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# A MULTIVARIATE MODEL TO PREDICT FIRM FINANCIAL PROBLEMS: THE CASE OF URUGUAY

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The paper develops a multivariate model to predict serious financial problems in firms belonging to the manufacturing industry of Uruguay. Samplings used to refer to small, medium and large enterprises. The variables which are included in the model are due to the fact that they have a greater discriminating power are: (a) net sales to total debts. (b) net earnings to total assets, and (c) long-term debt to social debt. The results of the validation tests applied show the reliability of the model as well as its prediction potentiality.

## 1. Introduction

Traditional ratio analysis involves the use of firm's financial statements to infer their earnings potential and vulnerability to adverse shocks. Measures of liquidity, indebtedness, and various rates of return are constructed by forming the ratio of particular financial statement items to one another, then these measures are compared across firms or time.

In the academic world, the usefulness of ratio analysis in evaulating the position of businesses has been questioned. The most important criticism arises from the fact that ratio analysis has not kept pace with development in certain fields of economics and finance: the measures of performance upon which it relies do not derive from a formal, unified theory of decision-making.

The lack of an analytical model which links firm performance and financial ratios does, no doubt, limit the usefulness of ratio analysis. However, this deficiency does not mean ratio analyses should be discarded altogether. If empirical linkages exist, it remains a useful tool. In this vein, efforts have been made to introduce ratio analysis, among other applications, into the forecasting model for the earnings of businesses, their growth and the building of sound portfolios. One area where the modern approach has

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been useful is the predicting of serious financial problems for firms, in which the ratios are used as part of multivariate statistical techniques, such as discriminant analysis. This paper seeks to develop and analyze the applicability for the case of Uruguay of a multivariate model for classifying and predicting serious financial problems for manufacturers.

The idea of predicting financial problems through discriminant multivariate analysis has been extensively discussed in many countries. The pioneering works in this field was done by Bearby (1968) and Altman (1968), who developed the first models in the United States for predicting manufacturer bankruptcies. Other research done in that country would include Edmister (1972) for small businesses; Deakin (1972) for manufacturers', Meyer and Pifer (1970) for banks; Sinkey (1975) for banks; Altman and Lorris (1976) for securities dealers', Altman, Haldeman and Narayanan (1977), for manufacturers and retailers and Altman (1977) for savings and loan associations.

The literature also includes the work of Taffler (1977) in the United Kingdom and of Altman, Margaine, Schlosser and Vernimmen (1973) in France. Discriminant analysis research to predict corporate bankruptcy has been done in other countries of Europe (Italy, Norway, Finland, Germany). In Brazil, the studies by Kanitz (1974) and Altman, Baidya and Ribeiro Dias (1979) are examples of models for less developed countries.

This paper is divided into five sections. Section 2 describes some recent aspects regarding the current economic situation of Uruguay. Section 3 deals with the development of the model. Section 4 focuses on the empirical results, the critical value of the model, its significance and results of the classification sample and a number of validations tests. Section 5 covers applications of the model and presents the concluding considerations.

## 2. Comments on the economic situation of Uruguay

From the mid 1950's until 1974, Uruguay implemented an import substitution program, as well as authorities pursued an extremely deep economic intervention in commodity and financial markets. By 1958 some problems began to appear: frequent balance of payment crises, high inflation rates, stagnation of exports and consequently very low rates of real growth.

In 1974 a new economic team instituted strong changes in economic policies, characterized by the liberalization and deregulation of the economy. The first goal was the balance of payments, and later on, the reduction of inflation rates.

The import substitution model and the price controls were markets took place. Controls on capital flows and credit were progressively lifted and by 1978 the Central Bank unified the trade and financial foreign exchange markets, prefixing the future value of the exchange rate in the goal of reducing the domestic rate of inflation. The government intervention in

Table 1
Classification of sample by firm sizes.

| | 50+ workers | Under 50 workers | Total |
|---|---|---|---|
| Firms with financial problems | 32 | 9 | 41 |
| Firms without financial problems | 34 | 10 | 44 |
| Total | 66 | 19 | 85 |

economic affairs was significant reduced, and a new tax policy was implemented.

The changes in economic environment, the increase of oil prices and the declining beef and wool prices, provided a real shock to Uruguayan firms. They had to face new markets conditions, a progressive dollarization of the economy, high real interest rates, decreasing protection and a slowed rate of devaluation, while inflation and unemployment were high and economic growth stagnated for several years.

