DETERMINANTS OF CORPORATE FRAGILITY IN COLOMBIA

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One of the biggest threats to any company is that of becoming insolvent. A threat of this kind to corporate financial stability is of relevance not only to investors and employees but also to financial-sector lenders, auditors and regulators, among others. Hence the importance of a model that helps to determine significant variables for forecasting financial stress or fragility in Colombian firms, to serve as a tool for taking preventive or corrective measures or simply monitoring the private corporate sector's credit risk.

The downside of Colombia's economic cycle, in the second half of the 1990s, was accompanied by recession in the real sector and big losses in the financial sector.[1] Corporate solvency was not proof against this difficult state of affairs, as evidenced by financial indicators between 1995 and 2002.[2] Balance sheets in general deteriorated, as indebtedness increased, asset prices fell and financing rates rose.[3]

This study aims to identify the determinants of corporate insolvency in 2001 on the basis of financial statements for 2000 reported by individual companies.[4] Given the heterogeneity of institutional structures, accounting practices and movements in macroeconomic variables over time, it is not possible to generalize from the findings of other countries. For Colombia, only Rosillo (2002) has developed a corporate bankruptcy prediction model, using discriminant analysis techniques with a limited sample size.

To estimate a suitable fragility model for Colombian companies in 2001, financial ratios will be used to detect periods of operating and financial difficulties.[5] In his pioneering study, Beaver (1966) carried out an analysis to determine corporate failure on the basis of financial ratios by using univariate models. Altman (1968) conducted a similar exercise but using multivariate models (also on the basis of discriminant analysis), which provide a clearer interpretation of the effect of each variable in the model. However, most studies that apply this discriminant-analysis technique do not meet the assumptions required by the maximum plausibility

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1 Both developments have been widely documented in recent years. Among others, Villar and Rincón (2001) describe the main factors that affected the Colombian cycle in the 1990s. For more information on the macroeconomic environment and credit behavior see Echeverry and Salazar (1999), Urrutia (1999) and Urrutia and Zárate (2000).

2 Banco de la República (2002).

3 Echeverry (2001) and Fedesarrollo (2003).

4 The year 2000 was chosen because the cycle at that point presented a large number of fragile companies and also because from 2001 the available information was about a smaller group of companies.

5 Using financial ratios makes it possible to control for company size and level of activity in the indicators analyzed.

estimation used.[6] Olson (1980), in his study, was the first to apply techniques with fewer assumptions about the distribution of explicative variables and the first to take a representative population sample for estimation.

Like the pioneering studies of Beaver (1966) and Altman (1968) in this field, the present study has analyzed the financial ratios reported every year in company balance sheets. But unlike studies undertaken in other countries it did not use the technique of discriminant multivariate analysis, because of the large number of assumptions this technique involves, which are moreover difficult to meet in practice.[7] Instead, the analysis was done by probit regression. This technique, like logit models (originally used by Ohlson (1980)), requires fewer assumptions. Estimation included heteroskedasticity testing to avoid problems of parameter specification and inconsistency (Greene, 2000).

I. Sample and Data

The information used was drawn from the financial statements at December 31, 2000 of companies regulated by the Superintendency of Companies and the Securities Superintendency. Some 9000 companies were included in the sample to reflect the population as closely as possible[8] and thereby avoid a balanced sample that transmits a selection bias to estimated parameters.[9]

This study's definition of fragility is connected with the company's legal status. As an independent variable, financial stress or fragility was deemed to exist in any company that had entered into a payment-restructuring agreement (Law 550 of 1999) or been placed under compulsory liquidation by the Superintendency of Companies in 2001.[10] One or other of these two legal situations was encountered in 171 companies, or about 2% of the total sample. Table 1 shows the fragility/nonfragility classification of sample companies by economic activity. The model's parameters were estimated by means of heteroskedastic probit regression analysis.

II. Selection of Variables

If each company is regarded as a reserve of liquid assets subject to positive and negative cash shocks (as in Beaver, 1996), its solvency will depend on its debt level, ability to generate new assets and current level of liquidity. Accordingly, the set of variables used in this study covers three aspects generally

6 The distribution of X (matrix of explicative variables), given the dependent variable (Y), should be normal multivariate (($X|Y$)~N in $Y=f(X)$), with a common variance-covariance matrix (Lo, 1986). The randomness assumption is violated by working with balanced samples of companies (similar proportions of healthy and fragile companies).

7 Most of these models have been created in developed countries, where corporate information is generally more complete. For a summary on corporate bankruptcy models in developed countries, see Altman and Narayanan (1997).

