

ALTERNATIVE APPROACHES TO THE ANALYSIS OF DEBT SERVICING CAPACITY IN LDCs

CHANGHEE CHAE*

I. INTRODUCTION

It has been pointed out by a number of 'alarmists' that the rapid increase in the external debt obligations of LDCs poses a grave danger for these LDCs as well as for the fabric of international financial system. The reason given is that an ever-increasing and huge accumulation of foreign debt will sooner or later lead to problems of debt servicing and may entail defaults in some cases. A country overburdened with an increasing amount of debt and debt service will either continue to borrow in ever increasing amount or declare default. In the latter case the country will be 'black listed', possibly preventing or impairing its further future borrowing. If some defaults occur, goes the argument, the fabric of the international financial system could be seriously jeopardized and a situation which could develop would be reminiscent of the world of the Great Depression.

External debt is not new to LDC's. Developing countries initially borrow foreign capital to finance development projects, i.e., mainly to finance investment. The external capital thus obtained can simultaneously serve two objectives: (1) to supplement domestic saving which is very low in LDCs, and (2) to augment the foreign exchange needed to finance the importation of capital goods for the investment purposes. Since the oil crisis of 1974, however, many developing countries have begun to borrow external capital to relieve balance of payments difficulties.

Whether such a country has debt problems or not can be analyzed in either a short-run or long-run context. That is, whether a country faces a short-run liquidity problem or a long-run insolvency problem. The study of debt problems can also be approached either from the demand side or from the supply side, i.e., either from the lender's point of view or from the borrower's. In this paper, we will examine three approaches to the analysis of debt service problems in LDCs.

In analyzing debt servicing capacity in LDCs, what are the relevant variables? That depends on a time horizon. Let us identify economic variables which are considered to be relevant, and briefly examine the effects of each variable to the debt servicing capacity of LDCs.

*University of Minnesota, Morris.

In the long run analysis, certainly growth factors are relevant. The growth rate of exports is a very important variable. Other things being equal, an economy with a higher growth rate of exports will increase foreign exchange earnings and therefore will increase the debt servicing capacity of that economy. The growth rate of imports, is also important and has two-sided effects on debt servicing capacity. One effect of a higher growth rate of imports is to increase the demand for foreign exchange earnings competing against debt service payments thereby decreasing debt servicing capacity to a country. On the other hand, to the extent that a higher growth rate of imports, therefore a higher level of imports, contains a larger proportion of non-essential (compressible) items, then the effect is to provide flexibility and a buffer against an unexpected fall in export proceeds and thereby has a favorable effect on debt servicing capacity. The growth rate of debt service payments is also a very important variable. This rate, of course, depends on the terms of loans, i.e., the maturity and the rate of interest on loans. If the growth rate of debt service payments is high relative to other variables such as the growth rate of exports and the rate of inflow of foreign resources, then the economy will eventually face a debt servicing difficulty. Ultimately, however, whether or not an economy will be able to pay back the whole debt in time (whether or not an economy will generate enough savings within the time limit) depends on the productivity of the economy and on the growth rate of per capita income. Therefore these two economic variables, the growth rate of per capita income and the productivity of economic resources in a country, are perhaps the most important economic variables in a long run analysis of LDCs debt servicing capacity.

In a short run analysis of debt servicing capacity, however, the emphasis will be mainly on components of balance of payments, which reflect a country's short-run transfer problems. The reason is that in the short run, debt servicing difficulties manifest themselves as a balance of payments crisis. Even when a country is basically sound in its economic management from a long-run perspective (say with a high level of productivity and a high growth rate of per capita income), its economy may face a temporary setback in its balance of payments position. Also, in a short-run analysis, growth factors are not included. The reason is that the time framework is not long enough to permit growth factors to affect debt servicing capacity of LDCs in the short run. Thus in a short-run analysis, relevant variables are in terms of absolute amounts of economic variables or the ratio of two economic variables in absolute amounts, e.g., the ratio of total debt service payments to the total outstanding debt. (The ratio is used for a comparative study among countries).

The most widely used ratio in a short-run analysis of LDCs debt servicing capacity is the debt service ratio (DSR). This ratio is calculated as total debt service payments (interest payments on debt plus the amount of debt amortization) divided by total exports and is taken as a measure of debt service burden.

This ratio, however, misses a very significant aspect of ability to service debt. If import-contents of exports are substantial, this ratio underestimates the burden of debt servicing (and overestimates the debt servicing capacity). As a measure of buffer against the possibility of unexpected fall in exports, the ratio of international reserves to imports is used as a relevant variable. If this ratio is high a country will most likely be able to withstand a temporary deterioration in its balance of payments position and therefore will have a higher debt servicing capacity. Another relevant ratio is the debt service payment compared to outstanding debt. This ratio is termed the average maturity of debt. The reasoning behind this measure is that a predominantly long term debt implies that a debt service burden cannot be alleviated in the short run by *reducing* the amount of new borrowing. Long term debts are fixed commitments for a long period of time. Thus this ratio is a measure of inflexibility and the higher the ratio, the lower will be expected debt servicing capacity.

With these economic variables, how do we proceed to empirically analyze the debt servicing capacity of LDCs? One approach is to assess debt servicing capacity by classifying countries according to whether they are with or without debt servicing difficulties. Another approach is to assign a probability to each country of its having debt servicing difficulties. Yet another approach is to analyze the debt servicing capacity in terms of a risk perceived by lenders. This will manifest itself in terms of a risk premium charged to borrowers by lenders to compensate for the perceived risk. For the first approach, we will use discriminant analysis, and for the second approach we will use a linear probability model and a logit analysis. Finally for the third approach we will use a multiple regression analysis. We will take a lender's point of view, and therefore all the analyses on LDCs debt servicing capacity are implicitly undertaken in a short run framework. We will begin with the third approach (a perceived risk-multiple regression) followed by a classification-discriminant analysis approach and then a probability assignment-linear probability model and logit analysis approach.