## 3. Development of the model

### 3.1. Sample selection

To implement the discriminant analysis, data on two basic types of private manufacturing firms were collected: those with serious financial problems (FPs) and those with no problems (NPs). FP cases were where businesses had experienced liquidation, bankruptcy, agreements with creditors, arrangements with bank syndicates and/or other financial backers, which did not always involve special formalities but entailed substantial changes in financial structure, and cessation of activities owing to financial problems. Firms with no financial problems were all others.

Ultimately, 44 firms with problems were selected, after others had been weeded out for reasons having to do with data compilation. Those selected in sectors such as food, beverages, footwear and apparel, leather, chemical and metal products. For the sake of statistical confidentiality and given the structure of certain industrial branches in Uruguay, no breakdown of the firms is given at this level of disaggregation. The firms selected had more than ten workers when the critical situation occurred.

After the sample of firms with problems was selected, a matched sample of similarly-sized firms with problems was chosen from the same branches of activity. Although size was the primary criterion, exact correspondence was not possible owing to a lack of data.

On terms of size, the samples have a high preponderance of firms with more than 50 workers, i.e. 66 of the 85 as seen in table 1. The breakdown into firms with problems and without problems is similar.

Both groups of firms were studied for the period from 1978 to 1982. Of the firms with problems, 77% experienced their difficulties in 1980 and 1981, and 11% in 1982.

### 3.2. Considerations regarding the computer program

For the statistical package used,[1] the variables making up the discriminant linear function were selected in successive steps. At each step, the variable adding the most to the separation between the groups was entered in the discriminant function, or the one adding least to the separation was removed, once the rest of those already entered were taken into account. In other words, the variables were incorporated or removed one at a time.

In the first step, the variable with greatest $F$ value upon entry was incorporated in the discriminant function, which was in this case the variable which best discriminated between the groups.[2] In the subsequent steps, $F$ was calculated on the basis of the residuals, after taking into account the variables already included in the discriminant function, in a covariances analysis, where the covariables were those previously introduced.

As such, the program required input regarding the threshold of $F$ for entering and removing variables. The variables to be entered had to have an $F$ value greater than the entry threshold and were removed whenever they had an $F$ value lower than the removal threshold. The values used in this research were: $F$ for entry $=4$ and $F$ for removal $=3.996$. This represented a significance level of 0.05, i.e. less than a 5% probability of obtaining the $F$ value if the means in the two samples for this variable were equal, which would mean that this variable did not contribute to the discrimination.

Likewise, the model required that a tolerance ceiling be set. The variables were not entered in the discriminant function whenever their $R^2$ with the variables already entered exceeded 1 minus the tolerance ceiling. A tolerance value of 0.01 was used, i.e. excluding variables having a high collinearity with those already entered – in this case, having a correlation of more than 0.99.

### 3.3. The model

The variables used in the analysis originated in part from the specialized literature, as well as actual experience in a number of less developed countries with high inflation.

[1] The software was BMDP7M Stepwise Discriminant Analysis from the University of California, Los Angeles.

[2] For this first entry, in accordance with the values taken by random variables, here the ratios in question, the $F$ values were calculated as follows: $F=\sum_{i=1}^{n} n_i(\bar{X}_i-\bar{X})/(g-1)\ \sum_{j=1}^{n} \sum_{i=1}^{g} (X_{ij}-\bar{X}_i)/(N-g)$, where $g$ is the number of groups, $n_i$ is the number of cases for each group and $N$ total observations. In this case, $g=2$, $n_i=41$ and 44 and $N=85$.

