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during the 1986-1989 period. A Linear Probability Model (LPM) which represents a special version of the Ordinary Least Squares (OLS) was used in the study. Two main hypotheses were tested in the study. The first hypothesis stated that the likelihood of granting bank credit can be predicated on the basis of the applicants financial statement data. The second hypothesis stated that the Linear Probability Model can achieve better classification/prediction accuracy than the chance model . The F-Test was used for evaluating the overall performance of the LPM. Since the computed F value was significantly higher than the critical F value, the first research hypothesis was accepted. Furthermore, the study results indicated that asset utilization ratio, debt ratio, debt paying capacity and the working capital adequacy all have significant impact on the likelihood of granting bank credit to the loan applicant. The second hypothesis tested in the study stated that the linear probability model can achieve better classification/prediction accuracy than the chance model. Tau statistic was computed for the purpose of comparing the percentage of correct classification/prediction produced by LPM with those of a chance model. The results of the comparisons have confirmed the superiority of the LPM model over the chance model in the classification/prediction of the likelihood of granting bank credit. The empirical evidence drawn from the study is expected to add to knowledge about credit-granting decisions on the one hand and to provide banks with an improved mechanism for the allocation of credit on the other hand.

group), one would expect to correctly classify 50 per cent of the cases by pure random assignment. Should the classification process of LPM yield more than 50 per cent correct classification, it may be concluded that LPM classification accuracy is better than that of a chance model. The proportional reduction in the error statistic, Tau as well as the classification and prediction results of both LPM and the chance model are reported in Table 5.

Table 5
COMPARISON BETWEEN CLASSIFICATION ACCURACY AND PREDICTION RESULTS OF LPM AND CHANCE MODEL

Type of Comparison	No. of cases Correctly Classified by LPM	No. of Cases Correctly Classified by a chance Model	Tau
Classification Accuracy	73	45	0.62
Prediction Results	68	45	0.52

The results presented in Table 5 suggest that LPM produced 62 per cent fewer errors than would be expected by random assignment in the classification of the study cases between the two groups of credit applicants. Furthermore, the results shown in the table also suggest that LPM produced 52 per cent fewer errors than would be expected by random assignment in the prediction of the correct group to which each case belonged. Based on the results in Table 5, it can be concluded that LPM achieves better classification and prediction results than the chance model. As a result, the second hypothesis of the study which stated that LPM can produce better classification and prediction accuracy than the chance model cannot be rejected.

V. Summary and Conclusion

This study was prompted by the growing need of the lending institutions for a practical and efficient technique for evaluating the credit applications of their loan applicants. A carefully selected set of financial ratios computed from the applicant's financial statements were used as explanatory variables in the study model. The study sample included 89 commercial loan applications reviewed by three large Bahraini Banks of comparable size

Missclassification Costs

One limitation of using missclassification rates to evaluate statistical models, as Altman et al (Altman et al. 1981). note, is that those missclassification schemes weigh all missclassifications equally. Accepting such assumption in the context of the present study means that rejecting the credit application of a credit-worthy customer, is as costly as accepting the credit application of a non-credit worthy customer. The former error-rejecting an applicant who must be accepted is known as type I error, while, the latter error is known as type II error. The relative costs of the two errors must be considered in the evaluation of the model. Those costs depend on the nature of the phenomenon under investigation.

A type I error in the present study would lead the bank management to conclude that the credit applicant does not meet the bank's credit standard, and as a result the application would be rejected. Banks that commit type I error are likely to miss profitable lending opportunities which will have a negative effect on the bank profits and the national economy at large. A type II error would lead the bank's management to accept the credit application of an applicant whose application must be rejected. Banks that commit type II will experience misallocation of their resources, since some of those customers may default on their loans thereby reducing the bank's profitability drastically.

In the present study, the missclassification rates were high for the accepted group than those of the rejected group indicating that bank loan officers had committed more type I error whose effects on bank performance are more serious than those of type II errors. Committing more of type I error in the evaluation of the creditworthiness of loan applicants will lead to asset quality problems; disappointing bank performance and intensified regulatory examinations (Wesely 1993). However, the drive for earnings by Bahraini banks during the study period, largely caused by intense competition in the credit market as well as the excess supply of bank credit may have been the cause of the over-extension of bank credit to a number of less creditworthy customers thereby leading to an increase in type II error as reported in the study.