II. THE MODEL-THREE APPROACHES

1. An Analysis of "Spread"—Multiple Regression

Lenders are naturally interested in analyzing debt servicing capacity of LDCs. When they advance loans to developing countries they surely want to know whether their "investments" (loans) are worthwhile undertaking in terms of risks and expected returns. It is well known in financial theory that there is a positive relation between risk taking and expected return. "An exact" relation between these two, risk and return, for different types of investment has to be investigated by empirical studies for verification.

Lenders do take risk factors into consideration for loan decisions. For example, Bank of Montreal developed a checklist system whereby the Bank can rank a

borrowing country on a scale of ten against fourteen "risk" indicators which include economic as well as political variables.¹ After assessment of risks, if lenders decide to make a loan to a higher risk country then they will charge a higher interest rate to compensate for a higher risk.

To the extent that the interest rate differentials ("spread") charged by commercial banks above the London Interbank Offered Rate ("LIBOR"), reflects lenders' perception of risk differentials, debt servicing capacity of LDCs can now be analyzed by using this "spread." In other words, given that the "spread" is primarily determined by the lending bank's assessment of a country's risk, the "spread" is a very good measure of a country's debt servicing capacity (or credit worthiness) as perceived by lending banks. Taking this perceived risk approach, a problem of analyzing debt servicing capacity of LDCs becomes a problem of analyzing "spread" charged to LDCs.

For an analysis of "spread",² we will use a standard multiple regression technique. For our purposes, "spread" over and above LIBOR is the dependent variable, hereafter called SPREAD. We will use four economic variables that we considered to be important in analyzing debt servicing capacity of LDCs in the short run. Thus independent variables are: the debt service ratio (DSR), the reserve-import ratio (RESIMPR), the ratio of amortization to total outstanding debt (AMORTDEBTR), and the ratio of total outstanding debt to GNP (DEBTGNPR).

We now postulate the following relationship between the dependent and the independent variables.

$$\text{SPREAD} = B_0 + B_1\text{DSR} + B_2\text{RESIMPR} + B_3\text{AMORTDEBTR} + B_4\text{DEBTGNPR} + u \quad (1)$$

where u is a disturbance term.

We are assuming in this model that the separate effects of each variable (indicator of debt servicing capacity) on the SPREAD are additive.³ In other words, we assume that there is no multiplicative ("togetherness") effects of independent variables on the dependent variable. We are, of course, referring to a functional specification rather than a problem of multicollinearity. As we noted earlier, DSR is a measure of debt service burden relative to export earnings, therefore we expect a positive relation between SPREAD and this variable. As a measure

¹See Nage (1978), p. 138.

²Two similar empirical studies by Fedar and Just (1977b) and Fedar and Ross (1982) analyzed the credit terms and risk premiums in the Eurodollar Market, but in both studies the underlying model is of a logistic form which we will use for our "probability assignment" approach in this paper.

³This rather simple assumption is based on the fact that many bankers use a checklist system which is basically additive. See for instance, Nagy (1978) and Thornblade (1978).

of buffer against an unexpected fall in export earnings, RESIMPR is expected to also have a positive relation with SPREAD. AMORTDEBTR, on the other hand, which is a measure of the average maturity of debt, is expected to have a negative relation with SPREAD. That is, the higher this ratio (shorter the average maturity of debt, therefore less inflexibility in terms of fixed commitment), the lower the SPREAD would be. The last ratio, DEBTGNPR, is expected to have a positive relation with SPREAD. This is a debt-income ratio which measures a country's income generating ability relative to its total outstanding debt. This ratio can also be taken as a measure of the degree of the LDC's dependence on external borrowing.⁴ As a "dependence" measure, we still expect this ratio to be positively related to SPREAD.

Data for the analysis involved a total of 19 country observations over the eight-year period from 1969 through 1976 on five variables (the SPREAD and four independent variables). The SPREAD for each country is an average weighted by the amount of official loans during 1974-1976, and all the four independent variables are five-year averages of 1969 through 1973, except some cases where three or four-year averages were used because of the absence of data for some countries. Using these data, the estimated equation for (1) and the resulting statistics are as follows:

$$\begin{aligned} \text{SPREAD} = & 10.406 + 0.115\text{DSR} + 0.034\text{RESIMPR} - 0.024\text{AMORTDEBTR} \\ & (6.239) \quad (1.265) \quad (0.304) \quad (0.221) \\ & + 0.08\text{DEBTGNPR} \\ & (1.978) \quad (t\text{-ratios}) \end{aligned} \quad (2)$$

$$\begin{aligned} \text{Multiple } R &= 0.63, R^2 = 0.39, \bar{R}^2 = 0.22, \\ \text{F-ratio} &= 2.31 \text{ (significance 0.1)} \end{aligned}$$

First of all, for overall goodness of fit, R^2 is 0.39, i.e., only 39% of the total variation in SPREAD can be explained by the variations in the four regressors. This is a poor fit.

Second, even though all of the estimated coefficients have a correct (theoretically expected) sign, they are not (with an exception of DEBTGNPR coefficient) found to be statistically significant at the level of 0.05 for a one-tailed test. The overall F-test is found to be significant at only the 0.1 level. That is, with a chance of 10% error, we reject the null hypothesis that none of the variables has an effect on SPREAD. That is we accept an alternative hypothesis that at least one variable has an effect on the SPREAD. This alternative hypothesis is a very vaguely defined one and we cannot find much encouragement from this result. There can be many interpretations of this poor result. First, of course, there is a

⁴For an issue of whether the influx of foreign capital has a harmful effect on domestic savings of LDCs, see Grinols and Bhagwati (1976 and 1979).

possibility of an error in model specification. Second, even with correct specification of the model, there is a possibility of using a "wrong" variable(s) in the model. Third, but by no means last, there is a possibility of omitting relevant variables. Let us only examine the second possibility.

