

# A SCORING MODEL FOR PORTUGUESE NON-FINANCIAL ENTERPRISES\*

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## ABSTRACT

This article presents an econometric model for identifying credit failure based on individual characteristics of Portuguese enterprises. The coefficients associated with the financial ratios proved to be significant and are consistent with economic intuition. The estimated model reveals a high level of sectoral heterogeneity with regard to firms' credit quality. From 2011 to 2012, there was, on average, an increase in the probability of default of firms with credit records, most notably in the cases of large enterprises and enterprises in the construction, real estate, restaurant & hotels and mining & quarrying sectors. As a result, in the recent period, there has been a general deterioration in the loan portfolio quality of the Portuguese banking system, which is heavily concentrated in higher risk firms.

## 1. INTRODUCTION

Two of the most important sources of information available for research and economic analysis are the Simplified Corporate Information (IES in Portuguese) and the Central Credit Register (CRC in Portuguese). The first is an annual mandatory and exhaustive repository of information on the balance sheet of companies legally registered in Portugal. The second is the Portuguese central credit register, a tool available for banks to assess the credit status of potential borrowers, on a monthly basis. The most interesting feature of these two sources of information is that they cover vast areas of interest: on the one hand, the firms' balance sheets; on the other hand, their access to credit. Through this feature, we can formulate models for identifying credit failure and thus monitor the credit status of firms, as well as assess the evolution of their credit quality and characterize the potential credit risk in the economy still not materialized in the prudential ratios of overdue credit.

This work benefited largely from previous studies. In fact, it was not intended to resume discussion on the determinants of credit risk and the discriminatory ability of financial ratios - on this issue already exists an extensive literature and conclusive<sup>1</sup> - but, rather, present a scoring model that is suitable for periodic update, as immune as possible to future changes in accounting standards or reporting models of IES, using major indicators of financial performance.

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\* The opinions expressed are those of the authors and not necessarily those of Banco de Portugal or the Eurosystem. Any errors and omissions are the sole responsibility of the authors.

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<sup>1</sup> See the work of Bonfim, D. (2007) and Soares, M.C. (2007), based on the former Central de Balanços, Altman, E. e Narayan, P. (1997), for a survey of studies conducted in several countries, and, Bardos, M. (1998), for an example of the use of a scoring model by a Central Bank.

## 2. DATA

In this study we used data from the IES and the CRC for the period 2009-2011. The limitation to this relatively recent period is related to the structural change of the IES's reporting model, following the introduction of the Accounting Normalization System (SNC in Portuguese) that replaced the Official Plan of Accounts (POC in Portuguese). The different valuation principles underlying the POC and the SNC would be, in principle, a factor distorting the analysis over a longer period. In fact, for some income statement and balance sheet variables used in the specification of the scoring model was not possible to obtain an univocal correspondence between the old and new IES,<sup>2</sup> which is why we only considered firms' financial information from 2009 onwards. Additionally, with regard to the CRC, in January 2009 a number of improvements were introduced, including a more detailed characterization of the credit liabilities reported to the Bank of Portugal and a greater efficiency in the identification of debtors. It was also in order to fully benefit from a more reliable CRC that the analysis was confined to the period 2009-2011.

## 3. DESCRIPTIVE ANALYSIS

In this section we present a characterization of the credit failure by branch of activity and firm size and a summary of some indicators of financial performance tested in the scoring model. The sectors of activity were defined by the highest aggregation level of *Classificação das Atividades Económicas*, revision 3.<sup>3</sup> The firm size, grouped as Micro, Small, Medium and Large, was defined according to the Decree-Law n.º 372/2007.<sup>4</sup> Within the set of firms that delivered the IES-2011, approximately 55 per cent had credit records in CRC. By branch of activity, the percentage of firms with bank financing access / borrowing needs varies from 40 per cent in case of non-financial holdings, and approximately 65 per cent in the case of mining & quarrying and manufacturing. The percentage of firms with some sort of credit failure differs between sectors, but it is particularly relevant in construction, mining & quarrying, real estate and restaurant & hotels (Table 1). With regard to size, the percentage of firms with bank financing access / borrowing needs is clearly lower in the case of micro enterprises (50 per cent), ranging from 88 per cent in the case of small firms and 94 per cent in the case of the large ones. The percentage of firms with credit failure is higher in micro and large categories. The evidence for micro firms differs from results obtained in earlier work, based on the former Central Balance-Sheet. This discrepancy may stem from the fact that, until 2005, this database integrates accounting information from a survey conducted by the Banco de Portugal to a sample of non-financial enterprises which tended to cover larger firms. Additionally, the survey could be answered voluntarily by enterprises not identified in the sample. As noted in Soares, M. C. (2007) this situation would generate a double bias in the data, first in favor of larger enterprises and, secondly, in favor of micro and small enterprises with good credit quality.

Table 2 synthetically presents the evolution of the distributions of several financial performance indicators for three mutually exclusive groups of enterprises: enterprises with no credit records (mostly micro firms), enterprises with credit records without default and enterprises with credit records with default. Note, however, that in this preliminary analysis was not imposed any filter on IES data. For this reason

2 Note that in the reporting model of IES - 2010 companies reported data again for 2009, to ensure a year of comparable information.

3 This is the Portuguese Classification of Economic Activities, in many aspects similar to the NACE, the statistical classification of economic activities in the European Union. From the set of enterprises reporting the IES only financial holdings are disregarded.

4 The category of micro, small and medium enterprises (SMEs) is made up of enterprises that employ less than 250 persons and whose annual turnover does not exceed € 50 million or annual balance sheet total does not exceed EUR 43 million. A small enterprise is defined as an enterprise which employs less than 50 persons and whose annual turnover or annual balance sheet total does not exceed EUR 10 million. A micro enterprise is defined as an enterprise which employs less than 10 persons and whose annual turnover or annual balance sheet total does not exceed EUR 2 million.

