-1.019	1	.313
	Block	6.547	4	.162
	Model	6.547	4	.162
Step 9[a]	Step	-.172	1	.678
	Block	6.374	3	.023
	Model	6.374	3	.023

a. A negative Chi-squares value indicates that the Chi-squares value has decreased from the previous step.

From **table 5**, It is clear that the $\chi^2\, test$ only significant for the model in the 9th step.

4.4 The Value Of Hosmer and Lemeshow Test:

The value of Hosmer is equal to 5.210 and the p-value associated with the test is equal to 0.708. The p-value exceeds $\alpha = 0.05$ which implies to accept the null hypothesis that the observed and the predicted values of the response variable (y) are not differ statistically. Therefore, we can conclude that the model fits the data very well .The results shown in **Table 6**.

Table 6 : Hosmer and Lemeshow Test

Step	Chi-square	df	Sig.
1	7.426	8	.491
2	5.478	8	.706
3	9.426	8	.308
4	3.227	8	.919
5	3.227	8	.919
6	6.042	8	.642
7	4.498	8	.810
8	4.492	8	.810
9	17.254	8	.028

4.5 The Predicted Logit Model

Using stepwise procedure the results of running Logistic regression on the financial ratios are shown in **Table 7**.

Table 7 : Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 9	X3	-15.869	7.989	3.946	1	.047	.000
	X8	10.499	7.991	1.726	1	.189	36272
	X11	-8.086	6.119	1.746	1	.186	.000
	Constant	.393	1.833	.046	1	.830	1.481

Only three of the eleven ratios initially entered into the logistic regression model were found to be significant in predicting the proportional of time periods in which the banks were expect to be financially distress. The estimated logit model is: $y = g(x) = 0.393 - 15.869\, X_3 + 10.499\, X_8 - 8.086 X_{11}$

4.6 Prediction Classification Accuracy for the Banks

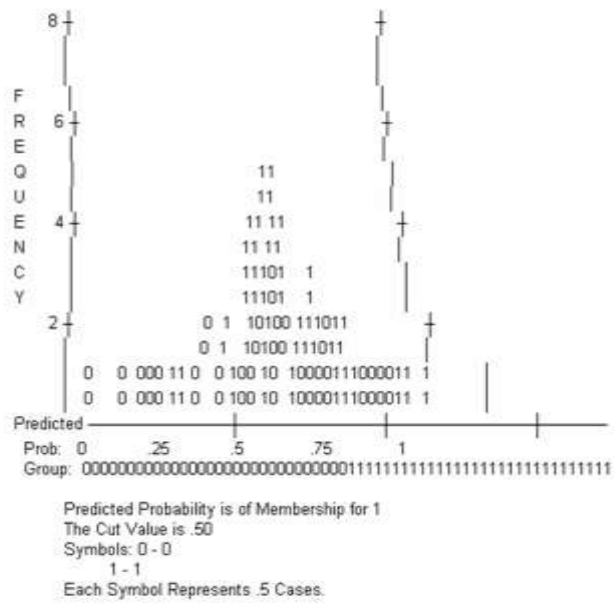
Using a cutoff value of 0.5, the model was able to correctly predict of 41.7% of the periods in which banks were expected to go into financial distress and 83.8% of periods in which banks were expected to be in a good financial situation. The overall predictability accuracy of the logistic regression model was 64.8%. These are shown in **Table 8.**

Table 8 : Prediction classification accuracy

		Predicted		
Observed		0	1	% Correct
	0	10	14	41.7
	1	5	25	83.3
Overall %				64.8

An alternative way to look at the prediction is through the histogram of predicted probabilities as shown in **Figure 1**. The x-axis represents the probability from 0 (distress) to 1 (non-distress). The y-axis is the frequency of the cases. Ideally, distress (non-distress) banks should be clustered on the right (left) side of the x-axis. Moreover, a U-shaped distribution with well differentiated predictions is more desirable over normal distribution. Because a model where predictions are close to 0 or 1 provides more information than one with predictions all cluster around the cut value 0.5. This U-shaped distribution might be less obvious in **Figure 1**, mostly because the sample size is rather small. As more observations are included in the model, a more desirable distribution can be clearly seen.