Evaluation of the Classification Accuracy and the Prediction Results of LPM

To evaluate the classification/prediction accuracy of the LPM as reported earlier, it is necessary to compare the missclassification rate for LPM with the missclassification rate that would occur had the cases been assigned by chance between the two groups representing the dependent variable. Since there are two groups in the analysis (rejected group and accepted

As a result, those two variables were excluded from the list of independent variables. Regarding the other financial ratios that may have some explanatory power in predicting the likelihood of granting bank credit, they were excluded because the data for computing those ratios were not available in all the credit applications used in the study. Finally, excess supply of bank credit as well as the intense competition in the credit market may have contributed to the extension of credit to a number of less credit worthy customers.

Prediction Accuracy of The Linear Probability Model (LPM)

As stated in the methodology section, the Lachenbruch's validation technique was used to evaluate the prediction accuracy of the LPM. According to this technique, one of the cases in the study sample was dropped, and the regression equation was estimated without that case. The next step was to use that estimated regression equation to predict the case that was omitted. This procedure was repeated 89 times, thus allowing for each case in the sample to be predicted by a regression equation that was estimated without that case. The results of the LPM predictions using Lachenbruch technique are shown in Table 4.

Table 4
PREDICTION RESULTS OF THE LINEAR PROBABILITY MODEL (LPM)

Actual Group	No. of Cases	Predicted Group	
		Rejected	Accepted
Rejected N	44	37	7
%		84.1	15.9
Accepted	45	14	31
%		31.1	68.9

The results presented in Table 4 indicate that the model achieved better predictions for the cases in the rejected group than it did for the cases in the accepted group. Of the 44 cases in the rejected group, 37 cases (84.1%) were correctly predicted. However, the percentage of correct prediction was lower for the cases in the accepted group. Of the 45 cases in the accepted group, only 31 (68.9%) were correctly predicted. The overall prediction accuracy of the model was satisfactory. Sixty eight cases of the total sample of 89 cases in both groups were correctly predicted (76.4%).

of loan applications in the accepted group may include a number of applicants who have maintained strong relationship with the bank for a long period prior to their applications. The empirical evidence drawn from previous studies suggests that commercial banks tend to value their long-term relationship with their customers when they apply for bank loans (Flunner et al. 1991). In general commercial banks are able to determine the long term risk status of their old customers more easily than the new customers. The informational costs of a thorough credit analysis are high for new customers and are likely to provide less information than the long-term banking relationship. As a result, commercial banks are more likely to show more tolerance to the short-term financial problems facing their old customers. Such tolerance may lead to the extension of bank credit to those customers despite the presence of some weaknesses in their financial performance. In a small country like Bahrain—where the data was collected—most businesses are dominated by a small number of well known families who have maintained strong relationships with their banks for generations. As a consequence, their short term financial performance may not be the sole basis for evaluating their credit applications. Instead the long-term bank relationship may play a key role in the credit evaluation of those customers.

Table 3

CLASSIFICATION RESULTS OF THE LINEAR PROBABILITY MODEL

Actual Group	No. of Gases	Predicted Group	
		Rejected	Accepted
Rejected N	44	39	5
%		88.6	11.4
Accepted	45	11	34
%		24.4	75.6

Second, there could be some factors that play a role in the credit-granting decisions other than the six variables considered in the model. Examples of those factors may include: the maturity of the loan, the purpose of the loan (i.e. financing the acquisition of fixed assets, financing working capital needs, or debt restructuring), or other financial ratios that were not included in the list of variables used in the model such as cash flow ratios (Chandler and Coffman 1982). The empirical evidence regarding the loan maturity and the purpose of the loan and their respective relationship to the likelihood of receiving bank credit is inconclusive (Methra 1986).

Classification Accuracy of the Linear Probability Model (LPM)

Although the linear probability model (LPM) lends itself to the ordinary least square model (OLS), it has several unique features that were discussed in the methodology section. As a result, the standard interpretations of OLS results as discussed above, may be insufficient for evaluating the LPM results. Empirical evidence suggests that the ordinary least squares' derived estimates may be robust against errors in some assumptions (Frasser 1983; Aldrich and Nelson 1980; Gujarati 1978). However, in the case of LPM, the dependent variable is a qualitative measure represented by 0 and 1 values and not an interval measure. As a result the strict application of OLS interpretation procedures lead to unreasonable estimates. As Aldrich and Nelson have stated "regression estimates with a qualitative dependent variable may seriously misestimate the magnitude of the effects of the independent variables."