Table 1

| CREDIT AND DEFAULT BY BRANCH OF ACTIVITY AND FIRM SIZE |                                       |   |   |  |  |
|--|---------------------------------------|---|---|--|--|
|  | Percentage of enterprises in IES-2011 | Percentage of enterprises in the subset of IES-2011 with credit register records as of Dec-2011 | Weight in total credit to non-financial enterprises | Percentage of enterprises with some sort of credit failure in IES-2011 | Percentage of enterprises with some sort of credit failure in the subset of IES-2011 with credit register records as of Dec-2011 |
| <b>Branch of activity</b>                              |                                       |   |   |  |  |
| Agriculture, livestock and fishing                     | 2.8                                   | 2.5   | 1.8   | 7.0  | 12.9   |
| Mining and quarrying                                   | 0.2                                   | 0.3   | 0.4   | 14.4   | 20.3   |
| Manufacturing  | 10.5                                  | 12.5  | 13.1  | 11.5   | 16.7   |
| Electricity, gas and water                             | 0.5                                   | 0.5   | 4.3   | 5.9  | 9.6  |
| Construction   | 12.3                                  | 12.8  | 20.0  | 14.2   | 22.8   |
| Trade  | 26.3                                  | 29.0  | 13.1  | 9.1  | 13.8   |
| Transport  | 5.1                                   | 4.8   | 8.5   | 9.3  | 16.8   |
| Restaurant and hotels                                  | 8.8                                   | 7.9   | 4.6   | 10.0   | 18.1   |
| Media  | 2.3                                   | 2.1   | 1.2   | 6.8  | 11.9   |
| Non-financial holdings                                 | 0.9                                   | 0.6   | 7.5   | 4.7  | 11.1   |
| Real estate activities                                 | 6.7                                   | 5.3   | 13.5  | 9.1  | 19.2   |
| Consultancy  | 12.7                                  | 11.6  | 7.5   | 6.5  | 11.5   |
| Education, health and other social care activities     | 10.1                                  | 9.4   | 3.6   | 5.8  | 10.3   |
| Other services   | 0.8                                   | 0.7   | 0.7   | 3.3  | 6.9  |
| <b>Size</b>  |                                       |   |   |  |  |
| Micro  | 88.2                                  | 81.1  | 36.9  | 8.9  | 16.0   |
| Small  | 10.0                                  | 15.8  | 23.9  | 11.2   | 12.5   |
| Medium   | 1.5                                   | 2.6   | 23.4  | 12.1   | 12.8   |
| Large  | 0.3                                   | 0.5   | 15.8  | 14.8   | 15.6   |

Sources: IES and CRC.

it was considered more useful the information regarding per centiles than the calculation of means and standard deviations, very sensitive to extreme values of the ratios.

Overall, firms' financial indicators deteriorated from 2009 to 2011, in the three groups analyzed. Enterprises with no credit records have wider ratios' distributions than enterprises with credit records (except for the financial debt ratio), which means that in this group there is a greater proportion of firms with lower credit quality, without access to bank financing, but also a higher proportion of firms with good credit quality, which are solely equity financed. Still, in the median, these firms have, generally, higher profitability levels and sales volumes than firms with default and lower than firms without default.

From the point of view of constructing the scoring model it is particularly interesting to compare the financial indicators of firms with credit records. Generally, the information of IES supports the economic intuition. Firms without default have typically lower debt levels (financial and non-financial), higher capital and liquidity ratios and greater ability to generate revenues and profits. These differences are observable either in the median or at the extremes of the distributions, suggesting that a well-specified model can be a valuable tool for analyzing firms' credit risk. As expected, the difference increases as we approach the tail of the distribution associated with a negative performance. It is however important to note that, given two firms, one without default and another with default, in many situations the latter may present financial ratios consistently better than the first. From this feature follows that, the probability that a

Table 2

| DISTRIBUTION OF SOME OF THE MAIN FINANCIAL RATIOS |   |        |        |  |        |        |   |        |        |
|---|---|--------|--------|--|--------|--------|---|--------|--------|
|   | IES-2011 enterprises with no credit register record |        |        | IES-2011 enterprises with credit register records, without default |        |        | IES-2011 enterprises with credit register records, with default |        |        |
|   | 2009  | 2010   | 2011   | 2009   | 2010   | 2011   | 2009  | 2010   | 2011   |
| <b>ROA</b>  |   |        |        |  |        |        |   |        |        |
| p10   | -0.475  | -0.559 | -0.704 | -0.189   | -0.211 | -0.284 | -0.281  | -0.326 | -0.458 |
| p50   | 0.000   | 0.000  | 0.000  | 0.011  | 0.010  | 0.005  | 0.000   | -0.001 | -0.012 |
| p90   | 0.179   | 0.176  | 0.176  | 0.140  | 0.129  | 0.114  | 0.072   | 0.066  | 0.046  |
| <b>TURNOVER</b>                                   |   |        |        |  |        |        |   |        |        |
| p10   | 0.000   | 0.000  | 0.000  | 0.074  | 0.085  | 0.067  | 0.000   | 0.000  | 0.000  |
| p50   | 0.602   | 0.576  | 0.537  | 0.956  | 0.955  | 0.923  | 0.553   | 0.492  | 0.392  |
| p90   | 2.711   | 2.836  | 2.965  | 2.617  | 2.654  | 2.702  | 1.833   | 1.818  | 1.742  |
| <b>DFIN</b>                                       |   |        |        |  |        |        |   |        |        |
| p10   | 0.000   | 0.000  | 0.000  | 0.000  | 0.000  | 0.000  | 0.000   | 0.018  | 0.009  |
| p50   | 0.000   | 0.000  | 0.000  | 0.112  | 0.236  | 0.232  | 0.213   | 0.358  | 0.366  |
| p90   | 0.609   | 0.673  | 0.656  | 0.642  | 0.730  | 0.772  | 0.786   | 0.958  | 1.091  |
| <b>DNFIN</b>                                      |   |        |        |  |        |        |   |        |        |
| p10   | 0.013   | 0.008  | 0.004  | 0.086  | 0.065  | 0.056  | 0.138   | 0.094  | 0.078  |
| p50   | 0.487   | 0.467  | 0.470  | 0.454  | 0.374  | 0.366  | 0.580   | 0.496  | 0.514  |
| p90   | 1.770   | 2.001  | 2.186  | 0.986  | 0.925  | 0.983  | 1.419   | 1.496  | 1.814  |
| <b>CAP</b>  |   |        |        |  |        |        |   |        |        |
| p10   | -1.152  | -1.535 | -1.847 | -0.172   | -0.247 | -0.401 | -0.773  | -1.185 | -1.702 |
| p50   | 0.294   | 0.301  | 0.311  | 0.254  | 0.252  | 0.255  | 0.109   | 0.085  | 0.052  |
| p90   | 0.965   | 0.976  | 0.985  | 0.750  | 0.740  | 0.759  | 0.518   | 0.530  | 0.544  |
| <b>LIQ</b>  |   |        |        |  |        |        |   |        |        |
| p10   | 0.001   | 0.001  | 0.000  | 0.003  | 0.003  | 0.002  | 0.000   | 0.000  | 0.000  |
| p50   | 0.106   | 0.113  | 0.114  | 0.071  | 0.070  | 0.059  | 0.023   | 0.021  | 0.018  |
| p90   | 0.769   | 0.824  | 0.862  | 0.472  | 0.466  | 0.451  | 0.335   | 0.380  | 0.398  |

Sources: IES and CRC.