One of the explanatory variables in our model is DSR. This ratio, as we noted earlier, misses a very important aspect of a country's ability to service the external debt. The denominator of this ratio, the total exports of goods and services, is the proper measure in computing the DSR only if the import-contents of exports are nil. Hence, in cases where exports of a given product require concomitant imports of, say, raw materials, the import-contents of exports must be subtracted from the total exports. Not only are the import-contents not negligible in LDCs, but they vary from product to product, from country to country, and from period to period. For instance, the aggregate ratio of import-contents of exports to total exports in South Korea ranged from a low of 37% to a high of 50% between 1966 through 1974 [Hong, 1976]. This suggests that as a measure of debt servicing capacity of LDCs, one should use the "right" DSR which is adjusted for import-contents of exports. Let us call this new ratio as DSRADJ. How do we obtain data for DSRADJ? Ideally the sources of this data are detailed input-output tables. However, because of lack of input-output tables for most of the countries under study, the "right" DSR is not available. As a second best approach, we will try the share of manufactured exports in total exports as a proxy variable⁵ for the import-contents of exports. Using this new DARADJ in place of DSR for (1), we have

$$\text{SPREAD} = B_0 + B_1\text{DSRADJ} + B_2\text{RESIMPR} + B_3\text{AMORTDEBTR} + B_4\text{DEBTGNPR} + u \quad (3)$$

The following is the estimated equation for (3) and its relevant statistics are:

$$\begin{aligned} \text{SPREAD} = & 8.485 + 0.127\text{DSRADJ} + 0.091\text{RESIMPR} \\ & (5.526) \quad (2.922) \quad (1.258) \\ & - 0.036\text{AMOTRDEBTR} + 0.098\text{DEBTGNPR} \\ & (0.441) \quad (3.179) \end{aligned}$$

$$\text{Multiple } R = 0.76, R^2 = 0.58, \bar{R}^2 = 0.46,$$

$$\text{F-ratio} = 4.89 \text{ (significance } 0.01)$$

The results are most encouraging. Compared to the previous results of (2),

⁵To see whether there is any ground at all for using the share of manufactured exports in total exports as a proxy variable for the importcontents of exports, a time series analysis was run between the two variables for S. Korea for the period 1966 through 1974. The R^2 was 0.895 and the level of significance was 0.001. This proxy variable itself may need further investigation to justify its use. This, of course, is a separate issue and does not negate the fact that one should use the correct DSR which is properly accounted for import-contents of exports.

there is first of all an improvement of R Square from 0.39 to 0.58. Now more than half (58%) of the variation in SPREAD can be explained by the variations in the explanatory variables. Second, all t-ratios are improved. Furthermore, the debt service ratio as adjusted (DSRADJ) is found to be a statistically significant variable. That is, the coefficient of DSRADJ is found to be significant at the level of .05 for a one-tailed test for the first time. Another noticeable difference from the previous result is that the estimated coefficient of DEBTGNPR is now significant at the level of 0.005. Accordingly, the observed F-ratio has also increased greatly from 2.31 to 4.89 raising the level of significance from 0.1 to 0.01. That is, we now reject the null hypothesis with 1% of an error that none of the four independent variables has any effect on SPREAD. With these encouraging results, we now turn to the second approach of analyzing debt servicing capacity of LDCs.

2. Classifying Debt Rescheduling and Non-rescheduling Countries: Discriminant Analysis

In the previous section, we analyzed the debt servicing capacity of LDCs in terms of perceived risks by lenders using SPREAD as a dependent variable (perceived risk) against four explanatory variables of LDCs debt servicing capacity. We now turn to our second approach to the analysis of debt servicing capacity of developing countries.

In addition to evaluating investments in terms of risks and returns, lenders are also interested in forecasting, if possible, whether a borrowing country will default or not. This forecasting is of interest to lenders on an on-going basis, that is, not only at the time of a loan decision, but even after a loan is made and until the entire loan is paid back. Grouping countries into one class (debt rescheduling) or another (nonrescheduling) is a classification problem. One approach is to forecast whether a developing country will belong to a class of defaulting countries or non-defaulting countries.

An appropriate econometric technique for our purpose is a discriminant analysis, and we will apply this method⁶ in analyzing debt servicing capacity of LDCs. This is our second approach. (Another approach, i.e., our third approach, is to find a way to assign probability of default to a borrowing country, which will be examined in the next section.)

Discriminant analysis provides a rule for classifying observations (LDCs) into two or more groups ("rescheduling country" versus "non-rescheduling country").

⁶For the analysis of LDCs' debt servicing capacity this method was first used by Frank and Cline (1977) and later by Sargen (1977). Frank and Cline ended up with only three variables as relevant for the analysis, and Sargen, on the other hand, found monetary variables such as the inflation rate and the foreign exchange rate to be relevant variables, especially for Latin American countries. cf., *ibid.*

The rule is selected so as to *minimize* the expected cost of making two types of errors in classifying observations. In our analysis, Type I error occurs when a rescheduling country is wrongly classified as a non-rescheduling country, and Type II error results when a non-rescheduling country is classified as a rescheduling country. Before proceeding any further, we have to make some basic assumptions. First, we assume that the expected costs of two types of errors are same, i.e., we assign equal weights to Type I error and Type II error. Second, we assume that the discriminant function (discriminating rule) is linear, rather than assuming another functional form such as the quadratic. We also assume that the covariance matrices of the two populations groups are equal⁷ and that the two populations are normally distributed. We further assume the multivariate normal distribution. In regard to misclassification, there are two cases in minimizing the expected cost of misclassifications. One occurs when we know the *a priori* probability p_1 , that a country comes from one population and p_2 , that a country comes from another population. The other case is when we do not know p_1 and p_2 . In the first case, one can take the Bayesian approach and in the second case, one can take the minimax approach.⁸ Since we do not know p_1 and p_2 , we will take the minimax approach to minimize the expected cost of misclassification. Finally, there are several methods (criteria) by which independent variables can be selected ("admitted") for inclusion in the discriminant analysis. One is the direct method by which all the independent variables are entered into the analysis *concurrently*. The other method is a *stepwise* method by which independent variables will be selected for entry into the analysis on the basis of their discriminating power. Under this stepwise method, there are several criteria for selecting variables.⁹ For example, one criterion to "admit" variables is based on each variable's "contribution" to the overall multivariate F ratio so that this F ratio can be maximized. Another criterion is to "admit" a variable which maximizes the smallest F ratio between pairs of groups. This is called MAXMINF. Yet another criterion (the one we will use for our analysis) is the same as MAXMINF except that the unequal sizes of the two groups are taken as weights in MAXMINF. This criterion is to maximize the Mahalanobis distance¹⁰ between the two groups (between the two closest groups if there are more than two groups among which to discriminate).