8 Only companies with positive operating income were taken into account and classified in some group of economic activity. A small group of companies with incongruent records (eg, negative values of financial income or expenditure or financial obligations) were excluded.

9 Greene (2000). Platt and Platt (2002) criticize the use of balanced samples in previous studies. The authors empirically demonstrate the existence of this bias by means of simulations with different proportions of the sample composition.

10 Law 550 of 1999 established a regime intended to promote and facilitate corporate reactivation through agreements between creditors and debtors. It responded to reduced financing possibilities for the productive sector and the pressure of debt incurred in previous years (in a climate of low demand growth, high interest and high devaluation), which affected the ability to pay and job creation.

Table 1
Numbers of Fragile and Nonfragile Firms, by Economic Activity

	Economic Activity	$Y = 0$	$Y = 1$	Total
D_1	Farming, ranching, hunting, forestry & fishing	775	9	784
D_2	Mining and quarrying	157	4	161
D_3	Manufacturing	2,281	71	2,352
D_4	Construction, electricity, gas & water	757	19	776
D_5	Commerce, hotels & restaurants	2,311	43	2,354
D_6	Transport, warehousing & communications	525	8	533
D_7	Auxiliary financial intermediation	668	3	671
D_8	Real estate, enterprise & leasing activities	1,084	4	1,088
	Teaching, health care & other services	271	10	281
Sample Total		8,829	171	9,000

Y = 1: Companies classified as fragile or under stress.

Source: Author's calculations.

accepted in the literature as determining corporate fragility: debt, profitability and liquidity.[11]

Most studies show that the higher the level of debt, the greater the fragility and the risk of insolvency; in contrast, higher levels of liquid assets that cushion against unexpected situations and higher profitability reduce the risk of insolvency. Moreover, given that the fragility index varies according to the type of industry the company is engaged in and its size, dummy variables were included for economic activity (D_i)[12] and size (D_a and D_s)[13].

The debt ratios analyzed were liabilities / assets, financial obligations / assets, and financial expenditure / (operating income + financial income). The first two measure the company's degree of leverage, which, if high, compromises its ability to make payments to debtors in the event of unexpected negative shocks. The third ratio captures the effect of the cash flows needed to meet interest payments, which may give rise to financial pressure.

The profitability ratios analyzed were: operating income / assets, pretax profit / assets, and pretax profit / operating income. The first ratio measures the amount of income that each asset unit is capable of generating, while the other two measure the

11 Banco de la República (2002), IMF (2001) and Higgins (2000). Initially, efficiency variables (such as administrative and sales costs as a ratio of assets and of operating income) were also analyzed but made no contribution to the estimation.

12 The classification was made on the basis of the nine groups of economic activity defined in Table 1; the control group was "teaching, health care and other services." Platt and Platt (1991) were the first to propose models including this differentiation, with each of the financial ratios adjusted for industry-related indicators.

13 The sample companies were classified as large, medium or small, according to their asset level (D_a) and sales level (D_s). The critical values used for classification were: for assets 6.33 bn pesos and 1.99 bn pesos asset, for sales 5.22 bn pesos and 0.99 bn pesos.

business's profitability once debt service and operating expenses have been paid.

Lastly, the liquidity ratios analyzed were: current assets / current liabilities, available assets / current liabilities, (current assets – current liabilities) / assets, and available assets / assets. These ratios capture the relation between easily realizable assets and short-term debt, and the level of liquidity in relation to assets, for each company. To the extent that there is a liquidity cushion that allows the company's operation to continue without affecting payment to debtors, the farther the company will be from potential insolvency.

III. Statistical Description of Data

Table 2 presents descriptive statistics–mean and standard deviation–for the variables used, discriminated by fragile and nonfragile companies.[14] The nil hypothesis, indicating no significant difference between the means values of fragile and nonfragile companies, is rejected for all financial ratios analyzed. Hence all variables appear to be individually useful in discriminating between companies.[15] Fragile companies exhibit higher debt and lower profitability and liquidity levels than do nonfragile companies. Moreover, as in Ohlson (1980), ratio variances for fragile companies are much higher than for nonfragiles.

IV. Estimation

Models 1 and 3 reported in Table 3 provide the final probit estimates. The initial selection of

[14] The transformation Ln(1+w) was applied to each one of the financial ratios (w) analyzed in this study.

[15] This does not ensure that their contribution is greater than that of other variables and that therefore they must all figure in the multivariate model.