Note: ROA= net income as a percentage of total assets; TURNOVER= sales volume as a percentage of total assets; DFIN= financial debt as a percentage of total assets; DNFIN= non-financial debt as a percentage of total assets; CAP=shareholders' equity as a percentage of total assets; LIQ=cash holdings and term deposits as a percentage of total assets.

scoring model under or overestimates the probability of default of a particular enterprise is relatively high. In fact, these models can be very useful in the analysis of diversified portfolios but the analysis of specific enterprises lacks other complementary pieces of information, not necessarily quantitative in nature.

#### 4. METHODOLOGY

The existing literature tends to favor the use of discriminant functions given its greater robustness over time, lower sensitivity to changes in the composition of the sample and ease of coefficients' interpretation. In this work, we chose a discrete variable model based on a logistic function:

$$z_t = \Pr(y_t = 1 | x_{t-1}) = \frac{1}{1 + \exp(-\beta x_{t-1})}$$

In this equation,  $y_t$  is equal to 1 if there is credit failure in  $t$  and to 0 otherwise. The z-score  $z_t$  is the probability of default during the period  $t$ , conditional on the variables that characterize firms in the previous period, summarized by  $x_t$ . In this formulation, it is possible to define a threshold score for firm classification

$\alpha$ : if  $\beta x_{t-1} \geq \alpha$ , we classify the firm as defaulted, otherwise, we classify the firm as not-defaulted. This allows that, by varying  $\alpha$ , the strictness of the criterion is changed: the higher the threshold, the fewer are the firms considered as defaulted. This notion allows us to compare the model predictions with the actual data in terms of default. We will come back to it later.

The logit-linear specification has as advantages the direct calculation of probabilities of default, without the need to define score intervals, and the lower sensitivity to extreme values of the financial ratios which, in the case of the discriminant function, can translate into probabilities of default that are excessively high or too low.<sup>5</sup> The dependent variable is the dummy variable representing entry into default. The explanatory variables are some of the main ratios commonly used in firms' financial analysis, dummy variables for the deterioration / improvement of the ratios and grouping variables regarding firm size and branch of activity. Given the predictive nature that is intended for the model, the explanatory variables appear with a lag of one period (one year) *vis-à-vis* the dependent variable.

### Definition of default

The results of a scoring model can differ considerably depending on whether the definition of default used is more or less demanding. In this work, it was determined that the firm presents credit failure in year  $t$  if it has at least a record of an overdue credit over one month in any of the financial products referred to in the CRC, either in case of an individual or a joint responsibility. Thus we only excluded records of overdue credits up to one month, in order to mitigate potential reporting errors by banks or extraordinary delays in the payment of installments, for example, due to operational issues.<sup>6</sup> Additionally, since the dependent variable in the model is the entry into default, we disregarded written off or renegotiated loans, which are usually preceded by a situation of arrears.

### Financial ratios

The choice of variables and the final specification of the model was performed in order to optimize quality of fit of the model, in the period under analysis, as measured by the *Pseudo-R*<sup>2</sup>.

In the final specification we used the following ratios:

- ROA = net income as a percentage of total assets
- TURNOVER = sales volume as a percentage of total assets
- DFin = financial debt as a percentage of total assets
- DNFIN = non-financial debt as a percentage of total assets
- LIQ = cash holdings and term deposits as a percentage of total assets

The dummy variables that capture the dynamics of improvement / deterioration in financial performance, assumes the value 1 when the respective ratio increases and the value 0 when it remains constant or decreases. It also imposed a set of conditions to mitigate potential reporting errors in IES and to help redefining the universe of relevant enterprises to analyze, namely:

- Total Assets > 0

<sup>5</sup> For further details see, for example, Bardos, M., "What is at stake in the construction and use of credit scores?", *Computational Economics* (2007) 29:159-172.

<sup>6</sup> Note that debtors can enter in default with respect to interest and other expenses from the date on which installment should have been paid. With regard to principal, generally this only happens after 30 days from the expiration date of the installment. For further details see "*Caderno n.º 5 do Banco de Portugal: Central de Responsabilidades de Crédito*" at <http://www.bportugal.pt/pt-PT/PublicacoesIntervencoes/Banco/CadernosdoBanco/Paginas/CadernosdoBanco.aspx> (only available in Portuguese).

- Sales volume > 0
- Financial debt > 0
- Exclusion of observations pertaining to the 1st and 99th percentile of each financial ratio.
- Exclusion of micro firms<sup>7</sup>

The z-score of a firm reflects the probability of defaulting on its credit liabilities in  $t$ , given the last known financial position (ratio levels) and its recent evolution (dummy variables) in  $t-1$ . Additionally, the inclusion of the categorical variables allows controlling for fixed-effects related to the activity sector and size, which might persist after controlling for the individual characteristics of the firms. More generally, the z-score is an indicator of a firm's credit quality, that can be calculated even for firms that are already in default situation or for firms that do not have credit records.

This type of model can be used to relate the failure of enterprises with the macroeconomic environment. In its simplest form, this can be done by adding one or more macroeconomic factors (such as the GDP growth rate or the change in the unemployment rate) with an across-the-board impact. However, since the model is estimated with data from 2009 and 2010, the estimation of a coefficient associated with a macroeconomic factor is not possible. Thus, the model results will not be sensitive to macro systemic variations not captured by the regressors used.

Table 3 presents the summary statistics of the sample. As in Table 2, which includes all available observations, in the sample also observe that firms that will entry into default in the next year present, in the current year, worse financial ratios than those that will not default. For example, while the return on assets of firms that enter into default is -6,0 per cent, this ratio is 0,7 per cent for those who do not enter into default. The standard deviation for this ratio, moreover, shows that there is a wide dispersion in their values. Also, the average financial debt of defaulting firms is equal to 41 per cent of assets, while for the non-defaulting is just 30 per cent. This behavior is also observed for the variation of these ratios.

As regards size, the table shows that most of the firms considered are small (85 per cent of total), and medium enterprises (13 per cent of total) are more numerous than large (two per cent of total). There appear to be no marked differences between these categories in what refers to default.

In terms of activity sectors, we observe that enterprises in the construction and real estate fall more than proportionately in default, while the opposite occurs for enterprises in manufacturing and trade.

## 5. RESULTS

The results for the preferred specifications are presented in Table 4. In the procedure for the selection of specifications of the regression model, we opted to present one case with the five financial ratios chosen, the respective indicators of variation plus the fixed-effects related to the activity sector and firm size and, another case, including the interactions between the financial variables and firm size.