⁷For a discriminate function with different covariance matrices, see Anderson, and Bahdur (1962).

⁸For these two approaches, see Anderson and Bahdur, (1962), pp. 427-29.

⁹Other criteria include: Wilks' lambda, largest increase in average multiple correlation, and largest increase in Rao's V. For all these criterias, see Atchley and E. H. Bryant (1975).

¹⁰This is also a distance between groups but taking the unequal sizes of two groups into consideration. This is more like the distance of an "ellipse" rather than of a "circle." See Mahalanobis, P. C., "On the Generalized Distance in Statistics," in Atchley and Bryant (1975), pp. 124-30.

With the aforementioned assumption of equal covariance matrices, minimax approach, and a stepwise-Mahalanobis distance criterion, we now wish to find the following linear discriminant function

$$Z = B_0 + B_1\text{DSR} + B_2\text{RESIMPR} + B_3\text{AMORTDEBT} \quad (5)$$

where Z is a discriminant score and DSR, RESIMPR, and AMORTDEBT are as defined in (1) and (2). We also wish to find a critical value of Z , Z^* , such that we can classify a country as coming from group one, G_1 , if $Z = Z^*$ and we can classify a country coming from group two, G_2 , if $Z < Z^*$. For this analysis, we will use the following observations involving eighteen LDCs of which eight LDCs had at least once experienced a debt rescheduling over the period from 1958 through 1969. Because of the absence of data for the independent variables for some countries in some years, there was only a total of 11 observations of rescheduling *country-years* versus 110 observations of non-rescheduling *country-years*. All of the independent variables are expressed as two-year lags.

Using the above observations, the first step of the analysis involved a determination of the linear discriminant function of the form (1). As we noted earlier, we assumed equal covariance matrices. The resultant discriminant function was:

$$Z = 1.211 + 0.124\text{DSR} - 0.6595 \text{RESIMPR} - 0.0073 \text{AMORTDEBT} \quad (6)$$

The critical value of Z , Z^* , is zero. The second step of the analysis is to see how well our analysis resulted in correct classification of the actual observations. To see this, we need classification functions, one for each group. Again there are many approaches to the derivation of classification functions. Some are based on the original values of the discriminant score, while others have a Bayesian adjustment for *a priori* estimates of group membership. Since we do not know *a priori*, p_1 and p_2 , our classification functions will be based on the original values of the discriminant score. With these values, classification equations can now be derived from the pooled within-groups covariance matrix and the centroids for the discriminating variables. The resulting classification functions (scores) for rescheduling-country group, C_1 , and for nonrescheduling-country group, C_2 , are as follows:

$$C_1 = -2.5450 + 0.26504\text{DSR} - 0.14452\text{RESIMPR} + 0.11265\text{AMORTDEBT} \quad (7)$$

$$C_2 = -1.4235 + 0.17098\text{DSR} + 0.36239\text{RESIMPR} + 0.12774\text{AMORTDEBT} \quad (8)$$

With these classification functions, each case will be classified into the group with the highest classification score.¹¹

¹¹Under the assumption of normal distribution, the classification scores can be converted into probabilities of group membership. The rule of assigning a case to the group with the highest score is then equivalent to assigning the case to the group for which it has the greatest probability of membership.

We are now in a position to classify the cases which we used to derive the functions in the first place and of comparing predicted group membership with actual group membership.

For the rescheduling country group, out of eleven actual cases, two cases were correctly classified and nine cases were misclassified. For the non-rescheduling country group of one hundred and ten, all the cases were correctly classified. Thus 92.6 percent of known cases were correctly classified. This is not a good "fit" at all. What went wrong? We will merely point out some possible explanations. The problems are of several different types. First of all, the observations that we used in our analysis were excessively "tilted" toward non-rescheduling cases, with 110 non-scheduling observations against 11 rescheduling observations. This fact alone presents some difficulty with: (1) the distribution of the variables, (2) the group dispersions, (3) the choice of appropriate *a priori* probabilities, and (4) the choice of costs of misclassifications.¹² Second, there is a possibility that the rescheduling-country group is not a homogeneous group after all. Third, the multivariate normality assumption which is essential in a linear discriminant analysis, may have been violated. One implications of this finding is that if one is to apply discriminant analysis for the predictability of rescheduling cases, at least more observations on rescheduling cases are necessary for a statistical reliability.

Even though the correct classification of rescheduling cases were poor, there was a 100% correct classification of nonrescheduling cases. Furthermore, there are still some interesting results.

Turning to the discriminating "power" of individual variables, it is noteworthy that the debt service ratio turns out to be the most important variable in the discriminant analysis. This finding is based on the following consideration. First, recall that we used a stepwise method instead of a direct method so that we can identify which variable is "admitted" as a discriminating variable first among the three variables.¹³ In the first step DSR was entered in the analysis, followed by RESIMPR and AMORTDEBTR in second and third steps, respectively. Second, only DSR has a significant F-ratio (4.9432)¹⁴ with 1 and 119 degrees of freedom at the conventional level of significance. F-ratio for the other two variables are: RESIMPR (0.4953) and AMORTDEBT (0.0621). Third, we can also note the importance of DSR as a discriminant variable in the following standardized discriminant function:

$$Z' = 0.9733DSR - 0.39047RESIMPR - 0.14058AMORTDEBTR \quad (9)$$

¹²Eisenbeis, (1982), p. 875.

¹³Other economic indicators such as the debt-GNP ratio and even some growth rates were tried. Among the many such indicators, none had a better statistical results than the three variable in equation (5).

¹⁴This is a Univariate F ratio which is the one-way analysis of variance test for equality of group means on a single discriminating score.

where Z' is a standardized discriminating score.