Table 2
Financial Ratios of Fragile and Nonfragile Companies 1/ by Economic Activity

Variables	Nonfragil Companies		Fragil Companies		Statistic t 2/
	Mean	Standard Deviation	Mean	Standard Deviation	
Financial obligations / assets	0.11	0.0010	0.27	0.0140	(15.29)
Financial expenditure / (financial income + operating income)	0.09	0.0030	0.23	0.0400	(5.17)
Operating income / assets	0.62	0.0050	0.50	0.0260	3.41
Pretax profit / assets	0.01	0.0020	(0.28)	0.0330	17.84
Pretax profit / operating income	0.06	0.0060	(0.43)	0.0560	10.64
Current assets / current liabilities	1.14	0.0090	0.60	0.0260	8.12
(Current assets – current liabilities) / assets	0.13	0.0030	(0.26)	0.0500	15.46
Available assets / assets	0.04	0.0007	0.01	0.0010	5.67
Available assets / current liabilities	0.19	0.0050	0.02	0.0030	4.96

1/ All analyzed values are for Ln(1+w); see footnote 14.
2/ Statistic associated with the nil hypothesis (mean of fragile firms – mean of nonfragile firms = 0).
Source: Author's calculations.

Table 3
Results of Probit Models of Corporate Fragility Prediction
Dependent Variable: Fragility ($Y = 1$)

	Model 1	Model 2	Model 3	Model 4
Constant	-17.806	-18.279	-16.529	-17.283
	(-11.39)	(-10.43)	(-10.23)	(-9.60)
Pretax profit / assets	-0.7517	-0.578	-0.6865	-0.5873
	(-8.90)	(-1.67)	(-8.00)	(-1.85)
Financial obligations / assets	1.7981	1.6690	1.6703	1.5608
	(8.93)	(6.72)	(8.09)	(6.22)
Available assets / assets	-10.9154	-11.2470		
	(-5.39)	(-4.94)		
Available assets / current liabilities			-55.690	-52.022
			(-6.10)	(-5.37)
D_1	-0.7237	-0.8114	-0.7291	-0.7957
	(-3.51)	(-3.38)	(-3.44)	(-3.26)
D_2	-0.2657	-0.3637	-0.2817	-0.3647
	(-0.93)	(-1.03)	(-0.96)	(-1.02)
D_3	-0.2569	-0.2531	-0.2861	-0.2734
	(-1.59)	(-1.34)	(-1.72)	(-1.47)
D_4	-0.464	-0.4082	-0.4875	-0.426
	(-2.48)	(-1.97)	(-2.55)	(-2.02)
D_5	-0.428	-0.4441	-0.4955	-0.5011
	(-2.54)	(-2.33)	(-2.87)	(-2.59)
D_6	-0.5943	-0.6889	-0.6035	-0.6865
	(-2.60)	(-2.50)	(-2,58)	(-2.47)
D_7	-10,707	-11,753	-10,373	-11,199
	(-3.87)	(-3.58)	(-3.64)	(-3.35)
D_8	-1.0678	-1.2029	-1.0709	-1.1857
	(-4.48)	(-4.24)	(-4.36)	(-4.11)
Heteroskedasticity				
Pretax profit / assets	-1.0814		-0,9972	
	(-4.94)		(-4,69)	
Maximum plausibility (log L)	-678.79	-645,02	-666,03	-637,44
LRI (%)	19.87	23,86	21,35	24,73

Note: Statistic z shown in brackets.

Source: Author’s calculations.

predictors was made by using backward and forward elimination methods. The final selection of these models was based on the statistical significance of the estimated ratios, their sign and sample classification.[16]

Statistical testing determined that in both cases the nil hypothesis of homoskedasticity was rejected, which led to estimation of the heteroskedastic probit Models 2 and 4. The LR statistic associated with the nil hypothesis of homoskedasticity was 67.54 for Model 1, and 57.18 for Model 3. The significance of the pretax profit / asset ratio in the heteroskedastic part confirms that this financial variable was the cause of the nonconstant error variance in Models 1 and 3.

The results for all the estimated models show that a company is more prone to becoming fragile when it presents low levels of profitability and liquidity and a high level of debt in its past-year's results. As may be seen from Table 3, the coefficients estimated for the financial ratios are significant in all the models. Among the indicators analyzed, pretax profit to assets (in the case of profitability), financial obligations to assets (in the case of debt), and the ratios containing available assets (in the case of liquidity) were the best predictors of corporate fragility.