As usual in binary models with micro data, the *pseudo-R*<sup>2</sup> of the two adjustments is low, close to 7 per cent. This means the variability in the observed default in the data will only be partially explained by variability in the financial ratios and other controls used. In turn, the model is able to classify firms in terms of default fairly efficiently. The ROC curve (Receiver Operating Characteristic) represents the sensitivity of the model as a function of the complement to 1 of the specificity of the model, for different values

<sup>7</sup> In fact, smaller firms (micro enterprises) and with fewer resources available should be more prone to present reporting errors and anomalous figures in IES. For this reason, and after verifying that the discriminatory ability of financial ratios decreased significantly with the inclusion of micro firms, we decided to exclude the respective category from the model's final specification. Note that micro firms were excluded only for the estimation purpose, being subsequently treated as small enterprises (through the categorical variable) for the calculation of the z-score.

Table 3

| IN-SAMPLE MEAN AND STANDARD DEVIATION OF EXPLANATORY VARIABLES |                  | Entry into default=0 | Entry into default=1 | Total sample |
|--|------------------|----------------------|----------------------|--------------|
| ROA  | Mean             | 0.007                | -0.060               | 0.001        |
|  | <i>Std. Dev.</i> | <i>0.151</i>         | <i>0.250</i>         | <i>0.163</i> |
| TURNOVER   | Mean             | 1.420                | 1.151                | 1.396        |
|  | <i>Std. Dev.</i> | <i>1.080</i>         | <i>0.939</i>         | <i>1.071</i> |
| DFIN   | Mean             | 0.301                | 0.412                | 0.311        |
|  | <i>Std. Dev.</i> | <i>0.246</i>         | <i>0.265</i>         | <i>0.250</i> |
| DNFIN  | Mean             | 0.412                | 0.479                | 0.418        |
|  | <i>Std. Dev.</i> | <i>0.341</i>         | <i>0.434</i>         | <i>0.351</i> |
| LIQ  | Mean             | 0.115                | 0.071                | 0.111        |
|  | <i>Std. Dev.</i> | <i>0.147</i>         | <i>0.125</i>         | <i>0.145</i> |
| DROA   | Mean             | 0.458                | 0.374                | 0.451        |
|  | <i>Std. Dev.</i> | <i>0.498</i>         | <i>0.484</i>         | <i>0.498</i> |
| DTURNOVER  | Mean             | 0.500                | 0.442                | 0.495        |
|  | <i>Std. Dev.</i> | <i>0.500</i>         | <i>0.497</i>         | <i>0.500</i> |
| DDFIN  | Mean             | 0.600                | 0.666                | 0.606        |
|  | <i>Std. Dev.</i> | <i>0.490</i>         | <i>0.472</i>         | <i>0.489</i> |
| DDNFIN   | Mean             | 0.410                | 0.440                | 0.413        |
|  | <i>Std. Dev.</i> | <i>0.492</i>         | <i>0.497</i>         | <i>0.492</i> |
| DLIQ   | Mean             | 0.508                | 0.462                | 0.504        |
|  | <i>Std. Dev.</i> | <i>0.500</i>         | <i>0.499</i>         | <i>0.500</i> |
| <b>Size</b>  |                  |                      |                      |              |
| Small  | Mean             | 0.849                | 0.845                | 0.849        |
|  | <i>Std. Dev.</i> | <i>0.358</i>         | <i>0.362</i>         | <i>0.358</i> |
| Medium   | Mean             | 0.129                | 0.134                | 0.130        |
|  | <i>Std. Dev.</i> | <i>0.336</i>         | <i>0.340</i>         | <i>0.336</i> |
| Large  | Mean             | 0.021                | 0.021                | 0.021        |
|  | <i>Std. Dev.</i> | <i>0.144</i>         | <i>0.145</i>         | <i>0.144</i> |
| <b>Branch of activity</b>                                      |                  |                      |                      |              |
| Agriculture and related  | Mean             | 0.022                | 0.015                | 0.021        |
|  | <i>Std. Dev.</i> | <i>0.146</i>         | <i>0.122</i>         | <i>0.144</i> |
| Mining and quarrying   | Mean             | 0.005                | 0.007                | 0.006        |
|  | <i>Std. Dev.</i> | <i>0.073</i>         | <i>0.081</i>         | <i>0.074</i> |
| Manufacturing  | Mean             | 0.272                | 0.257                | 0.271        |
|  | <i>Std. Dev.</i> | <i>0.445</i>         | <i>0.437</i>         | <i>0.445</i> |
| Electricity and gas  | Mean             | 0.012                | 0.005                | 0.011        |
|  | <i>Std. Dev.</i> | <i>0.107</i>         | <i>0.070</i>         | <i>0.105</i> |
| Construction   | Mean             | 0.143                | 0.251                | 0.152        |
|  | <i>Std. Dev.</i> | <i>0.350</i>         | <i>0.434</i>         | <i>0.359</i> |
| Trade  | Mean             | 0.247                | 0.188                | 0.241        |
|  | <i>Std. Dev.</i> | <i>0.431</i>         | <i>0.391</i>         | <i>0.428</i> |
| Transport  | Mean             | 0.041                | 0.041                | 0.041        |
|  | <i>Std. Dev.</i> | <i>0.199</i>         | <i>0.198</i>         | <i>0.199</i> |
| Restaurant and hotels  | Mean             | 0.079                | 0.072                | 0.078        |
|  | <i>Std. Dev.</i> | <i>0.269</i>         | <i>0.258</i>         | <i>0.268</i> |
| Media  | Mean             | 0.019                | 0.016                | 0.019        |
|  | <i>Std. Dev.</i> | <i>0.136</i>         | <i>0.126</i>         | <i>0.135</i> |
| Non-financial holdings   | Mean             | 0.002                | 0.002                | 0.002        |
|  | <i>Std. Dev.</i> | <i>0.046</i>         | <i>0.041</i>         | <i>0.046</i> |
| Real estate activities   | Mean             | 0.012                | 0.021                | 0.013        |
|  | <i>Std. Dev.</i> | <i>0.108</i>         | <i>0.144</i>         | <i>0.112</i> |
| Consultancy  | Mean             | 0.082                | 0.075                | 0.081        |
|  | <i>Std. Dev.</i> | <i>0.274</i>         | <i>0.263</i>         | <i>0.273</i> |
| Education and health   | Mean             | 0.062                | 0.048                | 0.061        |
|  | <i>Std. Dev.</i> | <i>0.242</i>         | <i>0.213</i>         | <i>0.239</i> |
| Other services   | Mean             | 0.003                | 0.003                | 0.003        |
|  | <i>Std. Dev.</i> | <i>0.052</i>         | <i>0.051</i>         | <i>0.052</i> |
| <b>Number of observations</b>                                  |                  | 31200                | 3030                 | 34230        |

Sources: IES, CRC and authors' calculations.