Table 2

Means of the variables and significant tests.[a]

| Variable | FP mean | NP mean | $F$ |
|---|---|---|---|
| Asset turnover | 1.11932 | 1.64829 | 16.397 |
| Current ratio | 1.02636 | 2.29415 | 39.594 |
| Changes in working capital | 0.03091 | 0.46927 | 4.514 |
| Sales/non-bank working capital | 2.94295 | 4.78073 | 10.433 |
| Leverage | 1.33432 | 3.03975 | 54.260 |
| Inventory/bank debt | 0.98568 | 4.58146 | 21.548 |
| Bank debt/total debt | 1.68295 | 2.84097 | 8.735 |
| Long-term debt/total debt | 0.07455 | 0.12659 | 2.912 |
| (Accounts receivable + inventories)/accounts payable + spontaneous sources) | 3.85841 | 3.06780 | 2.070 |
| Inventory turnover | 3.90432 | 7.68439 | 16.656 |
| Rate of return | −0.25068 | 0.23341 | 6.414 |
| Sales/debts | 1.53454 | 4.67829 | 68.243 |
| Net earnings/total assets | −0.08705 | 0.10756 | 27.057 |

[a] $F_{1.60}(0.05) = 4.00$, $F_{1.120}(0.05) = 3.92$, $F_{1.60}(0.01) = 7.08$, $F_{1.120}(0.01) = 6.85$.

The variable entry and removal process left 13 variables (ratios), which were calculated for each firm, whether they had problems (FP) or not (NP). These calculations were made for the year preceding the financial difficulties and for two and three years before that. This information was the data base input for processing.

The data for the year prior to the onset of serious financial problems were used to calculate the discriminate function. The other data were used to test the validity of the prediction model.

The calculation of the means of the ratios for each group as well as the initial $F$ value is shown in table 2.

Table 2 summarizes the means for each ratio in each group as well as univariate significance test for the values for one year prior to the onset of the problems. Notice that both the current ratio and asset turnover, although showing a substantial separation, are low in relation to other ratios. Other variables, such as sales/debt and inventory/bank debt, show significant differences between the means of the groups, which gives the first indication that it may be possible to obtain a multivariate discriminant function. The variables ultimately selected for the discriminant function were to be based on their greater contribution to the discrimination in accordance with the variable entry and removal procedures described earlier.

Based on the data and the iterative process discussed above, the discriminant function ultimately obtained was

$$Z = -3.70992 + 0.99418X_1 + 6.55340X_2 + 5.51253X_3$$

where $X_1$ = sales/debts, $X_2$ = net earnings/total assets, $X_3$ = long-term debt/total debt.

The model used three variables. The first measures indebtedness as compared with the level of activity, the latter is represented by sales' the second is the firm's net rate of return on assets; and the third is associated with the structure of indebtedness, considering the proportion of long-term debt to total debt. The higher the values of the ratios, the closer the firm approximates to the characteristics of those without problems. On the contrary, the lower their value, the more closely will the firm resemble those with financial problems. At this point, it might be useful to consider each of the variables included in the discriminant function.

*Sales/debts.* For the calculation of this ratio, sales were given in constant pesos from the beginning of the fiscal year and deflated for the average wholesale index of the industrial branch. The denominator is an average of debts at the beginning and end of the fiscal year, in constant pesos for the beginning of that period. Appendix 1 explains the methodological details of how the various headings of the financial statements were treated.

This ratio was the first variable selected for its discriminatory power, as its $F$ value was 68.243. It shows the importance of level of activity with regard to debt. In other words, it determines the significance of debts in the development of serious financial problems, in this case linked to sales. At higher sales levels, in relation to debts, a firm more closely approximates to those without problems.

Another ratio associated with this aspect of indebtedness, assets/debts, shows a marked difference in the means between the two groups of firms. However, it does not add any additional discriminatory power to the function, and consequently was not included in it.

*Net earnings/total assets.* Net earnings were calculated as $P_{t+1}-P_t+D-AC.$, i.e. the difference between the final and initial net worth, both valued in constant pesos for the beginning of the period.[3] Where applicable, dividends distributed during the fiscal year had to be added and new capital contributions subtracted, since both affect $P_{t+1}$ The denominator was calculated as an average of total assets at the beginning of the period, both valued in constant pesos for the beginning of the period.

This variable, the second variable to be integrated into the model, has an $F$ value of 10.4261 and is related to the firm's rate of return, such as the return on assets.

*Long-term debt/total debt.* These are two stock variables, calculated for the end of the fiscal year, after the items in questions were adjusted for constant purchasing power. (This adjustment was important only for items in foreign exchange.) Long-term debt was understood to entail maturities of

[3]See methodological details in appendix 1.

Table 3

Results of classification (original sample).

| Firms actually in the group | Firms classified in the group: With problems | Firms classified in the group: Without problems | Percentage correct |
|---|---|---|---|
| With problems (FP) | 43 | 1 | 97.7 |
| Without problems (NP) | 6 | 35 | 85.4 |
| Total | 49 | 36 | 91.8 |

more than a year. In actuality, most debts analyzed were due within three to five years.