The standardized discriminant function coefficients are of great analytic importance. The absolute value of each coefficient represents the relative contribution of its associated variable to that function. The interpretation is analogous to the interpretation of standardized multiple regression coefficients. Thus in our case, DSR is the most important discriminating variable. DSR is more than twice as important as RESIMPR and more than four times as important as AMORTDEBTR. This is the most significant finding in this analysis.

In the previous section we found that DSRADJ is the "right" ratio for the analysis of LDCs debt servicing capacity. Let us then employ DSRADJ in place of DSR for our discriminant analysis, and see whether there will be any improvement in the statistical results. Indeed there were several improvements once again. The resulting discriminant functions and some relevant statistics are as follows:

Unstandardized discriminant function,

$$Z = 1.182 + 0.1011\text{DSRADJ} - 0.5449\text{RESIMPR} - 0.0059\text{AMORTDEBT} \quad (10)$$

Standardized discriminant function,

$$Z' = 0.98513\text{DSRADJ} - 0.32387\text{RESIMPR} - 0.09289\text{AMORTDEBTR} \quad (11)$$

Classification functions, C_1 and C_2 , for rescheduling country-group and non-rescheduling country-group respectively,

$$C_1 = -2.3713 + 0.22494\text{DSRADJ} - 0.02145\text{RESIMPR} + 0.02848\text{AMORTDEBTR} \quad (12)$$

$$C_2 = -2.3715 + 0.13709\text{DSRADJ} + 0.45203\text{RESIMPR} + 0.033586\text{AMORTDEBTR} \quad (13)$$

We now compare these results involving an "adjusted" debt service ratio with those of the "unadjusted" debt service ratio. Comparing predicted and actual cases, there was no change in Type I and Type II errors in classification of non-rescheduling cases. However, for the rescheduling cases there was an increase of correct classification by almost 10%. There is one more case of correct classification of rescheduling-country group of eleven. Another important finding is that the standardized coefficient of DSRADJ is greater than the coefficient of any other variable. But more importantly, the coefficient of DSRADJ is even greater than that of DSR. Thus in terms of discriminating "power" DSRADJ is better than DSR, and corresponding test statistics such as F ratios are also improved. Once again, DSRADJ is found to be better than DSR as a relevant variable for analyzing debt servicing capacity of LDCs.

We now turn to our third approach (probability assignment) to the analysis of debt servicing capacity.

3. Probability Assignment Approach: Linear Probability Model and Logit Analysis

In the previous section we applied a linear discriminant analysis in analyzing LDC's debt servicing capacity. The relative importance of the function was found to be poor. This raises some important questions about the applicability of discriminant analysis to the study of LDC's debt servicing difficulties. The questions about the usefulness of discriminant analysis are twofold. The first concerns the multivariate normality assumption that is the basis of any discriminant function, i.e., not only a linear but, for example, a quadratic function as well. In practice, deviations from the normality assumption, at least in economics and finance, appear more likely to be the rule rather than the exception.¹⁵ The second concerns the application of a discriminant analysis in predicting (classifying) whether a country will belong to a rescheduling-country group or a non-rescheduling country group. Suppose that, based on a discriminant analysis, a country is predicted to belong to the rescheduling country group in one year and to the non-rescheduling country group in another year. Does this mean that a country can come from two different "populations"? It is this kind of objectionable behavioral assumption that one has to make in order to interpret predicted outcome. The underlying assumption of a discriminant analysis is that there are two or more distinctly different populations, and an observation (a country) can only come from one population. Therefore it is very hard to make the interpretation that one country can become a member of one population in one year and suddenly become a member of another population in another year.

If a discriminant function is so objectionable, are there any other econometric methods which would be appropriate for our purpose, i.e., for the study of LDCs debt servicing capacity, especially in predicting debt servicing difficulties in terms of rescheduling and non-rescheduling? Let us first examine a linear probability model, and then a logit model.

The question of rescheduling or non-rescheduling is a binary problem, where an outcome is a categorical rather than continuous in nature. The dependent variable in categorical cases is a so-called "dummy" variable. We already encountered a dummy dependent variable in our discriminant analysis, where the observed dependent variable took arbitrarily assigned value of 1 or 0.

A. Linear Probability Model

In a probability model, the dependent variable is the probability, and its observed value necessarily takes either 1 (probability of 1) or 0 (probability of 0). In this respect the observed dependent variable in both a linear probability model and in a discriminant function are same in taking a categorical value. However, unlike the case of a discriminant function, the fitted values of a dependent variable in a linear probability model take on a continuum of values, and even of

¹⁵ See Eisenbeis (1982), p. 875.

values beyond the limits of 0 and 1. Since the observed dependent variable in a linear probability model can take on only those two values, the assumption of normality is no longer tenable. Furthermore, even though the form is of a linear regression model, one of the basic assumptions of a linear regression model is violated. The disturbance terms are not homoscedastic, i.e., they are heteroscedastic. Heteroscedasticity comes from the fact that (1) the standard deviation of the disturbance term is equal to the standard deviation of the dependent variable (because of a Bernoulli distribution of the dependent variable) and that (2) the standard deviation of the dependent variable *depends on* regressor(s) through the probability assignment of 1 or 0, as does the standard deviation of each disturbance term.

With these "warnings" let us turn to the empirical results of our linear probability model. Our objective here is very limited. We wish to compare the results of two linear probability models, one involving DSR and the other involving DSRADJ. We also wish to ascertain whether or not the debt service ratio is the most relevant variable in the analysis of debt servicing capacity of LDCs.

For the above objectives we postulate the following two linear probability models, one with DSR and the other with DSRADJ.

$$P = B_0 + B_1\text{DSR} + B_2\text{RESIMPR} + B_3\text{AMORDEBTR} + u \quad (14)$$

$$P = B_0 + B_1\text{DSRADJ} + B_2\text{RESIMPR} + B_3\text{AMORTDEBTR} + u \quad (15)$$

where P's represent the probability of debt rescheduling and DSR, DSRADJ, RESIMPR, and AMORTDEBTR are same as used in (12) and (13).