Given the above limitation on the standard interpretation procedures followed with LPM results, it becomes necessary to introduce a more useful method for the evaluation of LPM results. The proposed method uses the classification accuracy of the LPM as a basis for evaluating the model performance. The classification accuracy of the model refers to its ability to discriminate between the groups or categories in the dependent variable. In the present study, the groups in the dependent variable are the "accepted" group and the "rejected" group. For evaluating the classification accuracy of the LPM model, the estimated regression will be used to predict all the values of the dependent variable. Since the dependent variable was stated as 0 for the cases in the rejected group and 1 for the cases in the accepted group, a cut off point was selected for the classification of the predicted values of dependent variable into those two groups (Aldrich and Nelson 1980). The selected cut off point was .500. If the predicted value of the dependent variable falls above .500, the value will be rounded to 1 and the case will be assigned to the accepted group. On the other hand, if the predicted value of the dependent variable falls below 0.50, the value will be rounded to 0 and the case will be assigned to the rejected group. The classification results of the LPM model are shown in Table 3.

Table 3 shows that the linear probability model performs exceedingly well in the classification of the cases between the two groups in the dependent variable. Of the 44 cases in the rejected group, 39 cases were correctly classified (88.6%). However, the model does not achieve the same accuracy in the classification of the cases in the accepted group. Of the 45 cases in the accepted group, only 34 were correctly classified (75.6%). Two explanations may be offered for the relatively low performance of the LPM in the classification of the cases in the accepted group. First, the sample

result which runs against the basic fundamentals of financial theory. However, one possible reason for this result could be that the firms in the "accepted" group have over-investment problem that is reflected in their relatively high level of assets which in turn will tend to lower their return on assets. Another reason for this surprising result could be that the firms in the rejected group had under-investment problem that is reflected in their relatively lower level of assets which in turn will lead to higher return on assets.

Testing The Overall Significance of the Regression Line

For the purpose of testing the overall significance of the regression line, the null hypothesis to be tested can be stated as follows :

$$H_0 : B_1 = B_2 = \dots = B_n = 0$$

The hypothesis is a joint hypothesis that B_1, B_2, \dots, B_n , are jointly or simultaneously equal to zero. The hypothesis can be tested by the analysis of variance (ANOVA) technique. Table 2 includes all the information necessary for testing the overall significance of the observed multiple regression.

The computed F value-as shown in Table 2 is equal to 59.040. The value is significant at the .0001 level (i.e., the computed F value is greater than the critical F value for 6 and 82 df). As a result, the null hypothesis that $B_1 = B_2 = \dots = B_6 = 0$ is to be rejected. Therefore, we conclude that the likelihood of granting bank credit can be predicted using a set of carefully selected set of financial ratios—namely those ratios that were used as independent variables in this study.

Table 2
ANALYSIS OF VARIANCE FOR THE SIX-VARIABLE REGRESSION MODELS

Source of Variation	Sum of Squares	df	Mean Square	F	P. Value
Regression (ESS)	18.1854	6	3.0110	59.0401	0.0000
Residual (RSS)	4.9626	82	0.0501		
Total (TSS)	22.2480				

borrower's debt paying ability. As a result, this ratio is expected to have a positive impact on the likelihood of extending credit to the loan applicant. The study results showed that the debt paying ability variable has a significant impact on the applicant's likelihood of receiving bank credit .4- the adequacy of the applicant's working capital. Since working capital provides the means of payments for the business obligations, adequate amount of working capital is expected to have a positive impact on the likelihood of extending bank credit to a particular applicant. The relationship was confirmed by the significant positive coefficient of the working capital adequacy variable.

Table 1
REGRESSION RESULTS

Explanatory Variables	Coefficient	T-Value
Sal / Ta	0.2951	4.30 *
W. Cap / Ta	0.1622	1.78 **
CA / CL	0.0616	0.80
TD / TA	-0.4441	-5.63*
NI / TD	0.3806	4.37*
Ni / TA	-1.0090	-1.59
Intercept	0.3787	3.07 *
Adjusted R2	0.7980	
Standard Error of Estimate	0.2402	