The results obtained with regard to the liquidity variable are not surprising, considering that it is the more liquid resources (in this case available assets) that are the first to begin to become depleted just before a company reaches the state of fragility. But the ability to generate earnings and the level of financial obligations were also effective financial indicators for early identification of the companies that saw their legal status deteriorating in 2001. This confirms the importance already given to these indicators at the time of analyzing the health of companies.[17]

The dummy variables that discriminate by economic sector were also jointly relevant in the four models.[18] The companies less prone to becoming fragile in 2001 (regardless of their financial indicators) were engaged in auxiliary financial intermediation, real estate, enterprise, and leasing activities. In contrast, given the negative coefficient of all dummies in the regression, the companies more pone to becoming fragile belonged to the sector of "teaching, health care and other services" (control dummy). Analysis of the data on companies engaged in mining and quarrying and manufacturing does not provide any conclusive results. This is not surprising where manufacturing is concerned, given the heterogeneity of the companies included in this large group.

In previous modeling trials size did not appear to be a determinant of corporate fragility, given the low significance of the variables D_a and D_s. Despite the importance of the size variable in differentiating Colombian firms' ease of access to credit and their capital structure (Tenjo and García (1998)), and despite the potential problem of moral hazard in large companies, size was not useful for identifying a worsening of the companies' legal status.

Table 3 also reports values for the maximum plausibility function (L) and the Likelihood Ratio

[16] The estimations were made by using the Stata 6.0 software, which automatically eliminates variables that cause multicolinearity problems in probit estimations.

[7] Banco de la República (2002).

[18] Statistic associated with Ho: $D_1 = \ldots = D_8 = 0$ LR of 67.76 (Model 1), 64.18 (Model 2), 60.35 (Model 3) and 57.24 (Model 4).

Index (LRI) as the model's measure of adjustment. The Likelihood Ratio Index compares the complete model and the model that includes just one constant; it is calculated as $LRI = 1 \frac{\log L}{\log L_0}$, where L_0 is the value of the plausibility function when the model is restricted to including just one constant. The LRI presented shows us the superiority of the heteroskedastic probit models over Models 1 and 3.

V. Precision in Classification

Since Y_i is a dichotomous variable and $F(I_i)$ continuous they cannot be compared directly. One way of examining the precision of the model's forecasting is by sample classification. In this process two types of correct classification arise, when $Y_i = 1$ and $F(I_i) = Y^*$, and when $Y_i = 0$ and $F(I_i) < Y^*$. The proportion of correctly classified fragile companies is known as *sensitivity*, while the proportion of correctly classified nonfragile companies is termed *specificity*. As in all probit models, classification depends entirely on the limiting value at which fragility Y^*[19] is considered to exist. The criterion used in this study established as appropriate the value of Y^* at which the correctly classified proportion of both populations is maximized, that is, the point at which specificity ≅ sensitivity ≅ proportion correctly classified by the model.[20] These proportions are reported in Table 4.

Models 2 and 4 exhibit greater in-sample forecasting ability. In both models 82% of the companies, whether fragile or nonfragile, are correctly identified. Models 1 and 3 register lower classification rates, which confirms how in this case correction of the problems of nonconstant error variance increased in-sample forecasting power.

VI. Marginal Effects of Coefficients

Given the difficulty of interpreting probit coefficients, the marginal effects of the three variables were

[19] The higher (lower) the value of Y^*, the larger the number of companies that the model will classify as nonfragile (fragile) and the lower the correctly classified percentage of fragile (nonfragile) companies.

[20] In studies in which Y^* is not simply selected as 0.5 (as in Neophytou, Charitou and Charalmabous (2000)), this limiting value is selected on the basis of Type I errors (fragile company classified as nonfragile) and Type II errors (nonfragile company classified as fragile), as is done in Lin Lin and Piesse (2001) or Tirapat and Nittayagasetwat (1999).

Table 4
Proportioin of Correctly Classified Companies
(Percentage)

	Model 1	Model 2	Model 3	Model 4
Nonfragile (*specificity*)	80.50	82.48	79.61	81.85
Fragile (*sensitivity*)	80.12	81.87	78.95	81.29
Total Classification	80.49	82.47	79.60	81.84

Note: Y^* was 0.025 for Models 1, 2 and 4, and 0.026 for Model 3.
Source: Author's calculations.

calculated for Models 2 and 4.[21] Marginal effects are to be understood as the change in $F(I_i)$ arising from a 1% variation in the financial ratio for the average sample company. Thus, a 1% rise in the average company's pretax profit to assets ratio caused Model 2's $F(I_i)$ to decrease by 0.000302.[22] For the dichotomous variables D_i the marginal effect is to be interpreted as the variation in the average company's $F(I_i)$ when $D_i = 0$ changes to $D_i = 1$.