As we noted earlier, since the observed P's only take either 1 or 0 for having rescheduled debt or not, the variance of the disturbance is heteroscedastic. After remedial measures were taken for the problem of heteroscedasticity,¹⁶ the following estimated equations are obtained for (14) and (15), and the resulting statistics are:

$$P = 0.027 + 0.0076\text{DSR} - 0.0403\text{RESIMPR} - 0.0027\text{AMORTDEBTR} \quad (16)$$

(0.442) (2.31) (0.914) (0.354) (t-ratios)

$$R^2 = 0.218, \text{ F ratio} = 1.95 \text{ (significance 0.124)}$$

$$P = 0.021 + 0.0071\text{SDRADJ} - 0.0369\text{RESIMPR} - 0.0021\text{AMORTDEBT} \quad (17)$$

(0.351) (2.64) (0.0369) (0.351) (t-ratios)

$$R^2 = 0.245, \text{ F ratio} = 2.45 \text{ (significance 0.063)}$$

Once again the debt service ratio is found to be the most relevant variable in

¹⁶To get rid of heteroscedasticity the following steps are taken: Step 1: ran the OLS regression on the above equations (14) and (15), and obtained the estimated P_i , \hat{P}_i . Step 2: obtained $(\hat{W}_i)^{1/2}$ where $\hat{W}_i = (\hat{P}_i)(1 - \hat{P}_i)$, and transformed the equation by dividing each term (data) in the equations by $(\hat{W}_i)^{1/2}$. Step 3: ran the OLS regression on the data thus transformed.

the analysis compared to other variables. In fact only the *t*-ratios for DSR and DSRADJ in each respective estimated equation are found to be significant. Comparing DSR and DSRADJ, once again DSRADJ is found to be better than DSR in terms of test statistics such as *t*-ratio, *F* ratio and the level of significance. We now turn to our last model involving a logistic form.

B. Logit analysis¹⁷

As we noted earlier, even though the observed *P*s can assume only 1 or 0 values, (rescheduling or non-rescheduling of debt), the estimated *P*'s can go beyond the boundary of 1 and 0, a result which is very difficult to interpret. One method that guarantees the estimated probabilities to be within the range of 0 and 1 is logit analysis, which involves a logit transformation of a linear probability model. Suppose a linear model is of the following form:

$$P = XB + u \quad (18)$$

where *P* is the dependent variable which takes a probability value and *u* is a disturbance term as before. *X* and *B* are now vectors of explanatory variables and of coefficients. Then, the corresponding logit form of the regression is

$$\ln(p/1 - p) = XB + v. \quad (19)$$

This specification uses $\ln(p/1 - p)$ as the dependent variable of the regression. Then we have

$$v = \ln(p/1 - p) - \ln(P/1 - P) \quad (20)$$

where *p* is the observed probability (relative frequency) and *P* is the true probability. Setting *v* = 0, and taking antilogs of eq. (19) we have

$$p/(1 - p) = e^{XB} \quad (21)$$

where $p/(1 - p)$ can be interpreted as odds in favor of the rescheduling probabilities which are represented by the dependent variable.

$$\text{Thus } p = (1 - p)e^{XB} = e^{XB} - p e^{XB} \quad (22)$$

$$\text{and } p(1 + e^{XB}) = e^{XB} \quad (23)$$

$$\text{and } p = e^{XB}/(e^{XB} + 1) = 1/(1 + e^{-XB}) \quad (24)$$

Therefore the predicted probability for (23) is

$$\hat{p} = 1/(1 + e^{-XB}) \quad (25)$$

For our analysis, that is for the purpose of obtaining estimated probabilities of debt rescheduling for LDCs, we applied a logit form of (23). A vector of explana-

¹⁷A logit model was used by Fedar and Just for the analysis of differential interest rates. They also used the logit analysis for predicting rescheduling and non-rescheduling cases of LDC's debt. cf., Fedar and Just (1977a, b), and Fedar, Just and Ross (1981).

tory variables included DSR, RESIMPR, and AMORTDEBT in one case, and DSRADJ, RESIMPR, and AMORTDEBTR in another case. For these explanatory variables, we used the same data that we used in our linear probability models.

Since a logit form of regression model is nonlinear, estimated p values and other statistics can only be obtained by an iteration method. We had ten iterations to obtain the estimated p value asymptotically. Comparing once again the two cases, one involving DSR and another involving DSRADJ, we found the following results. First of all in both cases, the residual sum of squares converged at the sixth iteration, and the asymptotic value of the residual mean square was very small in both cases (0.069 for the case with DSR and 0.068 for the case with DSRADJ). This indicates “the goodness of fit” of the functional form. This is a very important finding in view of the fact that the analysis involved the same data that was used in the previous discriminant analysis. Recall that in discriminant analysis, the relative importance of the discriminating score was very poor. We are referring to a functional specification, not a “power” of predictability. Because even with correct specification of the model, if some of the observations are from unusual and extreme cases (tail-end of their distributions) then poor predictability will result. There will be good predictability within the range but not necessarily outside of the range. In predicting rescheduling non-rescheduling cases, one has to choose a critical value of p since estimated p values are on a continuous scale bounded by 1 and 0. Again in prediction, there are two types of errors, the Type I error, (a failure to predict a rescheduling which in fact occurred) and Type II error (a prediction of a rescheduling when none occurred). When the probability 0.5 was chosen as the critical value, there were nine Type II errors for both cases, i.e., one involving DSR and the other involving DSRADJ, hereafter called DSR-case and DSRADJ-case, respectively. However, there was one type II error for the DSR-case and none of the Type II error for the DSRADJ-case. When the non-rescheduling probability of 0.6 was chosen as the critical value (somewhat more conservative criterion) there were no changes in Type I and Type II errors for the DSR-case. But for the DSRADJ-case, there was a reduction of Type I error (a failure to predict a rescheduling which in fact occurred) by one, and no change in Type II error (a prediction of a rescheduling when none occurred), of which there was none in the first estimate. In other words, with a conservative criterion (of 0.6 for non-rescheduling probability, i.e., of 0.4 of rescheduling probability) there was an improvement of correctly predicting the rescheduling case by one, thus reducing the Type I error by one. This amounts to a reduction of Type I error by almost 10%, i.e., one out of eleven rescheduling cases. By raising the critical value to 0.7 for the non-rescheduling probability (an even more conservative criterion) for the DSRADJ-case, there was no change in Type I error but there was a change in Type II error by two. Turning to the comparison between DSR-case and DARADJ-case, once again