This ratio was the third and last variable to be accepted as adding discriminatory power to the function. Its $F$ value upon incorporation was 5.7088. The values of the ratios used in developing the model were expressed in relation to one. As such, for the purposes of their application, the values representing the indicators of a firm had to be expressed in the same way.

## 4. Empirical results

### 4.1. Critical value

The critical discrimination value of function $Z$ is zero. This is interpreted in the sense that whenever the model is applied to a firm and $Z$ is greater than zero, the firm is classified as having characteristics similar to firms not experiencing serious financial problems, and alternatively, where $Z$ is less than zero, the firm is considered to have characteristics similar to the firms not experiencing serious financial problems.

### 4.2. Significance and results of classification

The multivariate significance test showed that $F = 32.364$, which is significant at 1%. In other words, the sample means do in fact represent different populations.

The 85 firms in the total sample were classified on the basis of data for the year prior to the onset of the serious financial problems. As the discriminant function was determined from the sample of the same firms to which the classifications model was later applied, high classification accuracy could be expected.

Of the 85 firms in the sample, 7 were misclassified. To use the terminology of Prof. Altman (1968), there are two types of errors: Type I, in which a firm with serious problems is misclassified as one without problems and Type II, when a firm without serious financial problems is misclassified into the first group.

Table 3 summarizes the results of classification.

Table 4

Results of classification (Lachenbruch test).

| Firms actually in the group | Firms classified in the group | | Percentage correct |
|---|---|---|---|
| | With problems | Without problems | |
| With problems (FP) | 43 | 1 | 97.7 |
| Without problems (NP) | 7 | 34 | 82.9 |
| Total | 50 | 35 | 90.6 |

Overall, 91.8% of the firms were correctly classified into two groups. Type I errors were minimal, 2.3% as only one firm of the 44 in the group with problems was misclassified. Type I errors, misclassifications of 14.6%, occurred for six firms. A more thorough analysis of the types of errors shows that there is a gray zone in which misclassifications were made, and consequently, where confidence in the model is lower. This zone covers from −1.05 to 0.4.

### 4.3. *Validation tests*

Although the results of the classification for the discriminant function are encouraging, there may be certain biases in the classification of the original sample. Three were performed to obtain more information on the accuracy of the model.

*Lachenbruch test.* The first test was the one designed by Peter Lachenbruch (1967). For it, each case is classified in a group in accordance with the discriminant function calculated with all available data except those for the case in question. This process is repeated as many times as there are cases, which virtually eliminates any potential bias.

The results are given in table 4.

The results of this test do not significantly change from those obtained for the classification of the original sample and provide great assurance about the model.

### 4.4. *Validation with random subsamples*

In this test, the classification function is derived from a subset of the original sample. The holdout subsample of the original groups was classified to calculate the quality of classification. For each group there were two subsamples. For one of them in each group the function was calculated and then the second subsamples classified in accordance with that function, without their being included. The results of the classification of these groups that were not included in the calculation of the function thus provided an empirical measurement of the quality of discrimination.

Table 5

Results of classification with random subsamples.

| Test | Accuracy in the subsample used for the calculation of the function (%) | Accuracy in the subsample not used for the calculation of the function (%) | $F^a$ |
|---|---|---|---|
| 1 | 85.5 | 93.8 | 37.753 |
| 2 | 87.7 | 75.0 | 38.606 |
| 3 | 92.1 | 88.9 | 26.651 |
| 4 | 86.1 | 84.6 | 36.334 |
| 5 | 91.4 | 80.0 | 39.047 |
| 6 | 92.2 | 85.7 | 24.238 |
| 7 | 90.9 | 94.7 | 24.144 |
| 8 | 84.6 | 85.0 | 38.297 |
| 9 | 86.6 | 94.4 | 26.790 |
| 10 | 88.4 | 100.0 | 26.119 |
| 11 | 87.7 | 85.0 | 35.745 |
| 12 | 86.4 | 89.5 | 33.430 |
| 13 | 87.3 | 78.6 | 37.007 |

[a]Degrees of freedom between 2.69 and 3.66 in accordance with the subsamples.