However, the magnitude of the marginal effect is unintuitive, given the small variation in the ratio. To better understand the effect of the variables in determining whether a company is fragile or not, in Model 2 a calculation was made of what the average company's ratio value should be in order for $F(I_i)$ to reach 0.025 (that is to say, in order for the firm to become fragile). Our average sample company presented a 2.25% profitability level, 13.6% debt level and 4.39% liquidity level (available assets / assets), from which $F(I_i)^{av}$ was estimated to be 0.002966. It was calculated that for a company of these characteristics to reach the state fragility, its profitability should have fallen to –20.97% in 2000. Likewise, the average company will come to have an $F(I_i)$ of 0.025 if its debt level rises to 79.6% while its profitability and average liquidity remain at the levels indicated above.[23]

As regards liquidity, it may be stated that the average company does not become fragile by reducing its ratio of available assets to assets (even to zero). Hence, a company with profitability and debt ratios similar to the average company's should not present any sign of fragility. Vulnerable companies whose legal status worsened in 2001 displayed lower-than-average profitability and debt ratios. Once these ratios deteriorated, the liquidity indicator became increasingly important in determining corporate fragility, as explained above regarding the findings of Table 3. This result helps in understanding the difference between illiquidity and insolvency, since an illiquid company is not necessarily insolvent, as in the hypothetical case of the average company.

VII. Validation by the Lachenbruch Jackknife Method

This technique is widely accepted for validating how precisely a model classifies out of sample. A number of companies representing 90% of the sample were randomly selected for estimating Models 2 and 4 anew. The purpose of this technique is to validate the model's forecasting ability artificially by classifying the 10% remaining companies excluded in the estimation. Table 5

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21 Calculations were made assuming a 1% variation in each ratio. Taking into account that work was done with $x_j = \ln(1+ w_j)$, where w_j is the financial ratio j, the marginal effects were calculated on the average of w_j, not on x_j.

22 If variable x_j is in the heteroskedastic part of the model, the rate of offset between variables *i* and *j* at which the fragility index *Y* does not vary will depend on indicator levels. Bernhardsen (2001), using the following numerical example from Laitinen and Laitinen (2000), explains how, when $\left.\frac{\partial x_i}{\partial x_j}\right|_{dY=0} = -\frac{\beta_i}{\beta_i}$ as in the case of a probit, a constant rate of offset does not seem reasonable. If $\left.\frac{\partial\,(\text{Util.antes impuestos / activo}}{\partial\,(\text{Disponible / activo})}\right|_{dY^*=0} = -\frac{2}{5}$ and both indicators for the company are 5%, the company will continue to be fragile if the liquidity indicator gets to be 3% and the profitability indicator 10%. But this also means that for a firm with a high initial level of liquidity (50%) and the same 5% profitability, if liquidity falls to 48%, profitability will have to rise to 10% in order for the risk level to remain the same. In our case, the rate of offset between profitability and any other indicator that will keep the risk level constant will depend on the levels of the indicators.

23 For 479 sample companies the profitability ratio was less than -20.97%, while 84 had a debt ratio greater than 79.6% (which does not indicate a priori that they were fragile).

Table 5
Summary of Lachenbruch Jackknife Validation Testing

Test Number	Model 2 Nonfragile (Specificity)	Model 2 Fragile (Sensitivity)	Model 2 Total Classification	Model 4 Nonfragile (Specificity)	Model 4 Fragile (Sensitivity)	Model 4 Total Classification
1	85.13	88.89	85.20	81.43	75.00	81.30
2	81.13	70.00	80.80	82.56	56.00	81.90
3	80.97	69.70	80.60	80.59	87.50	80.70
4	83.69	80.00	83.60	82.47	70.00	82.10
5	82.49	91.67	82.60	82.26	76.00	82.10
6	84.29	85.00	84.30	81.65	78.95	81.60
7	81.46	92.31	81.60	80.35	82.61	80.40
8	82.24	85.00	82.30	84.15	62.50	83.80
9	81.00	66.67	80.70	82.65	80.00	82.60
10	85.06	75.00	84.90	82.84	100.00	83.10
Average	**82.75**	**80.42**	**82.66**	**82.10**	**76.86**	**81.96**

Source: Author's calculations.

presents the classification power on the 10% of companies not used in the estimation, on the basis of 10 Lachenbruch Jackknife tests (with $Y^* = 0.025$).

The power of classifying the excluded sample of each one of the ten tests is very close to the classification power obtained in Table 5. The stability in the forecasting results and estimated coefficients shows how robust both estimations are to sample variations. As in Table 4, Model 2 is slightly better than Model 4 in forecasting corporate fragility.