Note: The sample was defined according to the criteria described in section 4 (methodology).

of the latent variable,  $y$ , default threshold (see equation (1)). The sensitivity is defined as the fraction of defaults observed correctly classified by the model, using a given threshold. The specificity is the fraction of observed defaults not correctly classified by the model, with the same threshold. The complement to 1 of the specificity is then the fraction of non-defaults incorrectly classified by the model. In other words, is type 2 error of the model, or the likelihood of a false positive. For various thresholds, the ROC curve gives us the sensitivity (true positive) versus type 2 error (false positives). A default threshold high enough will lead the model to classify all cases as non-defaults, which in Chart 1 correspond to the lower left corner of the ROC curve, a threshold sufficiently negative will classify all cases as defaults, corresponding to the upper right corner. A perfect model is such that, for some threshold, the type 2 error is 0 and the sensitivity is 1, which corresponds to the point (0;1) in the chart and to a ROC curve horizontally flat. A random model will have a ROC curve equal to the line segment between (0;0) and (1;1), also represented in the chart. The area under the ROC curve is a measure of the accuracy of the model. In the case of a perfect model, its value is 1, in the case of a random model, its value is 0,5. For the model on the right side of Table 4 the area is 0.7121, a reasonable value given the parsimony of the model and the fact that it applies to all sectors and all size categories. One would get better results by estimating this type of models sector by sector, or for the various size categories, but the robustness required in this type of application would be lost.

In the regression in the left side of Table 4, the coefficients associated with the levels of financial ratios proved to be significant and with the expected signal. The z-score of a firm increases both with its level of financial and non-financial debt. Conversely, the ROA, the turnover ratio and liquidity ratio contribute to decrease the probability of default, *i.e.* give a downside contribution to the z-score. In the case of the dummies capturing the improvement / deterioration of financial ratios the results are alike.<sup>8</sup> Firms recording an increase in sales and profits and are less likely to enter into default while the reverse applies for firms that increase their financial and non-financial debt.

When controlling for firms' specific attributes it does not appear to exist any fixed-effect / premium associated with firm size. In turn, the statistical significance of some of the coefficients associated with the sectoral dummies suggests the existence of differences between the z-scores of firms from different branches of activity.

In the right panel specification (Table 4) were also included interactions between the financial variables and firm size, which did not significantly improve the predictive ability of the model but has highlighted some differences between types of firm. It is interesting to note that, in general, small and medium enterprises have similar coefficients in size and magnitude, while the large ones presented marked differences. In particular, the coefficients associated with the return on assets and the variation of financial debt are significantly different. This result suggests the existence of a distinct behavior by banks when it comes to large enterprises. On the one hand, the return on assets has a much greater influence on the creditworthiness of large firms than for smaller ones. In the case of financial debt, the behavior of large firms is opposed to the others: if the debt increased, the probability of default decreased.<sup>9</sup> This can be interpreted as an indicator of evergreening of loans, a situation in which the bank, in face of an imminent default by the enterprise chooses to renegotiate loan terms or approve new credit lines, thereby attempting to postpone default. However, given the short time span of the sample, a better assessment of this thesis requires an analysis in longer period of time.

Table 5 summarizes the estimated z-scores based on the last specification presented.<sup>10</sup> From 2011 to 2012,

<sup>8</sup> Except for the dummy associated with the liquidity ratio which did not prove statistically significant.

<sup>9</sup> See Mata, Antunes e Portugal (2010) for a discussion of various mechanisms that justify that the probability of default depends on the level of debt.

<sup>10</sup> Recall that 2011 z-scores, calculated on firms' financial information for 2009 and 2010 are in-sample estimates. 2012 z-scores, calculated on firms' financial information for 2010 and 2011 are out-of-sample estimates, since the 2012 credit records were not incorporated in the model estimation.