Fig 1: Observed Groups and Predicted Probabilities



5. Conclusion

The article focused on predicting financial distress for Kuwaiti commercial banks based on time (in years). This study is first to predict the financial distress cycle for Kuwaiti commercial banks in the GCC region. A logistic regression was used to analyze the financial data collected for this purpose. To examine the relationship between the financial distress and the various financial ratios, eleven ratios have been included in the study, and it was observed that only three ratios were considered as the crucial variables to predict the financial distress for Kuwaiti commercial banks.

Profitability as measured by the Ratio (Investments in securities to Assets) is significantly and negatively related to financial distress probability. Capital Structure as measured by the ratio (Loans to Assets) is significantly and positively related to financial distress probability. Finally the Capital Structure as measured by the ratio (Loans to Deposits) is significantly and negatively related to financial distress probability. The results presented in this study are useful in describing financial distress risk in the context of the commercial banks in Kuwait. As a risk manager of a bank, he or she would first look at borrowers (companies)' capital structure profitability.

6. Future Research/Implications

The current study has a few limitations that should be taken into consideration. One of them is that the multicollinearity problem cannot be fully dealt with. Two main solutions adopted in the research which are reducing explanatory variables in the models and increasing sample size with respect to periods of time instead of the sample of the commercial banks of Kuwait, ensuring that multicollinearity is to a large extent under control. Another limitation is the limited number of the commercial banks in Kuwait, therefore, our analysis was based on time. Adjusting for these limitations should be noted in further research.

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Appendices

Appendix – One
Formulas of the Financial Ratios

$R_1 = \frac{net\ profit}{assets}$
$R_2 = \frac{net\ profit}{equity}$
$R_3 = \frac{banking\ income}{assets}$
$R_4 = \frac{investment\ in\ securities}{assets}$
$R_5 = \frac{liquidity\ assets}{assets}$
$R_6 = \frac{cash\ \&\ short\ term\ note}{assets}$
$R_7 = \frac{equity}{assets}$
$R_8 = \frac{profitable\ assets}{assets}$
$R_9 = \frac{fixed\ \&\ other\ assets}{assets}$
$R_{10} = \frac{loans}{assets}$
$R_{11} = \frac{depts}{assets}$

Appendix-Two
The Values Of Financial Ratios For Kuwaiti Commercial Banks

ALAHLI BANK

	R1	R2	R3	R4	R5	R6	R7	R8	R9	R10	R11
2001	.01	.07	.03	.21	.13	.97	.02	.74	.85	.51	.88
2002	.01	.05	.03	.28	.12	.96	.02	.79	.86	.39	.93
2003	.01	.04	.04	.27	.12	.74	.02	.57	.86	.34	.66
2004	.02	.05	.05	.29	.12	.85	.02	.64	.86	.34	.74
2005	.02	.06	.05	.28	.12	.82	.02	.64	.88	.25	.72
2006	.02	.07	.06	.29	.09	.78	.01	.63	.88	.19	.71
2007	.03	.07	.06	.28	.09	.78	.01	.63	.88	.15	.71
2008	.02	.07	.05	.22	.09	.85	.02	.70	.88	.85	.80
2009	.01	.06	.15	.15	.11	.97	.02	.68	.87	.28	.78

BURGAN BANK

	R1	R2	R3	R4	R5	R6	R7	R8	R9	R10	R11
2001	.01	.06	.05	.23	.06	.86	.03	.52	.89	.48	.44
2002	.01	.05	.09	.21	.05	.78	.03	.51	.89	.37	.47
2003	.01	.04	.05	.41	.05	.89	.03	.52	.46	.44	.96
2004	.02	.05	.05	.43	.06	.83	.02	.50	.86	.39	.50
2005	.02	.06	.05	.47	.06	.78	.02	.46	.92	.36	.46
2006	.03	.07	.05	.49	.05	.85	.02	.43	.93	.42	.46
2007	.03	.07	.04	.44	.04	.84	.02	.52	.93	.34	.54
2008	.01	.06	.03	.38	.03	.83	.03	.57	.93	.29	.59
2009	.01	.05	.04	.32	.03	.83	.05	.58	.94	.28	.59