VIII. Classification of Fragile Companies Two Years Ahead

The aim of this final section is to investigate how good Models 2 and 4 are at forecasting fragility two years ahead. About 18% of the nonfragile companies were wrongly classified as fragile by Models 2 and 4; on the basis of this 18% it was determined what proportion of this population was under restructuring or compulsory liquidation in 2002. That is to say, what percentage of the 18% companies wrongly classified as fragile in 2001 were fragile in 2002.[24]

Model 2 was capable of correctly forecasting as fragile 69 of the 102 companies reported to be under restructuring or compulsory liquidation in 2002, that is to say, 68% of those classified as fragile.[25] Model 4 in turn identified 67 of the 102, giving a 66% degree of specificity.

It may be concluded that the variables included in Models 2 and 4 made it possible not only to

[24] Of the 277 companies identified as fragile in 2002 (for being under either restructuring or compulsory liquidation), accounting information was available for 116 in 2000, of which 14 were not taken into account because they were under compulsory liquidation in 2002 after restructuring in 2001.

[25] $Y^* = 0.025$ was used again for classification in both models.

differentiate healthy companies from fragile ones one year ahead but also to identify two out of every three fragile companies two years in advance. That is to say, of the 18% companies that were classified as fragile but were healthy in 2001, it was possible to correctly identify 68% as fragile in 2002. As expected, the proportion of correctly classified fragile companies was smaller when identified two years ahead than only one year ahead (the correct classification of fragile companies fell from 82% in 2001 to 68% in 2002).

IX. Conclusions

The aim of this study was to develop a statistical model for forecasting corporate fragility in 2001. Though plenty of studies have developed such models in other countries of the world, the present study has sought to make up for the absence of estimations for Colombia by using a representative sample of the corporate population and applying probit techniques.

The broad sample used comprised accounting information on 9000 companies, for which estimates were made of the profitability, debt, liquidity and efficiency ratios frequently employed in financial analyses. Using a heteroskedastic probit model the following financial ratios were identified as relevant: pretax profit to assets, financial obligations to assets, and available assets to assets. With these three financial ratios and dummy variables for economic sectors it was possible to identify correctly 82% of fragile companies and an equal proportion of nonfragile ones.

Model 2's marginal analysis of the financial ratios led to the assertion that a company with profitability and debt ratios similar to the average company's should not present any sign of fragility, regardless of its level of liquidity. But if either of these two ratios deteriorates liquidity becomes increasingly important in determining corporate fragility. Further testing on the model confirmed both the stability of the findings in the face of sample variations and the model's ability to identify two years ahead two out of every three fragile companies in 2002. Though the size variable has been important in studies on access to credit in Colombia, it is not useful for identifying the worsening of the companies' legal status.

This study makes it possible to identify the relevant financial ratios for forecasting deterioration in the legal status of companies. However, the model used is cross-sectional and the results are not suitable for making an intertemporal analysis. Variables such as company age and market value, relevant in previous studies, were not included for lack of availability. Future work in this area will show whether the financial ratios presented here continue to be determinants despite macroeconomic changes in the country's economy.

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Financial Movements in Pension Fund Managers

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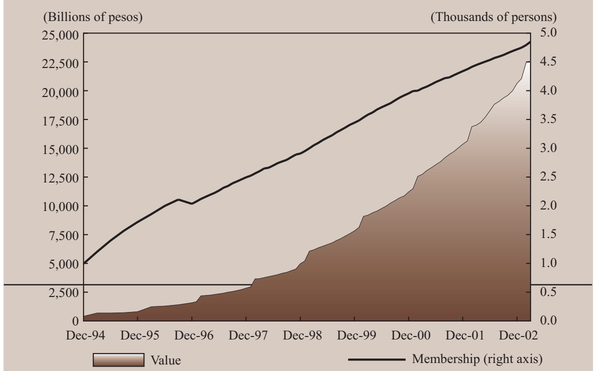
Santiago Muñoz T.*

The present Report includes a small, purely descriptive section on other financial-market agents in Colombia that have become important in recent years, providing a review of movements in the private pension funds' main financial variables.

I. Portfolio Growth

The value of funds administered by the *Administradoras de Fondos de Pensiones* (Pension Fund Managers–PFM) has increased dramatically since the creation of these entities in 1993. In March 2003, the investment portfolio of managers of pension and severance-pay funds amounted to 22.6 bn pesos (or 11% of GDP), of which 16.7 bn pesos represented compulsory pensions (Figure 1). Moreover, the PFM's portfolio made up 25.13% of the financial system's assets in March 2003.

Figure 1
Pension Funds Managers' Membership And Value
December 1994 – March 2003



Source: Banking Superintendency.