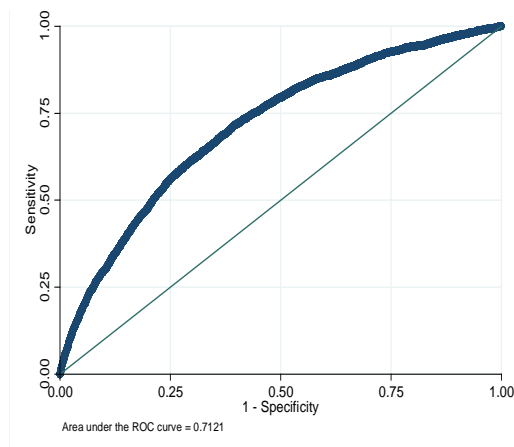


Table 4

| OUTCOMES OF THE TWO MODELS ESTIMATED              |                |        |  |                |        |
|---|----------------|--------|--|----------------|--------|
| Logit model without the size category interaction |                |        | Logit model with the size category interaction |                |        |
|   | N              | 34230  |  | N              | 34230  |
|   | R <sup>2</sup> | 0.0684 |  | R <sup>2</sup> | 0.0703 |
| entryintodefault_f1                               | Coef.          | P> z   | entryintodefault_f1                            | Coef.          | P> z   |
| <b>ROA</b>  |                |        | <b>ROA</b>                                     |                |        |
| ROA   | -0.521         | 0.000  | Small  | -0.508         | 0.000  |
| TURNOVER  | -0.305         | 0.000  | Medium   | -0.501         | 0.208  |
| DFIN  | 1.286          | 0.000  | Large  | -5.447         | 0.004  |
| DNFIN   | 0.560          | 0.000  | <b>TURNOVER</b>                                |                |        |
| LIQ   | -1.926         | 0.000  | Small  | -0.312         | 0.000  |
| DROA  | -0.206         | 0.000  | Medium   | -0.254         | 0.000  |
| DTURNOVER   | -0.167         | 0.000  | Large  | -0.484         | 0.013  |
| DDFIN   | 0.208          | 0.000  | <b>DFIN</b>                                    |                |        |
| DDNFIN  | 0.105          | 0.023  | Small  | 1.286          | 0.000  |
| DLIQ  | -0.066         | 0.099  | Medium   | 1.536          | 0.000  |
| <b>Size</b>                                       |                |        | Large  | 0.352          | 0.402  |
| Small   | -              | -      | <b>DNFIN</b>                                   |                |        |
| Medium  | 0.098          | 0.092  | Small  | 0.549          | 0.000  |
| Large   | 0.097          | 0.479  | Medium   | 0.614          | 0.000  |
| <b>Branch of activity</b>                         |                |        | Large  | 0.874          | 0.185  |
| Agriculture and related                           | -0.486         | 0.002  | <b>LIQ</b>                                     |                |        |
| Mining and quarrying                              | 0.092          | 0.706  | Small  | -1.775         | 0.000  |
| Manufacturing                                     | -              | -      | Medium   | -3.416         | 0.000  |
| Electricity and gas                               | -1.083         | 0.000  | Large  | -1.778         | 0.295  |
| Construction                                      | 0.632          | 0.000  | <b>DROA</b>                                    |                |        |
| Trade   | -0.096         | 0.103  | Small  | -0.207         | 0.000  |
| Transport   | 0.069          | 0.509  | Medium   | -0.091         | 0.431  |
| Restaurant and hotels                             | -0.079         | 0.347  | Large  | -0.839         | 0.006  |
| Media   | -0.166         | 0.297  | <b>DTURNOVER</b>                               |                |        |
| Non-financial holdings                            | -0.399         | 0.396  | Small  | -0.147         | 0.001  |
| Real estate activities                            | 0.242          | 0.100  | Medium   | -0.330         | 0.003  |
| Consultancy                                       | -0.027         | 0.743  | Large  | -0.061         | 0.833  |
| Education and health                              | -0.380         | 0.000  | <b>DDFIN</b>                                   |                |        |
| Other services                                    | 0.126          | 0.739  | Small  | 0.220          | 0.000  |
| <b>Constant</b>                                   | -2.529         | 0.000  | Medium   | 0.263          | 0.038  |
|   |                |        | Large  | -0.642         | 0.043  |
|   |                |        | <b>DDNFIN</b>                                  |                |        |
|   |                |        | Small  | 0.082          | 0.104  |
|   |                |        | Medium   | 0.355          | 0.004  |
|   |                |        | Large  | -0.631         | 0.045  |
|   |                |        | <b>DLIQ</b>                                    |                |        |
|   |                |        | Small  | -0.068         | 0.120  |
|   |                |        | Medium   | -0.061         | 0.583  |
|   |                |        | Large  | 0.000          | 0.999  |
|   |                |        | <b>Size</b>                                    |                |        |
|   |                |        | Small  | -              | -      |
|   |                |        | Medium   | -0.128         | 0.552  |
|   |                |        | Large  | 1.500          | 0.004  |
|   |                |        | <b>Branch of activity</b>                      |                |        |
|   |                |        | Agriculture and related                        | -0.485         | 0.003  |
|   |                |        | Mining and quarrying                           | 0.097          | 0.691  |
|   |                |        | Manufacturing                                  | -              | -      |
|   |                |        | Electricity and gas                            | -1.069         | 0.000  |
|   |                |        | Construction                                   | 0.632          | 0.000  |
|   |                |        | Trade  | -0.093         | 0.115  |
|   |                |        | Transport                                      | 0.083          | 0.422  |
|   |                |        | Restaurant and hotels                          | -0.086         | 0.306  |
|   |                |        | Media  | -0.159         | 0.320  |
|   |                |        | Non-financial holdings                         | -0.386         | 0.412  |
|   |                |        | Real estate activities                         | 0.248          | 0.091  |
|   |                |        | Consultancy                                    | -0.022         | 0.783  |
|   |                |        | Education and health                           | -0.379         | 0.000  |
|   |                |        | Other services                                 | 0.148          | 0.697  |
|   |                |        | <b>Constant</b>                                | -2.534         | 0.000  |

CHART 1

## ROC CURVE OF THE SECOND MODEL ESTIMATED (TABLE 4 - RIGHT PANEL)



**Source:** Authors' calculations based on the outcome of the logit model with interactions between financial ratios (including dummies) and the size category.

there was a deterioration of firms' average z-score, from 0,126 to 0,136. This evolution has, however, implicit a dynamics of exit and entrance of firms in IES. Firms that disappear have a z-score significantly higher than the population, while the opposite is true, although to a lesser extent, in the case of new firms. Thus, when considering only firms that are common to both years, the deterioration is more pronounced, from 0,120 to 0,137. As regards the breakdown by activity sector and size the results are, to some extent, consistent with the evolution of prudential ratios of overdue credit. Enterprises in the construction and real estate sectors stand out clearly in the negative way, from micro to large enterprises. Additionally, it is worthwhile mentioning the worst credit quality of large firms in the transportation sector, micro firms in restaurant and hotels, as well as micro firms in mining and quarrying.

A useful way to classify firms by financial strength is to define intervals and distributing firms according to their z-score. The construction of 10 risk classes, based on the distribution of z-scores for 2011, shows that 31 per cent of firms move upwards in the risk class and 21 per cent move downwards, from 2011 to 2012. The mobility occurs mainly towards the deterioration of the risk profile. It is worth noting an increase of 25 per cent in the number of firms in the last risk class (associated with lowest credit quality), which is also the class where there was less mobility. Even with regard to the evolution from 2011 to 2012, it should be noted that about 58 per cent of firms have worsened or remained unchanged in terms of z-score, while 42 per cent improved.

Chart 2 shows the dynamics of rise / fall in risk class by activity sector between 2011 and 2012. In construction, real estate and non-financial holdings the evolution of z-scores was processed mainly towards increased risk. Instead, media and other services had a balance close to zero.

## 6. Z-SCORE AND THE CENTRAL CREDIT REGISTER (CRC)

An interesting exercise is to examine the relationship between the amounts of outstanding loans and firms' credit quality. In this case, we analyzed the transition between December 2011 and September 2012.

Starting with risk classes defined in the previous section, Chart 3 shows the amount of credit granted to firms in each risk class, as a percentage of total credit granted, as of December 2011 and September