* Sign H0.01

** Sign H0.05

The joint impact of the six explanatory variables on the dependent variable appears to be relatively high as indicated by the adjusted $R^2 = 0.798$. However, two of the six explanatory variables the current ratio and the return on assets, were found to have insignificant coefficients, with an incorrect sign for the return on assets. Although there is no theoretical justification for the limited importance of the return on assets in the evaluation of the applicant's credit worthiness, it can be argued that banks tend to put more emphasis on the applicants profit in relation to his debt as evidenced by the significant debt paying capacity variable (ni/td) rather than the overall profitability of the applicant (ni/ta). As for the negative sign of the return on assets variable, it is worth noting that this is a surprising

$$\text{tau} = \frac{nc - \sum_{i=1}^g P_i n_i}{n - \sum_{i=1}^g P_i n_i}$$

Where :

nc = the number of cases correctly classified by the model

P_i = the prior probability of groups membership

n = the number of cases in the sample

g = the number of groups

n_i = the case i in a particular group

IV. ANALYSIS AND RESULTS

This section includes the analysis and the results of the study as well as the interpretation of those results. The section is divided into six subsections. Those subsections include: the results of the Linear Probability Model (LPM), the overall significance of the model, the classification accuracy of the model, the prediction accuracy of the model, the missclassification costs, and the overall evaluation of the model.

Results of the Linear Probability Model (LPM)

The regression results including the magnitude of the coefficients and their statistical significance as indicated by the t statistic are shown in Table 1. The overall results are quite satisfactory in terms of goodness of fit, as well as the signs and the statistical significance of the coefficients.

The results tend to support the hypothesis that the probability of extending credit to a loan applicant depends to a large extent on several key financial dimensions (variables) which were found to have significant impacts on the dependent variable. Those variables are: 1- applicant's efficiency in utilizing the total business resources (assets) to generate revenues (sales).

This variable was measured by the asset turnover ratio. As expected, the ratio was found to have a positive significant impact on the probability of approving the applicant's request for bank credit. 2- the applicant's debt utilization ratio. A higher debt ratio is indicative of the increased risk and as a result the ratio is expected to have a negative impact on likelihood of granting bank credit. This relationship is confirmed in this study as indicated by the significant negative impact of the debt ratio on the dependent variable. 3- the debt paying ability of the applicant. The income of the applicant in relation to his debt level can be used as a proxy for the

Although this condition is true a priori, there is no guarantee that the estimated Y will necessarily fulfil the above condition. Two remedies are available for dealing with those estimated values of Y that are less than 0 or greater than 1. The first remedy is to make the LPM a constrained model by setting negative value of Y equal to 0, and setting the values greater than 1 equal to 1. The second remedy involves the use of some special estimating techniques to guarantee that the estimated value of Y lies between 0 and 1 (Aldrich and Nelson 1980). The first remedy is utilized in the present study.

Validation

There are two main techniques to validate the results of the linear probability models. The first technique is known as the hold-out sample which requires the LPM equation derived from a set of observations (cases) known as the analysis sample to be used in the prediction of another sample referred to as the hold-out sample. The second technique is known as the Lachenbruch validation technique. According to this technique, LPM equation is to be developed using all cases except one (i.e., $n-1$). The developed equation is then used in the prediction of the case that was excluded from the sample. This procedure is repeated several times until each case has a chance to be predicted by an LPM equation developed from other cases in the study sample. Although both techniques have been widely used in the financial literature, the Lachenbruch validation technique is adopted in the present study due to the availability of the appropriate software .

Evaluation of the Overall Results of LPM

To evaluate the classification accuracy and the prediction accuracy of LPM, it is necessary to compare the miss-classification rate produced by LPM with the missclassification rate that would occur had the cases in the study sample been assigned by chance between the two groups. Since there are two groups in the study sample one would be expected to correctly classify 50% of the cases by pure random chance. If the correct classifications produced by LPM exceeds 50%, it may be concluded that the classification accuracy of LPM is better than that of the chance model, and as a result the second hypothesis of the study is to be accepted.

The proportional reduction in the error statistics' Tau' which gives a standard measure of the improvement produced by a particular model regardless of the number of the groups is computed as follows :

As a result, it becomes evident that the model derives its name from the fact that the fitted values of the regression the equation represent the probability of y_i given a set of x_i .

2. In the Linear Probability Model, the error term of LPM has two characteristics that may cause problems when using and interpreting the results of the model. First, the less serious problem is that the error term of the LPM has a binomial distribution instead of being normally distributed. Like the dependent variable Y which takes on two values 0 or 1, the error term also takes one of the two values 0 or 1. However, Gujarati, (1978 p. 201) states that the non-fulfilment of the normality assumption with regard to the error term is not a serious problem in the LPM models since OLS point estimates still remain unbiased.