The growth in portfolio value has proceeded at much the same pace as expansion in the number of pension-fund members. Membership to March 2003 was 4.8 million, with approximately half this number being active members, that is, persons making periodic contributions to the funds. This membership size is a major achievement for the system of individual capitalization, representing as it does 46% of all people covered by Colombia's general pension system. The other 54% come under the Social Security system, characterized by average contributions and defined benefits.

Moreover, the pension funds have also become increasingly important as a proportion of private savings in the economy. Thus, savings channeled through the PFM represented 5% of private savings in 1996, rising to 20% six years later.

* The authors are on the staff of the Banco de la República's Financial Stability Department. They are solely accountable for the opinions contained here, which do not necessarily reflect those of the Banco de la República or its Board of Directors.

II. Pension Fund Managers' Portfolio Composition

a. Classification by type of asset and counterpart

The composition of the fund managers' portfolio may be analyzed using various classifications employed by the Banking Superintendency that are relevant to this part of the Report. Assets are first decomposed into fixed- income (89%) and variable-income (10%) investments (Figure 2).

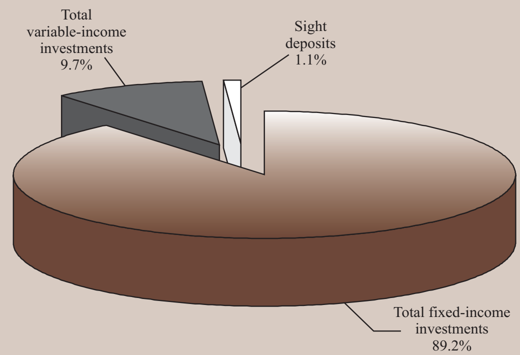
Public-debt paper makes up the biggest share of fixed-income investments (57%), followed by investments in the financial system (18%) and investments in institutions not regulated by the Banking Superintendency (17%) (Figure 3).

Figure 4 details the composition of public-debt investments in the Pension Fund Managers' portfolio. In March 2003 such investments amounted to 11.8 bn pesos, representing 9.06% of nonfinancial public-sector debt.

As shown by Figure 4, Treasury securities (TES) accounted for the biggest share (48%) of the portfolio's public-debt investments, followed by external-debt securities issued by the Nation (40%). The 5.71 bn pesos of TES held by the pension funds in March represented 11.4% of the total in the market and 29.5% of those held by the nonfinancial private sector. The PFM's share of Colombian external-debt bonds was 14.4%.

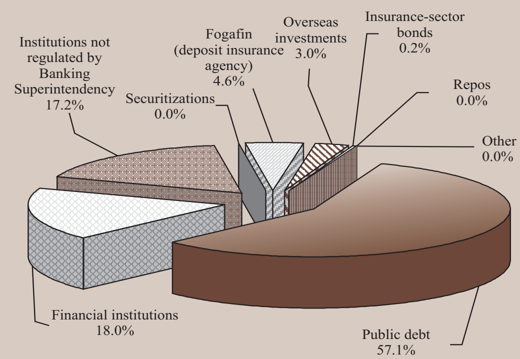
Table 1 shows the composition of the Pension Fund Managers' fixed-income investments with the

FIGURE 2
PFM'S PORTFOLIO COMPOSITION:
FIXED- & VARIABLE-INCOME INVESTMENTS
(MARCH 2003)



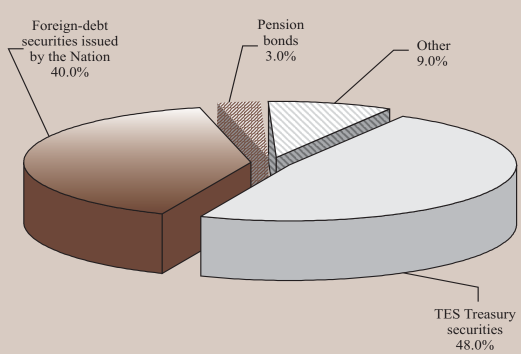
Source: Banking Superintendency.

FIGURE 3
PFM'S FIXED-INCOME INVESTMENTS
(% OF TOTAL FIXED-INCOME)



Source: Banking Superintendency.

FIGURE 4
PFM'S PUBLIC DEBT INVESTMENTS, MARCH 2003
(% OF FIXED-INCOME INVESTMENTS)



Source: Banking Superintendency.

