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Andrew Benito
Francisco Javier Delgado
Jorge Martínez Pagés

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Andrew Benito (*)
BANK OF ENGLAND

Francisco Javier Delgado (*)
Jorge Martínez Pagés (*)
BANCO DE ESPAÑA

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Abstract

In this paper, we construct a firm-level estimate of the probability of default for a large sample of Spanish firms that can be interpreted as a composite measure of individual corporate financial pressure. By combining firms' accounting data from the Central Balance Sheet Data Office of the Banco de España with credit data from the Spanish Central Credit Register, we obtain a large data set (80,701 observations) covering a significantly longer time period (1985-2001) than is usual in the literature. Our results point to the importance of income leverage (together with other relatively standard financial ratios) for the financial pressure on firms, but also to the relevance of non-linearities and the inability of purely firm-level variables to capture completely the temporal behaviour of aggregate firm default rates. Thus, the real GDP growth rate and an average interest cost of debt are significant additional predictors of a firm's probability of default.

1 INTRODUCTION

In recent years, increasing attention has been devoted to the potential macroeconomic implications of financial imbalances of the private non-financial sector in an economy (firms and households). Thus, for example, the financial accelerator literature [see, for example, Bernanke *et al.* (1999)] emphasises how pro-cyclical movements in borrowers' net worth tend to amplify business cycle fluctuations by reducing the ability of fragile firms to undertake new investments in times of declining profitability and asset values while increasing it when the economy is booming. Similarly, there is now a clear concern over the potential impact on the current world economic recovery of the high level of indebtedness of non-financial firms and households in many developed countries. Financial pressures on the sector may also have adverse macroeconomic consequences if translated into defaults and bank losses that weaken the banking system.

Focusing on the analysis of non-financial firms, the literature points to many different possible indicators of corporate financial health (market values, profitability, gearing, liquidity, etc.), as well as to the importance of analysing not just the behaviour of the average indices but also of their distribution across firms, since some firms' vulnerabilities may be masked in an aggregate analysis. For example, Benito (2002) examined the behaviour of a set of relevant financial ratios for Spanish non-financial firms, looking at both their aggregate behaviour and their cross-sectional dispersion.

But when there are various indicators for the same phenomenon, in this case financial soundness, they can give different signals and it is important to be able to glean a single message from them. Hence some kind of aggregation is necessary. A good summary measure should be based on the predictive content of each potential indicator on the probability of a firm failing. This is the approach we adopt in this paper in constructing a synthetic indicator of financial pressure for the non-financial corporate sector in Spain[1].

Our starting point is to construct a firm-level estimate of the probability of default for a large sample of Spanish firms that can be interpreted as a composite measure of individual corporate financial pressure. Although we are basically interested in the aggregate situation of the non-financial firms sector as a whole, the use of micro data can be useful in two ways. First, the greater variation in the micro data can help to improve the precision and accuracy of estimates of the predictive content of the different indicators, for instance by reflecting how the combination of factors at the micro-level influences default risk. Second, micro data allow us to analyse not only the mean behaviour, but also the performance of those companies on the upper tail of the distribution, which are the more relevant for risk analysis.

Our analysis is demanding in terms of data requirements. We combine micro information on financial ratios for a rich set of Spanish non-financial firms obtained from the Central Balance Sheet Data Office of the Banco de España with information on the credit status of those firms derived from the Central Credit Register of the Banco de España. The latter dataset offers unique information on the credit status of all loans in excess of a very low threshold.

This approach is just one among those used to estimate the probability of a company defaulting (see, for example, Caouette, Altman and Narayanan, 1998). Others are, for example, Merton-type models –which require market equity prices– or estimates based on public ratings historical default experience –which require a public rating for the company–. Each has its advantages and disadvantages, but we focus on the financial-accounting-ratios

1. For alternative measures based on the impact of various financial ratios on the real decisions of firms (i.e. investment and employment), see Hernando and Martínez-Carrascal (2003). See Bunn and Redwood (2003) for an approach very similar to ours, applied to UK firms.

model for two reasons. First, one of the objectives of the paper is to gauge the relative importance of the existing financial indicators. Second, this method can be applied more widely since the number of Spanish firms quoted on stock exchanges is relatively limited and those with a public rating are even fewer. The Merton approach is therefore rather limited in ability to offer a broad assessment of credit risk in the Spanish economy.