3. In the Linear Probability Model, the variance of the error term is heteroscedastic because it depends on the conditional expectation of y_i , which in turn depends on the value taken by x_i . The problem of heteroscedasticity is likely to be more common in cross sectional than in time series data. In cross sectional data, one usually deals with members of a population at a given point of time, such as individual consumers, firms, countries, cities, etc. These members may be of a different sizes, such as small, medium, or large. In the time series data, on the other hand, the variables tend to be of similar orders of magnitude because one generally collects the data for the same entity over a period of time.

To handle the problem of heteroscedasticity in LPM models several procedures have been proposed in the literature (Aldrich and Nelson 1980). Most of those procedures involve the transformation of the data; i.e., dividing both sides of the LPM equation by a special term (w_i). However, these procedures will not be followed in the present study for two reasons. First, the data used in this study can be described as time series data, since the values of the variables are computed as five year average, i.e., five years data prior to the date of applying for a bank loan. As a result, the heteroscedasticity problem as stated earlier is expected to be less serious in the type of data used in the study. Second, even if a particular data transformation procedure is to be followed to handle the heteroscedasticity problem, a new type of problems will arise in the interpretation of the LPM results since the computed R^2 will be based on the transformed data and not the original data, and as such it will be of limited use in the interpretation and analysis of the results.

4. As stated earlier, LPM model measures the conditional probability of Y occurring given a particular set of x_i . As a result, the following condition needs to be fulfilled:

$$0 < E(Y_i / X_i) < 1$$

probability of "granting" or "denying" the credit to a loan applicant. This variable is known as a dichotomous variable and it will take values of 0 representing the probability of denying the credit and 1 representing the probability of granting the credit.

Adjustment of each ratio to reflect deviations from industry average has been used in several previous studies to control industry variations in the ratios which are used as independent variables (Foster 1987). Due to the lack of published data on industry averages in Bahrain as well as the conceptual problems of defining what constitutes an industry, those adjustments were not made in this study.

The Statistical Model

The statistical model used in the study is the linear probability model (LPM). The model is a special regression model and it can be stated as follows :

$$y_i = \bar{b}_0 + b_i x_i + e_i$$

Where :

y = a dichotomous dependent variable with assigned values of 0 and 1. In the present study the "0" represents the "rejected" status of the loan application and "1" represents the "accepted" status of the application.

\bar{x}_i = independent variable(s). In the present study there are six independent variables. Those variables are denoted: x_1, x_2, \dots, x_6 .

\bar{b}_0 = the regression intercept

b_i = vector of slope parameters for each of the variable in the independent variables list.

e_i = the regression error term, $E(e_i) = 0$

The Linear Probability Model has several unique characteristics. These characteristics are :

1. In the Linear Probability Model the dependent variable "y" can only have two values 0 and 1. As a result, the conditional probability of "y" given a set of "xi" can be viewed as the expected value of y, given a particular set of xi. This conditional probability is commonly stated as follows :

$$E(y_i / x_i) = y_i = \bar{b}_0 + b_i x_i$$

(note that there is no error term since $E(e_i) = 0$).

The linear probability model as stated above fulfils the two requirements of the probability density function—namely that :

$$0 < P_i < 1 \quad \text{and} \\ \sum P_i = 1$$

explanatory power in predicting corporate events such as failure, financial distress, and bond rating changes (Flunner et al. 1991). The main advantages of using this short list of financial ratios include ease of computation from the financial information provided by credit applicants at the time of their application, and their representation without redundancy to the principal dimensions of financial statement data provided by the credit applicants.

The six financial ratios that were selected for use as independent variables in this study include :

1- Asset Turnover: calculated by dividing the net sales by total assets. This ratio measures the efficiency in the utilization of the firm's assets or total resources in producing sales. This ratio is expected to have a positive impact on the dependent variable-the likelihood of granting/denying credit to the loan applicant.

2- Working Capital Adequacy Ratio: calculated by dividing the gross working capital (current assets) by total assets. This ratio measures the proportion of total assets which are liquid. Theoretically, the higher the applicant's working capital as a percentage of total assets, the higher the degree of his liquidity taking into account the nature and capital intensity of the industry. The ratio is expected to have a positive impact on the dependent variable.

3- Current Ratio: calculated by dividing current assets by current liabilities. This ratio measures the firm's ability to cover its short term obligations with liquid assets. The ratio is expected to have a positive impact on the dependent variable.

4- Financial leverage: calculated by dividing total debt by total assets. This ratio measures the extensiveness in using debt to finance the firm's assets. This ratio is expected to have a negative impact on the dependent variable.