Table 1
Pfm's Investments With The Financial System, March 2003
(Amount, And As % Of Total Fixed-Income)

	Millions of pesos	Percentage
Certificates of deposit	2,125,954	10.31
Bonds	1,017,312	4.93
Credit securities from mortgage-loan securitizations	213,208	1.03
Investment certificates	134,446	0.65
FEN savings securities	79,384	0.39
Credit securities from securitizations of other-than-mortgage assets constituting ineligible investments	60,963	0.30
Credit securities from securitizations of other-than-mortgage assets constituting eligible investments	38,439	0.19
Mortgage bonds	25,423	0.12
Securities backed or guaranteed by Fogafin	11,193	0.05

Source: Banking Superintendency

Table 2
Pfm's Fixed-Income Investments Other Than Public Debt And Financial Sector, March 2003
(Amount And As % Of Total Fixed-Income)

	Millions de pesos	Percentage
Institutions not regulated by Banking Superintendency	3.546.349	17,20
Bonds	3.282.620	15,92
Credit securities from mortgage-loan securitizations	251.724	1,22
Bonds backed, accepted or guaranteed by financial institutions	8.965	0,04
Commercial paper	3.039	0,01
Fogafin bonds	941.939	4,57
Investments in securities issued by overseas entities	591.735	2,87
Bonds issued by multilateral credit organizations	286.672	1,39
Fixed-income securities issued by overseas banks	179.528	0,87
Fixed-income securities issued by foreign governments	75.902	0,37
Fixed-income securities backed, guaranteed or accepted by overseas banks	14.791	0,07
Fixed-income securities issued by overseas central banks	34.842	0,17
Insurance-sector bonds	45.936	0,22
Total investments other than public debt and financial system	5.125.959	24,87

Source: Banking Superintendency

financial system. CDs stand out with 10.3% of the PFM's overall fixed-income investments, while mortgage securities made up a surprisingly low percentage.

As detailed in Table 2, some 25% of the PFM's total fixed-income investments were with other domestic agents and overseas entities.

Bonds issued by such agents or entities represented 16% of total fixed-income holdings, while the share of mortgages securities was once again surprisingly low.

As regards variable-income holdings, they were concentrated in overseas investments (48%), followed by investments with the financial system (27%) and institutions not regulated by the Banking Superintendency (25%) (Figure 5).

B. Classification by financial conditions

The composition of the pension fund managers' portfolio may be analyzed by the currency and/or unit of account of assets. Assets denominated in pesos made up the biggest portion of the portfolio(56%), followed by assets denominated in dollars (24%) and investments denominated in Real Value Units (20%).

Further analysis of the portfolio's composition shows that instruments indexed to inflation account for a very moderate share of it, despite the fact the Pension Fund Managers' liabilities are tied to movements in inflation. In effect, the sum of the instruments denominated in Real Value Units and CPI comes to 39.8% of the portfolio. Hence there is an enormous growth potential for financial instruments indexed to the Real Value Unit, considering the indexation nature of the PFM's liabilities.

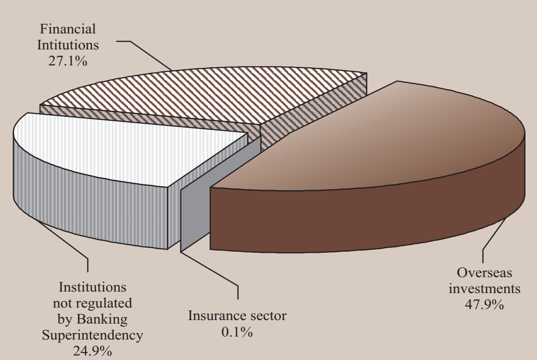
Breakdown of the PFM's portfolio into fixed- and variable-rate instruments shows fixed-rate investments accounting for 50.3% of the portfolio and variable-rate investments for 44%.

C. Breakdown by maturity

Lastly, decomposing the Pension Fund Managers' portfolio by maturity reveals that 90.27% of their assets mature in less than 10 years, while the remaining 9.73% have maturities of over 10 years.

In this connection, attention is drawn to the contrast between the age composition of fund members and the maturity composition indicated above. In effect, while assets are concentrated in relatively short maturities, 43% of fund members are between 25 and 34 years old, indicating a misalignment between the maturities and durations of assets and expirations of liabilities.

FIGURE 5
PFM'S VARIABLE-INCOME INVESTMENTS



Source: Banking Superintendency.

Although the above-described maturity composition of the PFM’s assets is characteristic of less developed capital markets, it has been improving in line with the development of longer-term (mainly public-debt) financial instruments. Moreover, it is important to point out the growth potential of longer-term financial instruments issued by the private sector as well as the and public sector, which should produce a better alignment between the Pension Fund Managers’ liabilities and assets.

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