NBK BANK

	R1	R2	R3	R4	R5	R6	R7	R8	R9	R10	R11
2001	.02	.07	.13	.33	.06	.93	.03	.35	.94	.59	.37
2002	.02	.05	.13	.38	.05	.91	.02	.41	.95	.50	.43
2003	.02	.05	.02	.15	.05	.95	.02	.22	.95	.73	.23
2004	.03	.06	.17	.19	.04	.84	.02	.49	.96	.35	.51
2005	.00	.11	.08	.26	.04	.88	.02	.54	.96	.34	.57
2006	.03	.19	.08	.27	.04	.87	.02	.55	.96	.32	.57
2007	.02	.06	.08	.33	.03	.80	.02	.51	.97	.29	.53
2008	.02	.15	.10	.23	.04	.84	.02	.58	.96	.26	.60
2009	.02	.04	.14	.27	.03	.84	.04	.49	.97	.35	.50

GULF BANK

	R1	R2	R3	R4	R5	R6	R7	R8	R9	R10	R11
2001	.02	.07	.04	.39	.06	.78	.01	.53	.85	.25	.62
2002	.02	.06	.05	.39	.06	.81	.01	.53	.92	.28	.58
2003	.02	.04	.03	.38	.05	.90	.01	.57	.93	.34	.61
2004	.03	.06	.04	.31	.06	.89	.01	.64	.92	.25	.69
2005	.03	.06	.04	.29	.06	.83	.02	.63	.84	.20	.75
2006	.03	.07	.04	.28	.04	.79	.01	.64	.94	.15	.68
2007	.03	.07	.05	.26	.04	.85	.01	.66	.95	.19	.69
2008	.07	.09	.03	.25	.04	.90	.01	.70	.92	.20	.76
2009	.02	.05	.19	.10	.09	.93	.02	.69	.89	.24	.78

BKME BANK

	R1	R2	R3	R4	R5	R6	R7	R8	R9	R10	R11
2001	.01	.06	.04	.32	.09	.95	.02	.60	.89	.56	.67
2002	.01	.04	.06	.28	.07	.85	.01	.56	.92	.42	.61
2003	.01	.04	.05	.27	.07	.84	.01	.55	.92	.40	.59
2004	.01	.04	.06	.38	.06	.88	.02	.54	.93	.41	.58
2005	.03	.06	.06	.37	.14	.90	.03	.53	.80	.43	.66
2006	.03	.07	.03	.36	.13	.84	.04	.54	.78	.36	.70
2007	.02	.07	.00	.31	.14	.80	.03	.57	.84	.24	.67
2008	.02	.07	.00	.22	.10	.81	.04	.67	.86	.15	.79
2009	.03	.06	.11	.23	.09	.90	.03	.63	.90	.27	.71

COMMERCIAL BANK

	R1	R2	R3	R4	R5	R6	R7	R8	R9	R10	R11
2001	.02	.06	.04	.32	.12	.81	.01	.52	.86	.29	.60
2002	.02	.05	.05	.29	.06	.74	.01	.52	.91	.21	.57
2003	.03	.05	.07	.29	.12	.76	.05	.54	.86	.22	.63
2004	.03	.06	.06	.23	.14	.73	.02	.54	.82	.19	.65
2005	.03	.06	.05	.30	.13	.63	.02	.42	.84	.21	.50
2006	.03	.07	.07	.18	.12	.65	.01	.52	.85	.13	.61
2007	.03	.06	.06	.13	.09	.62	.01	.52	.89	.10	.58
2008	.02	.07	.03	.13	.08	.65	.05	.56	.89	.09	.63
2009	.03	.06	.16	.14	.12	.91	.02	.68	.88	.23	.77