5- Debt paying ability: measured by dividing the net income by the total debt. A more accurate measure of the firm's debt paying ability is the firm's cash flows divided by its total debt (Berstein 1984). However, the latter measure was not used in the study despite its superiority over the former measure due to the lack of information necessary to compute cash flows of most credit applicants in the study sample . The ratio of net income/total debt was suggested by Frasser (Frasser, Lynn M. 1983) as a measure of debt paying ability. The ratio is expected to have a positive impact on the dependent variable.

6- Return on Assets: calculated by dividing the firm's net income by its total assets. The ratio measures the firm's overall profitability and is expected to have a positive impact on the dependent variable.

The dependent variable: the dependent variable used in this study is the

more appropriate than the univariate analysis in the study of the credit-granting decisions. As a result, this study employs a multivariate Linear Probability Model (LPM) to investigate the credit decisions made by a number of Bahraini banks. A detailed description of this model is presented in this section.

Study Sample

The study sample includes 89 loan applications reviewed by three large Bahraini banks during the 1986 - 1989 period, including loan application from different banks, was designed to reduce the impact of the differences in the lending policies of individual banks on the validity of the study results. Before the final selection of the cases in the sample, a large sample of 140 cases were reviewed. The criteria for selecting cases in the final sample included: (a)- Availability of financial statements data for four years prior to the date of the credit application, and (b)- suitability of the financial statements data for comparison with those of other credit applicants. Furthermore, all loan applications selected in final sample were limited to business loans due to the similarities that exist among different banks in their credit evaluation procedures related to this type of loans. For example, banks normally analyse the credit history as well as the prospective financial position of the borrower as part of their credit review of a business loan request. The final sample included 44 credit applications that were rejected and 45 applications that were accepted.

Study Hypotheses

Two main hypotheses are tested in this study. These hypotheses can be stated as follows:

Ho1 : The likelihood of granting bank credit can be predicted on the basis of financial statement data provided by the credit applicant.

Ho2 : The Linear Probability Model (LPM) can perform better than the chance model in predicting the likelihood of granting bank credit.

Variable Selection

The six independent variables used in this study were selected on the basis of the empirical evidence drawn from previous studies on credit evaluation and on the prediction of specific corporate events (Rufael 1992, Flunner et al. 1991, Metawa and Agapos 1990, Srinivasan and Kim 1988; Webb 1982; Altman et al. 1980). Those studies have identified from a large number of financial ratios, a set of ratios that represent the financial statements' principal independent factors. Those ratios were found to have a strong

The diagram shows that the decision inputs (x_1, x_2, \dots, x_n)-listed on the left hand side of the diagram-are grouped together to form several key dimensions which can be described as **hidden layers** in the credit decision. Those layers represent the core of the credit evaluation process. Critical evaluation of each of those dimensions will partially contribute to the final decision-the output as indicated by the arrows in the diagram. Those hidden layers differ from one lending institution to another. As a result, it is not surprising to find an applicant who is able to receive credit from an institution after his credit application was turned down by other lending institutions.

The compensatory nature of this credit index-the basis for the credit granting decision-allows for the negative aspects of certain dimensions to be offset by the positive aspects of other dimensions. Although the loan applicant knows the input information that will be provided to the bank and expects to know the final credit decision-output, the loan applicant normally doesn't know the nature and procedures followed in the evaluation process or the schemes of formulating certain credit dimensions-hidden layers-by the bank's loan officers.

III. Methodology

A common characteristic of all early studies utilizing ratio analysis is the emphasis on univariate analysis as a means of providing an early warning of an imminent corporate event such as failure, merger, financial distress, or a bond rating change (Dietrich and Sorenson 1984; Zavgren 1983). However, there has been widespread disagreement as to which financial ratio is more useful than others for the prediction of a certain corporate event. The lack of uniformity in the findings of the univariate ratio analysis in the prediction of corporate events has led many researchers in recent years to use multivariate ratio analysis in their studies on the prediction of corporate events (Flunner et al. 1991; Metawa and Agapos 1990; Campbell and Dietrich 1983).