Table 6

Classification with original model.

| Firms belonging to the group | Two years before: Firms classified into the group FP | NP | % correct classification | Three years before: Firms classified into the group FP | NP | % correct classification |
|---|---|---|---|---|---|---|
| With problems (FP) | 34 | 7 | 82.9 | 34 | 7 | 82.9 |
| Without problems (NP) | 9 | 34 | 79.1 | 6 | 25 | 80.6 |
| Total | 43 | 41 | 80.9 | 40 | 32 | 81.9 |

Given the random nature with which the subsamples were selected, the foregoing classification test was made several times (13 in all), as shown in table 5.

The test shows that classification accuracy is still significant, even with the random subsamples.

*Prediction over time.* The calculation of the discriminant function was based on the data for the year preceding the onset of serious financial problems. It may be useful to analyze the predictive ability for longer lead times. To that end, the data for two and three years prior to the problems were plugged into the model obtained with the data from the previous year.

The results were as shown in table 6.

The number of firms decreased because of a lack of data. Two years before there were 84 firms and three years before, 72.

The results show that predictive accuracy was virtually unchanged for two and three years lead time, although lower than originally (91.8%).

## 5. Applications and concluding considerations

The model can be used in a variety of situations to provide an early warning signal for serious financial problems of firms. One of the most concrete possibilities would be credit analysis by banks and other financial institutions. The model can also be a useful analytical tool in providing the external auditor an overall view of changes that have occurred in a firm. In addition, it is helpful for government offices whose work is affected by the behaviour of manufacturing firms. Finally, it is clearly of use for internal performance as well.

Although the model is easy to use, it requires information that is not always available from the firms and a good deal of calculations plus appopriate computer software.

The results of the research are highly significant. Accuracy was nearly 92% in the original sample. A number of validations tests corroborate the classification results. The Lachenbruch tests resulted in 90.6% classification accuracy. Validation using random subsamples also showed the high degree of accurate classification. As is usual with this type of analysis, validity over time shows that the classification accuracy fell to about 81% for two and three years lead time. Neverthless, there is a gray zone when $Z$ values lie between $-1.05$ and 0.4.

Likewise, some of the limitations to such models hinge on statistical assumptions about their development, while others are associated with the actual sampling. Consequently, the risks of considering this type of model infallible must be borne in mind, while one must also guard against the illusion that the models can in and of themselves provide solutions to financial problems.

For the future, it would be interesting to extend this research to other economic sectors in developing countries such as banking, commerce and the manufacturing industry, distinguishing between the branches within that sector and even firm size, in which the multivariate discriminant analysis models can provide useful information for an understanding of the multivariate profiles of the economic units.

## Appendix 1: Methodological aspects for accounting data treatment

*General*

Data from the financial statements were requested from the firms via a prepared questionnaire so as to standardize the items and provide a degree of disaggregation even at that level for the later research. Published balance sheets, to be used for verification, were also requested. Special emphasis was placed on quality control of the data to be processed at a subsequent point, particularly as regards the following aspects:

(a) Correct classification of the data in the headings proposed in the questionnaire;
(b) Correct valuation of assets and liabilities in foreign exchange, using for this purpose the end-of-period exchange rate;
(c) Valuations of fixed assets, standardizing them in a first approximation in accordance with tax regulations.

The information furnished by the firms was in current values, and deflated to the first year of the series in order to yield constant pesos. The main features of this process are set forth below.

*Specifics*

(a) Current assets and liabilities in local currency were deflated by the wholesale price index in the appropriate branch.
(b) Investments (excluding fixed assets) and other long-term assets and liabilities in local currency were deflated using the general consumer price index.
(c) Current and non-current assets and liabilities in foreign exchange were valued in local currency, converting the balances into foreign exchange at the financial exchange rate on the closing date of the balance sheet. The procedures explained in (a) and (b) were then applied, as appropriate.
(d) Fixed assets were computed at their value for tax purposes for the first year of the series of balance sheets available for each firm. In subsequent years, that value was adjusted for purchases and sales in constant prices. These values were deflated by using the implicit price index for fixed gross investment.
(e) Net worth, in constant terms, was calculated as the difference between assets and liabilities adjusted in accordance with the methodology outlined above.
(f) Sales were deflated as flow variables using the wholesale price index for the appopriate branch.

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