Our results point to the importance of income leverage (together with other relatively standard financial ratios) for the financial pressure on firms, but also to the relevance of non-linearities and the inability of purely firm-level variables to capture completely the temporal behaviour of aggregate firm default rates. The decline in interest rates observed in the Spanish economy during the nineties has contributed to a large extent to the current favourable position of Spanish non-financial firms both on average and in terms of dispersion across firms.

The remainder of the paper is organised as follows. In the next section we summarise the theoretical arguments that link firm's financial ratios or variables to its probability of failure, together with some previous empirical results, both in Spain and in other countries. Section 3 presents the data we use. Section 4 provides the estimated default prediction results and the corresponding implicit weights for the different financial indicators. Section 5 analyses the behaviour and distribution of the summary indicator of Spanish firms' financial pressure and, finally, Section 6 concludes.

2 LITERATURE REVIEW

There are several papers analysing the theoretical determinants of a firm's default (see, for example, Wadhwani, 1986, and Vlieghe, 2001). Nonetheless, the problem turns out to be complex enough so that, in the end, they do not derive a direct connection between the theoretical and empirical model, but generate a list of potentially relevant variables to be incorporated into the latter.

A simple conceptual way to analyse the determinants of default is to look at firms' required payments and available resources. Payment obligations are determined mainly by the outstanding debt of a firm. However, for firms with the same debt level, differences derived from their temporal structure or from the conditions in which they have to meet the debt are observed. In this way, firms with a similar debt level may bear a different interest burden owing to their individual characteristics and the subsequent different treatment dispensed by financial institutions. It is necessary to take into account not only a total debt ratio, but also a measure of interest paid. Also, a concentration of payments in the short run may increase the likelihood of default. So it may be necessary to include a variable measuring that part of total debt that is payable in the short term.

Concerning the availability of resources to meet payments, income generated by the company is the main source in the long run. Different profitability measures can be used to capture this effect, while the volatility of profits is also important. The level of capital is also relevant since it is related not only to the level of debt, but also to the capacity of the firm to absorb losses. At some point in time, it may be necessary for the firm to dispose of assets in order to make interest payments or repay principal. The liquidity of those assets will therefore determine the ability of the firm to generate resources in a quick and inexpensive way.

Finally, the firm may raise additional resources, whether debt or equity. The more profitable the company, the greater is its capacity to raise equity or debt finance on attractive terms. For instance, the availability and terms of new debt will depend on financial leverage (income and capital gearing), since an excessively indebted firm may find difficulty in attracting new funds. Any other variable that could affect investors' expectations of the firm's future performance –such as a dividend omission, sales growth, or stage of the business cycle– may also be relevant. Finally, the firm's size, age and sector may be pertinent, reflecting a combination of the factors described above.

As regards empirical results, there is an ample literature about determinants of firms' failure, approaching the issue from different points of view and using different data types and methodologies. Using aggregate information, Wadhwani (1986) sets up a model in which real wages and real input prices (as determinants of profitability), capital gearing, real and nominal interest rates and measures of aggregate demand are significant in explaining corporate liquidations. He starts from the usual belief that a high level of inflation has adverse effects on the real economy and his objective is to show that in the absence of index-linked loans, higher inflation implies higher liquidation rates. Hudson (1986) uses a specification very similar to that of Wadhwani, based on real interest rates (with a negative impact), measures of profitability and the birth rate of new companies (positive impact, since younger firms are more risky). Davis (1987) also bases his analysis on Wadhwani's model, using the debt/GNP ratio instead of capital gearing as a measure of leverage. Moreover, he finds nominal interest rates, real input prices, real GNP and debt to GNP ratio to be important. Cuthbertson and Hudson (1996) analysed the determinants of compulsory liquidations only. They use income gearing, a measure of profitability and the lagged birth rate of new companies. Young (1995) points out that the important variables are not interest rates and inflation, but the possible differences between the level of those variables and the levels expected by agents. Finally Vlieghe (2001) finds that the debt-to-GDP ratio, real interest rate, deviations of GDP from trend and real wages are long-run determinants of the liquidation rate, while the birth rate of new companies, an index of property prices and nominal interest rates have short-term effects.