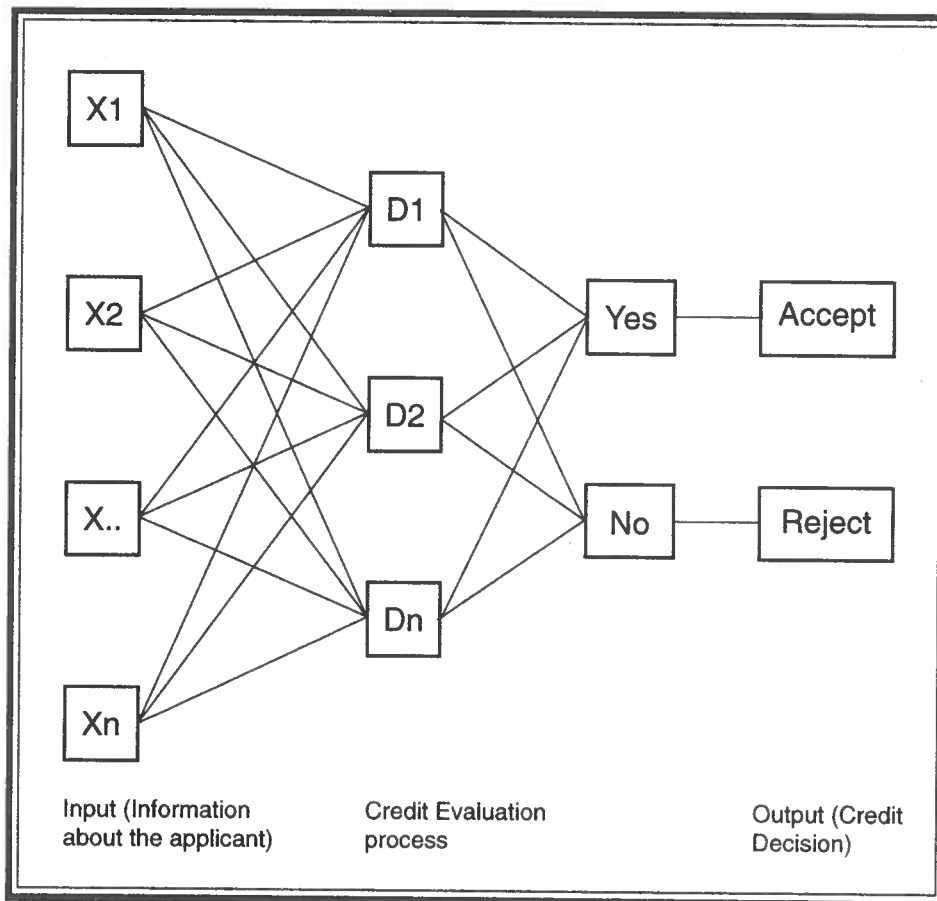
The idea behind the widespread use of multivariate analysis in the financial literature has been that a combination of ratios or ratio behaviour can be used to form an index which in turn can be used to assign cases into two or more different groups of a prior known cases (Kendall 1980; Bock 1975). The superiority of the multivariate ratio analysis over the univariate ratio analysis is the ability of the former to utilize the synergy derived from the interaction among the different ratios. Since the credit evaluation process explicitly recognizes the interactions among the different attributes of the credit applicant, it becomes evident that multivariate analysis would be

factor grouping in the factor analysis (Bock 1975). Each dimension captures the synergy derived from the interaction among the different variables that are related to that dimension. For example debt ratio as well as debt coverage ratio are related to one dimension—debt utilization, while the current ratio, quick ratio, and working capital ratios are all related to another dimension—liquidity of the applicant. Other dimensions are normally formulated in the same manner. Those dimensions are to be used as a basis for establishing a credit index in the output phase.

Credit Evaluation System

The relationships among the three main elements of the credit decision—the input, the process and the output—are illustrated by a network diagram as shown in Figure 1

Figure 1
Credit Evaluation: A Network Approach



The model is a special version of the ordinary least squares (OLS) regression in which the dependent variable--the likelihood of granting credit in the present study--is expressed as a conditional probability. A detailed description of the model is presented in the methodology section of this paper.

The empirical evidence drawn from this study is expected to provide more insights into the credit-granting decisions made by the financial institutions on one hand and to improve our understanding of the credit allocation process on other hand.

The remainder of this study is arranged as follows: section two presents an overview of the credit granting decisions. Section three presents the research method used in this study. Section four presents the data analysis and results. The study summary and conclusions are presented in section five.

II. Credit Evaluation: An Overview

In today's competitive environment, the loan officers of most financial institutions rely on a variety of techniques for the screening of the loan applicants (Flunner et al. 1991; Chandler and Coffman 1979). The technique selected depends on the sophistication of the lending institution, the average size and type of the loans involved. The techniques employed by most financial institutions range from purely judgmental to highly sophisticated statistical techniques. Since judgmental techniques are more likely to yield inconsistencies in the credit granting decisions, a large number of financial institutions have turned to the use of the more sophisticated and objective statistical techniques. However, it is essential to state that those sophisticated techniques are not completely free from the influence of the human element for two reasons. First there is always an element of subjectivity in the selection of the cutoff credit index (score) when evaluating the credit applicants. Second, the selection of the explanatory variables as well as the computational methods used in the application of those techniques are affected by the human judgment.