Table 5

| Z-SCORES FOR 2011 AND 2012 BY BRANCH OF ACTIVITY AND FIRM SIZE |                         |                      |               |                     |              |       |           |                       |       |                        |                        |             |                      |                |       |
|--|-------------------------|----------------------|---------------|---------------------|--------------|-------|-----------|-----------------------|-------|------------------------|------------------------|-------------|----------------------|----------------|-------|
| z-score 2011   | Agriculture and related | Mining and quarrying | Manufacturing | Electricity and gas | Construction | Trade | Transport | Restaurant and hotels | Media | Non-financial holdings | Real estate activities | Consultancy | Education and health | Other services | Total |
| Micro  | 0.09                    | 0.16                 | 0.13          | 0.06                | 0.19         | 0.12  | 0.08      | 0.15                  | 0.12  | 0.12                   | 0.17                   | 0.12        | 0.11                 | 0.09           | 0.13  |
| Small  | 0.06                    | 0.11                 | 0.09          | 0.04                | 0.15         | 0.07  | 0.08      | 0.08                  | 0.08  | 0.07                   | 0.15                   | 0.09        | 0.07                 | 0.08           | 0.09  |
| Medium   | 0.07                    | 0.13                 | 0.10          | 0.05                | 0.16         | 0.07  | 0.10      | 0.09                  | 0.08  | 0.07                   | 0.17                   | 0.08        | 0.07                 | 0.09           | 0.10  |
| Large  |                         |                      | 0.09          | 0.04                | 0.18         | 0.06  | 0.14      | 0.14                  | 0.08  |                        |                        | 0.08        | 0.10                 |                | 0.09  |
| Total  | 0.09                    | 0.15                 | 0.11          | 0.06                | 0.18         | 0.12  | 0.09      | 0.14                  | 0.11  | 0.12                   | 0.17                   | 0.12        | 0.11                 | 0.09           | 0.13  |
| z-score 2012   | Agriculture and related | Mining and quarrying | Manufacturing | Electricity and gas | Construction | Trade | Transport | Restaurant and hotels | Media | Non-financial holdings | Real estate activities | Consultancy | Education and health | Other services | Total |
| Micro  | 0.09                    | 0.17                 | 0.14          | 0.08                | 0.20         | 0.13  | 0.09      | 0.17                  | 0.13  | 0.12                   | 0.18                   | 0.13        | 0.13                 | 0.08           | 0.14  |
| Small  | 0.06                    | 0.11                 | 0.09          | 0.04                | 0.15         | 0.07  | 0.08      | 0.09                  | 0.09  | 0.07                   | 0.15                   | 0.09        | 0.07                 | 0.09           | 0.09  |
| Medium   | 0.06                    | 0.12                 | 0.10          | 0.05                | 0.16         | 0.08  | 0.10      | 0.10                  | 0.08  | 0.08                   | 0.18                   | 0.09        | 0.07                 | 0.10           | 0.10  |
| Large  |                         |                      | 0.10          | 0.04                | 0.24         | 0.08  | 0.16      | 0.11                  | 0.15  |                        |                        | 0.09        | 0.16                 |                | 0.12  |
| Total  | 0.09                    | 0.15                 | 0.12          | 0.07                | 0.19         | 0.13  | 0.09      | 0.16                  | 0.12  | 0.12                   | 0.18                   | 0.13        | 0.12                 | 0.08           | 0.14  |

**Source:** Authors' calculations based on the outcome of the logit model with interactions between financial ratios (including dummies) and the size category.

**Note:** Given the reduced number of large firms in agriculture and related, mining and quarrying, non-financial holdings, real estate activities and other services, it was decided to omit the average z-scores of these subsets.

2012.<sup>11</sup> A first observation is that the amount of credit granted to riskier firms is considerably high. Although this effect can be expected, as financial debt has a negative impact on the z-score, it is still worrying that the three deciles of highest risk accounted for about 60 per cent of the total portfolio in December 2011. When we look at the figures for September 2012, we observe that the total weight of these three deciles increases to 64 per cent at the expense of a reduction in lower deciles. Note, however, that this development mainly reflects the across-the-board deterioration in firms' credit quality (shift to the right of the z-scores distribution), though more pronounced in some activity sectors, rather than a significant increase in credit granted to riskier firms.

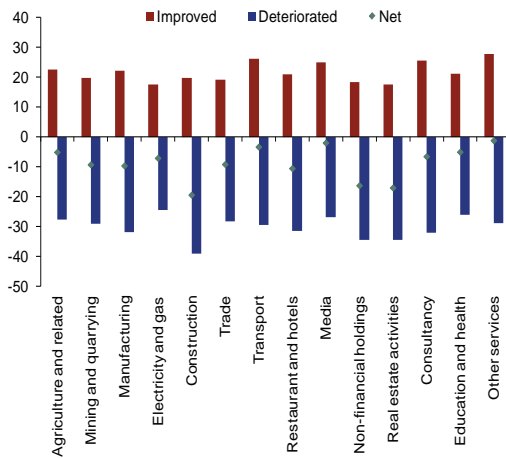
Table 6 shows the sectors in which the z-score increased the most, considering only the subset of enterprises in IES credit with records. The trend is similar to that shown in Table 5 (that refers to the universe of enterprises in IES). With regard to activity sector, firms in the construction, real estate, restaurant & hotels and mining & quarrying, experienced the largest increases in z-score in absolute terms. Regarding firm size, the z-score increase mainly in for enterprises. Note that the z-score increased slightly less in the subset of firms with credit records than in the universe of IES.

The risk structure of credit portfolio is quite heterogeneous by branch of activity. In September 2012, the largest sectors in terms of outstanding credit were construction, real estate, manufacturing and trade (Table 7). However, the risk profile varies dramatically across sectors. The three worst risk classes are dominated by construction, real estate and transportation that have a clearly disproportionate weight against the weight they have in total credit. On the other hand, in the top three risk classes, which account for only 5 per cent of total loans, trade and electricity & gas have more weight.

<sup>11</sup> Risk classes (deciles) are computed from the 2011 z-score distribution, both for December 2011 and September 2012.

CHART 2

PERCENTAGE OF ENTERPRISES THAT MOVED TO A LOWER/HIGHER Z-SCORE DECILE

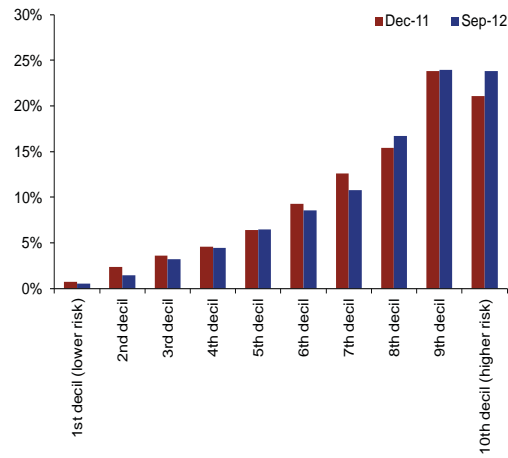


Source: Authors' calculations.

Note: Deciles are computed from the 2011 z-score distribution and are kept constant for 2012.

CHART 3

PERCENTAGE OF ENTERPRISES THAT MOVED TO A LOWER/HIGHER Z-SCORE DECILE



Sources: CRC and authors' calculations.

Note: The profile of the loan portfolio as of Dec-2011 is made according to the z-score of 2011. The profile of the loan portfolio as of Sep-2012 is made according to the z-score of 2012. Deciles are computed from the 2011 z-score distribution and are kept constant for 2012.