DARADJ is found to be better than DSR in terms of reducing Type I error especially when the criterion is conservative. This raises some interesting questions. That is, even though there was no *actual* rescheduling for a country in a particular year (recall that each observation is a country-year) could it not be the case that in a particular instance rescheduling may have been a problem but *somehow* the necessity of rescheduling avoided? In retrospect, if indeed some explanations can be found for debt not being rescheduled when in fact rescheduling *should* have occurred, then the usefulness of this logit analysis can be increased.

Let us now recapitulate the important results of our empirical analysis. In analyzing debt servicing capacity of LDCs we applied three different econometric methods with three different approaches. From the analysis of "spread" (perceived risk approach) applying the multiple regression technique, we found that (1) among the variables that were predicted from our theoretical analysis to be relevant in analyzing debt servicing capacity, the most widely used debt service ratio was indeed, the most significant variable. We also found that in terms of test statistics, DSRADJ is better than DSR. From the discriminant analysis, even though the relative importance of the discriminating variables (our "relevant" variables) are poor, we found that only the debt service ratio has any discriminating power while other variables do not have such discriminating power. Once again, DSRADJ is found to be better than DSR in terms of test statistics and discriminating power. From the logit analysis, our "relevant" variables are found to be good explanatory variables with a very small value of residual mean square. Here again DSRADJ is found to be better than DSR in correctly predicting rescheduling cases, especially when a conservative criterion is applied. For overall predictability of rescheduling and non-rescheduling cases, both discriminant and logit analysis exhibited over 92%–93% correct predictability. However, one should be cautioned about not using excessively "tilted" data, especially if the cost of incorrect prediction of rescheduling countries is large. Comparing the logit analysis and discriminant analysis, we note that less strict assumptions are required for the logit analysis.

III. SUMMARY AND CONCLUSION

In this paper, we analyzed the debt servicing aspect of LDC debt problems in a short run context and from a lender's perspective, taking three different approaches and utilizing four different econometric methods.

First, we focused our attention on the analysis of interest rate differentials charged by the lenders (in the Eurodollar market) to different LDCs. Our rationale was that in analyzing debt servicing capacity one can take the "perceived risk" approach, and that interest rate differentials ("spread") charged by the lenders reflect the perceived risk, which differs among the LDCs. Therefore,

we used multiple regression analysis to test a hypothesis that "spread" is a good measure of debt servicing capacity. "Spread" was regressed on several key economic variables. The most important finding in this analysis of "spread" is that the debt service ratio, when it is adjusted for the import-contents of exports (DSRADJ), is found to be the most significant variable. This is followed in importance by the ratio of total outstanding debt to GNP and the ratio of international reserves to imports. The ratio of amortization to total outstanding debt was not found to be significant. One interpretation is that the lenders are not concerned with the LDC's debt structure when assessing LDC's debt servicing capacity.

After our encouraging findings in the perceived risk approach, we proceeded to analyze the problem of LDC's debt servicing capacity by our second approach, i.e., the "classification" approach. Our rationale is that lenders are interested in predicting which LDC will or will not be in "trouble" in servicing debt. For this classification purpose, we applied a linear discriminant analysis. The data we used were heavily weighted away from countries with debt servicing difficulties. That is, we had a very large number of observations (110) for the nonrescheduling cases and only a very small number of observations (11) for the debt rescheduling cases. In general, the results are not as enlightening as those of "spread" analysis. However, the main purpose was still accomplished: to find out which economic variables are most important in determining debt servicing capacity. In the discriminant analysis, the debt service ratio adjusted for the import-contents of exports (DSRADJ) was found to be the most significant variable, and in terms of discriminating power it was more important than any other variable, such as the ratio of international reserves to imports or the ratio of debt amortization to total outstanding debt.

Our third approach is the "probability assignment" approach. This approach is also to analyze the problem of debt servicing capacity, and to predict whether a developing country will or will not face debt servicing difficulties. The most suitable econometric method for this purpose is logit analysis. In the logit analysis, the debt service ratio which is adjusted for the import-contents of exports was once again found to be the most significant economic variable in analyzing the debt servicing capacity.

The most significant finding in our empirical analysis is that in analyzing debt servicing capacity of LDCs, our DSRADJ (the debt service ratio which is adjusted for import-contents of exports) is found to be the most important explanatory variable.

In addition to this important finding, there are two additional points that merit our attention. Our second approach (classification-discriminant analysis) and third approach (probability assignment-logit analysis) to predicting rescheduling and nonrescheduling cases, two econometric methods are used, i.e., discriminant and logit analysis. First, because of some of the restrictive assumptions of discrim-

inant analysis such as multivariate normality and the existence of distinctly different populations, and because of the objectionable behavioral assumption that one ceases to be a member of one population and suddenly becomes a member of another population, logit analysis is a more appropriate tool to apply to the study of debt servicing capacity. Second, even though the results of our logit analysis are better than those of discriminant analysis in terms of model specification, one should be reminded that observations on the rescheduling cases are far fewer than the number of observations on the nonrescheduling cases. To have reliable statistical results, therefore, especially for the purpose of predicting debt rescheduling or nonrescheduling cases, one will need more observations on rescheduling cases to increase confidence in the logit analysis.