The basic elements of the credit evaluation system include: inputs, evaluation process and output. The input variables in the credit evaluation system include detailed information on the applicant, such as the applicants' total assets, sales, debt, equity, income, cash flows as well as other types of financial and non-financial information. The information gathered represents the input variables which are used by the loan officer to formulate certain dimensions in the credit evaluation process. Those formulated dimensions as they appear in second phase of Figure 1 are similar to the

I. Introduction

Credit granting decisions received widespread attention over the past two decades. Several studies have been conducted to identify the main features, attributes and dimensions of the credit decisions as well as to develop quantitative models that can improve the quality of those decisions (Alexander 1989; Overstreet and Kemp 1986; Campbell and Dietrich 1983). The importance of the credit decision is due to the long standing desire of the lending institutions to make intelligent decisions for the best allocation of their limited financial resources. In addition, the credit decisions have far reaching effects on the institution's shareholders, borrowers, and the economy at large. A well designed credit evaluation system can be used to identify those borrowers who have greater disposition toward default before credit decisions are made. Such identification would enable the lending institution to allocate its funds to those borrowers who have a greater ability to repay the loan without delay. This efficient allocation of resources is expected to have positive impact on the institution's performance, which in turn will benefit the shareholders. Furthermore, the efficient allocation of the financial resources ensures that efficient borrowers receive first priority in credit allocation. Those efficient recipients of bank credit are likely to contribute more to the development of the national economy .

Previous credit-granting models have used different borrower attributes (both quantitative and qualitative) as explanatory variables (Flunner et al. 1991; Wynn 1991; Methra 1986). The superiority of those models over subjective methods of credit evaluation is well documented in the literature (Capon 1982). However, there has been disagreements among researchers regarding the appropriate set of variables affecting the likelihood of granting credit.

The purpose of this study is to use a carefully selected list of six financial ratios as explanatory variables in a linear probability model for the prediction of the likelihood of granting bank credit. The selected set of financial ratios were made after a review of several leading studies on credit evaluation (Rufael 1992; Srinivasan and Kim 1988; Bierman and Hausman 1970), and a number of studies on the prediction of corporate events whose nature is similar to the nature of the credit-granting decision in many respects. Studies on the prediction of financial distress, bond rating changes, and bankruptcy (Metawa and Agapos 1990; Dietrich and Sorenson 1984; Zavgren 1983)) were found to be extremely useful in the selection of the six financial ratios used in the present study.

The linear probability model (LPM) used in the study was selected because of the suitability of its nature to the study of the credit granting decision.

CREDIT GRANTING DECISIONS : AN EMPIRICAL INVESTIGATION

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Abstract

Credit granting decisions have received widespread attention over the past two decades. Such popularity is due to the role of credit in financing economic activities. Previous credit granting decision models have used different borrower attributes - quantitative as well as qualitative - as explanatory variables. The results of these models provided insufficient evidence regarding the best set of variables which can be used in the prediction of the likelihood of granting credit. The purpose of this study is to examine the explanatory power of a set of financial attributes in the prediction of the likelihood of granting bank credit. The sample included 89 loan applications reviewed by three leading Bahraini banks during the 1986 - 1990 period. The loan applications reviewed were limited only to business loans. A Linear Probability Model (LPM) was developed to examine the simultaneous effect of the selected key financial ratios on the dependent variable. The results of the study indicated that the likelihood of granting bank credit can be predicted on the basis of the applicants financial statement data. Furthermore, the results showed that the asset utilization ratio, debt level, debt paying capacity and working capital adequacy all have significant impact on the dependent variable. Finally a Tau statistic was used to compare the percentage of correct classification/prediction produced by the LPM with those of a chance model. The results of the comparisons indicated that LPM can achieve better classification/prediction accuracy than the chance model. The empirical evidence drawn from this study provides more support to the increasing role of the quantitative models in improving the managerial decision making process in the various types of organizations in general and in the banking industry in particular. Furthermore, the predictive accuracy of the LPM can be enhanced by adding more explanatory variables other than those used in the study such as cash flows/debt, earning stability, as well as some measures of the general economic conditions.