Table 6

| AVERAGE Z-SCORE OF ENTERPRISES WITH CREDIT REGISTER RECORDS |        |        |
|---|--------|--------|
|   | Dec-11 | Sep-12 |
| Non-financial enterprises (total)                           | 0.111  | 0.118  |
| <b>Branch of activity</b>                                   |        |        |
| Agriculture, livestock and fishing                          | 0.076  | 0.078  |
| Mining and quarrying  | 0.124  | 0.134  |
| Manufacturing   | 0.098  | 0.103  |
| Electricity, gas and water                                  | 0.049  | 0.054  |
| Construction  | 0.174  | 0.186  |
| Trade   | 0.094  | 0.100  |
| Transport   | 0.084  | 0.086  |
| Restaurant and hotels                                       | 0.120  | 0.130  |
| Media   | 0.096  | 0.104  |
| Non-financial holdings                                      | 0.120  | 0.126  |
| Real estate activities                                      | 0.175  | 0.185  |
| Consultancy   | 0.106  | 0.111  |
| Education, health and other social care activities          | 0.091  | 0.098  |
| Other services  | 0.094  | 0.092  |
| <b>Size</b>   |        |        |
| Micro   | 0.115  | 0.122  |
| Small   | 0.096  | 0.101  |
| Medium  | 0.102  | 0.105  |
| Large   | 0.098  | 0.129  |

Sources: CRC and authors' calculations.

## 7. FINAL REMARKS

This article presents an approach that allows classifying Portuguese enterprises by level of credit risk. Using data from the Informação Empresarial Simplificada between 2009 and 2011 and data from the Central de Responsabilidades de Crédito (the Portuguese central credit register) for 2010 and 2011 is traced a risk profile by activity sector, size and a set of variables and financial indicators of the firm. The data confirm some of the known facts about the Portuguese business structure. Firstly, there is a strong predominance of micro and small enterprises. Secondly, there is a large concentration of credit in large enterprises, representing only 0.3 per cent of total enterprises, hold 16 per cent of total credit registered in the CCR. The data also show that some financial indicators, such as the return on assets, sales volume or the financial debt, are significantly different between firms with and without credit default.

This finding was explored through a model that allows to discriminate between firms that will potentially default on their credit liabilities and the others. We used a logit specification for the probability of default of the company and estimated a model that included several financial indicators and fixed-effects for activity sector and size. The results confirm the intuition conveyed by the data. In particular, the higher the return on assets, the lower the probability of default (z-score) in the one-year horizon. The same applies for sales volume and the liquidity ratio. The financial debt and financial debt does not, however, contribute to increase the probability of default of the enterprise. The estimation also shows that the sensitivity of the probability of default to these financial ratios vary with firm size.

Applying the model to firms' financial data, we can classify them according to z-score. There is a strong sectoral heterogeneity in terms of z-score. The highest values refer to construction, real estate and mining & quarrying. The lowest values refer to electricity & gas, transportation and agriculture & related. In a dynamic perspective, the deterioration of z-scores was also more pronounced in construction and real estate activities.

**Table 7**

| Branch of activity   | Sector weight in the      |                            |                        | Percentage of loans to the sector in the |                      |
|--|---------------------------|----------------------------|------------------------|--|----------------------|
|  | 3 best risk classes total | 3 worst risk classes total | credit portfolio total | 3 best risk classes                      | 3 worst risk classes |
| Agriculture, livestock and fishing                         | 4%                        | 1%                         | 2%                     | 9.3%                                     | 19%                  |
| Mining and quarrying                                       | 0%                        | 1%                         | 0%                     | 0.6%                                     | 74%                  |
| Manufacturing  | 14%                       | 10%                        | 14%                    | 5.2%                                     | 48%                  |
| Electricity, gas and water                                 | 29%                       | 0%                         | 5%                     | 30.3%                                    | 0%                   |
| Construction   | 1%                        | 28%                        | 19%                    | 0.3%                                     | 97%                  |
| Trade  | 31%                       | 5%                         | 13%                    | 12.4%                                    | 23%                  |
| Transport  | 3%                        | 14%                        | 10%                    | 1.6%                                     | 89%                  |
| Restaurant and hotels                                      | 3%                        | 5%                         | 4%                     | 3.7%                                     | 69%                  |
| Media  | 1%                        | 1%                         | 1%                     | 4.2%                                     | 49%                  |
| Non-financial holdings                                     | 1%                        | 6%                         | 7%                     | 0.7%                                     | 55%                  |
| Real estate activities                                     | 0%                        | 18%                        | 12%                    | 0.2%                                     | 96%                  |
| Consultancy  | 5%                        | 9%                         | 8%                     | 3.6%                                     | 74%                  |
| Education, health and other social care activities         | 7%                        | 2%                         | 4%                     | 10.1%                                    | 42%                  |
| Other services   | 0%                        | 1%                         | 1%                     | 1.7%                                     | 91%                  |
| <b>Weight of the 3 risk classes in the portfolio total</b> | <b>5%</b>                 | <b>64%</b>                 | <b>100%</b>            | <b>5%</b>                                | <b>64%</b>           |

Sources: CRC and authors' calculations.

Note: The profile of the loan portfolio as of Sep-2012 is made according to the z-score of 2012.

By matching the information about z-scores with CRC data, for December 2011 and September 2012, two relevant observations are brought to light. Firstly, credit outstanding amounts are concentrated in higher z-score deciles, with the enterprises in the three riskier holding about 60 per cent of total credit as of December 2011. Secondly, in recent years, this level of concentration increased. Given the weight that construction and real estate have in total credit, this effect was mainly due to the more pronounced risk deterioration in these sectors than in others.

The approach for calculating the z-score presented in this article can be improved at various levels. On the one hand, with the enlargement of the time span of the data will be possible to estimate coefficients for macroeconomic factors – this time, the results are invariant to the macroeconomic situation of the country, except for the component absorbed in financial ratios. Moreover, in specific applications there may be some advantage in estimating this type of models for smaller groups of firms. These two tasks, among others, will keep the interest in developing scoring models to deal with issues related to credit risk, financial stability and sectoral analysis of the Portuguese economy.

### References

- Altman, E e Narayan, P. (1997), "An International Survey of Business Failure Classification Models", *Financial Markets, Institutions & Instruments*, 6(2), pp. 1-57.
- Bardos, M., "What is at stake in the construction and use of credit scores?", *Computational Economics* (2007) 29:159-172.
- Bardos, M., "Detecting the risk of company failure at the Banque de France?", *Journal of banking & Finance* 22 (1998) 1405-1419.
- Bonfim, D. (2007), "Credit risk drivers: evaluating the contribution of firm level information and macroeconomic dynamics", *Journal of Banking and Finance*, 33(2), pp. 281-299.
- Soares, M.C. (2007), "Modelling of an Indicator for Credit Scoring of Non-Financial Corporations – a Preliminary Research Based on Discriminant Analysis", *Financial Stability Report – 2006*, Banco de Portugal, pp. 143-160.
- Mata, J, Antunes, A, e Portugal, P, (2010), "Borrowing Patterns, Bankruptcy and Voluntary Liquidation", *Working Paper*, Banco de Portugal.