Our final point concerns some suggestions and recommendations to solve the debt problems of LDCs in the coming years. As we pointed out at the beginning of this paper there is a series of two-sided problems of LDC's external debt: a borrowing aspect and a debt servicing aspect; a long run and a short run horizon; and perspective from either a borrower's or a lender's point of view. There is a tendency in the current literature for theoretical analysis to focus on the long run context and for empirical analysis to emphasize the short run. Our study claims no exception to this dichotomy. However, it clearly recognizes this dichotomy and makes explicit the nature of debt problems from each different perspective. In so doing we make clear the necessity of not assessing debt problems from any particular point of view but rather from an overall perspective. That is, LDC's debt problems cannot be solved by merely concentrating on the borrowing aspect or debt servicing aspect in isolation. These two aspects are interconnected. Equally important is the point that debt problems of developing countries cannot be understood by an attempt to analyze the problems separately from the borrower's point of view or from the lender's point of view. The problem should be attacked from an integrated point of view. After all, lender's and borrower's interests are not mutually exclusive. Finally, the LDC's external debt should be treated as a dual problem of short-run adjustment of liquidity and of long-run development finance. One should also recognize another duality in the nature of the problem. Some LDC's debt problems are country-specific (e.g., mismanagement of a country's economy), but at the same time it cannot be denied that many current debt problems are due to factors which are beyond the control of the individual country; general world economic conditions, trade policies of developed countries, and mismatch of short term financing with long term needs, coupled with "bunching" of debt maturities in the debt structure. Therefore, further studies of LDC's debt problems should recognize the various forms of "duality" inherent in LDC's debt problems, and future analytical models should attempt to explicitly incorporate this duality into the analytical framework.

REFERENCES

- ANDERSON, T. W. and R. R. BADHADUR (1962), "Classification into Two Multivariate Normal Distributions with Different Covariance Matrices, *Annals of Mathematical Statistics*, 33, pp. 420-431.
- ATCHLEY, W. R. and E. H. BRYANT (eds.), Part II, (1975) *Discriminant Analysis Multivariate Statistical Methods Among Groups Covariation*, 1, Dowden: Hutchinson Ross, Inc..
- AVRAMOVIC, DRAGOSLAV, et al. (1958), *Debt Servicing Capacity and Post-War Growth in International Indebtedness*, Baltimore: Johns Hopkins Press.
- _____ (1964), *Economic Growth and External Debt*, Baltimore: Johns Hopkins Press.
- BANK of KOREA. *Input-Output Tables*, various issues, Seoul, Korea.
- DHONTE, PIERRE (1979), *Clockwork Debt: Trade and External Debt of Developing Countries*, Massachusetts: Lexington.
- _____ (1981), "Debt with Potential Repudiation: Theoretical and Empirical Analysis," *Review of Economic Studies*, 48, pp. 289-309.
- EINZIP, PAUL and BRIAN SCOTT QUINN (1977), *The Eurodollar System: Practice and Theory of International Interest Rates*, New York: St. Martins, Sixth Edition.
- EISENBEIS, R. A. (1982), "Pitfalls in the Application of Discriminant Analysis in Business, Finance and Economics," *The Journal of finance*, 37.
- FEDER, GERSHEN and RICHARD E. JUST (1977a), "A study of Debt Servicing Capacity Applying Logit Analysis," *Journal of Development Economics*, 4, pp. 25-38.
- _____ and _____ (1977b), "An Analysis of Credit Terms in the Eurodollar Market," *European Economic Review*, 9, pp. 221-43.
- _____ and KNUD ROSS (1981), "Projecting Debt Servicing Capacity of Developing Countries," *Journal of Finance and Quantitative Analysis*, 16, pp. 651-69.
- _____ and KNUD ROSS (1982), "Risk Assessments and Risk Premiums in the Eurodollar Market," *Journal of Finance*, 37, pp. 679-91.
- FRANK, CHARLES R., JR. and WILLIAM R. CLINE (1971), "Measurements of Debt Servicing Capacity: An Application of discriminant Analysis," *Journal of International Economics*, 1, pp. 327-44.
- GOODMAN, LAURIE S. (1981), "Bank Lending to Non-OPEC LDCs: Are Risks Diversifiable?" Federal Reserve Bank of New York, *Quarterly Review*, Summer, pp. 10-20.
- GRINOLS, EARL and JAGDISH BHAGWATI (1976), "Foreign Capital, Savings, and Dependence," *Review of Economics and Statistics*, 58, pp. 416-56.
- _____ (1976), "Foreign Capital, Savings and Dependence: A Reply to Mr. Wasow," *Review of Economics and Statistics*, 61, pp. 154-56.
- IMF, *Balance of Payments Yearbook*, various years.
- _____, *IMF Survey*, various issues.
- _____, *International Financial Statistics*, various issues.
- MAYO, ALICE L. and ANTHONY G. BARETT (1978), "An Early-Warning Model for

- Assessing Developing-Country Risk," Ch. 12 in Stephen H. Goodman(ed.), *Financing and Risk in Developing Countries*, New York, pp. 81-87.
- MCFADDEN, DANIEL (1974), "Conditional Logit Analysis of Qualitative Choice Behavior," Ch. 4 in Paul Zarembka (ed.), *Frontiers in Econometrics*, New York and London, pp. 105-42.
- _____ (1976), "A Comment on Discriminant Analysis 'versus' Logit Analysis," *Annals of Economic and Social Measurement*, 5, pp. 511-23.
- OECD (1976), *Financial Statistics*.
- _____ (1982), *External Debt of Developing Countries: Survey*.
- SARGEN, NICHOLAS (1977) "Economic Indicators and Country Risk Appraisal," Federal Reserve Bank of San Francisco, *Economic Review*, pp. 19-35.
- THORNBLADE, JAMES B. (1978), "A Checklist System: The First Step in Country Evaluation," Ch. 11 in Stephen H. Goodman (ed.), *Financing and Risk in Developing Countries*, New York: pp. 73-80.
- UN, *Yearbook of International Trade Statistics*, various years.
- UNCTAD (1975), *Debt Problems of Developing Countries*.
- WALTER, INGO (1981), "Country Risk, Portfolio Decisions and Regulation in International Bank Lending," *Journal of Banking and Finance*, 5, pp. 77-92.
- WORLD BANK, *Annual Reports*, various years.
- _____, *World Debt Tables*, various issues since 1977.
- _____, *World Development Report*, various years.