The other branch of the literature uses firm-level data, in conjunction with either discriminant analysis or logit or probit models, to model company failure[2]. Most recent papers use the second option. Lennox (1999) finds important roles for measures of profitability, liquidity and capital gearing as expected. The size of the firm is negatively related to the probability of failure while certain industrial sectors, in particular construction and financial services, are more prone to financial distress. Geroski and Gregg (1997) use a probit model to examine the likelihood of firm failure. Their sample period covers both an expansionary and a recessionary period, and they allow for non-linear effects of several financial ratios. Financial losses raise the probability of failure, while the debt to assets ratio and firm size have a positive and a negative impact, respectively. Bhattacharjee *et al.* (2002) report that higher cash flow and profitability, as well as the size of the firm, reduce the probability of liquidation. The cycle has a significant impact only for firms that have been reported in the database within the previous five years. Bunn and Redwood (2003) find a number of results confirming these earlier findings using firm-level data. Based on Benito *et al.* (2001), they construct a “debt at risk" indicator, calculated as the product of default probability and debt.

Hence, many different variables have been found to be significant predictors of default in diverse circumstances. The more common are profitability, liquidity, capital and income gearing, GDP growth, size, age and sector[3].

With respect to Spanish firms, few published studies exist that use firm-level financial data to construct aggregate fragility indicators. A recent paper by Corcóstegui *et al.* (2003) uses similar data sources to ours[4] to estimate individual firms’ probabilities of default. These are then used to construct a rating system of obligors and to analyse the potential procyclicality of capital requirements under the new Basel II rules.

In this study, several financial ratios of firms are used to develop an obligor classification system (based on estimated default probabilities). Also taken into account in the classification are the credit guarantee requirement for firms and information about the sector they belong to. They find a negative coefficient for the capital to assets, short-term debt to total debt, sales, liquid to total assets and profitability ratios, while a significant positive coefficient is found for the variable that reflects the use of collateral, showing that financial institutions identify high-risk firms, requiring them to post some collateral. Once the obligor classification system has been built, it shows the importance of the economic cycle in the flow of firms from one rating group to another, as well as in the capital requirements derived from the model.

2. See Tudela and Young (2003) for an example of an application of the Merton approach to corporate default risk applied to a sample of quoted UK companies.
3. A more complete survey of the literature can be found in Bunn and Redwood (2003).
4. Though they complement the Banco de España’s Central Balance Sheet Data Office company accounts database with a private database (SABE) and focus only on firms with at least EUR 9 million sales for a shorter time period (1992-2000) than ours.

3 DATA

We employ two large-scale micro-datasets for our analysis. The first is a comprehensive set of accounting information on a group of Spanish non-financial firms collected by the annual survey of the Central Balance Sheet Data Office of the Banco de España (CBA; see Banco de España, 2002). It comprises 131,335 annual observations for 27,220 firms over the period 1984-2001. Apart from the first two years of the sample period, the coverage is relatively stable: around seven to eight thousand companies per year representing approximately 35 per cent of the total gross value-added of the non-financial corporate sector in Spain. As we will see below, there is a bias towards large companies in the sample. However, the time coverage of this sample is unrivalled by any other dataset available on Spanish non-financial companies and, in our view, this is very important for our purpose here. Given the cyclical behaviour of default ratios, having a long sample period (with more than one business cycle) allows us to better capture the effect of the declining interest rates since 1993.

The second dataset is obtained from the Central Credit Register of the Banco de España (see the description in Jiménez and Saurina, forthcoming). It contains monthly information on all credits above a certain threshold granted by Spanish credit institutions. That threshold, although varying over time, has been very low in general[5]. Therefore, the coverage of this dataset is very high. The information in the Central Credit Register includes an item indicating the credit status of the loan that we use to define each loan as defaulted or non-defaulted[6]. We define a company as defaulted at time t when at least 10 per cent of the total exposure in the Central Credit Register to that company at time t is in default[7]. For the purpose of matching the two datasets and since we are interested in predicting defaults, we relate accounting data for year t to the credit status of the firm in December of year t+1. But we also collect information on the credit status of the firm in December of year t. This allows us to distinguish between new defaulters (companies not paying interest at t+1 but paying it at t) from other defaulters (companies not paying interest neither at t+1 nor at t).

The sample after matching the two datasets contains 106,156 observations on 21,814 firms for the same period, 1984-2001. This accounts for more than 89% of the total company debt in the original CBA data. We then apply some logical filters, such as dropping those firms with zero assets or sales, those more than 50% owned by general government and observations in which the firm is involved in a merger, acquisition or split. Finally, the first observation for each company is lost due to the need to construct growth rates for some of the variables. All this leaves us with a final sample of 80,721 observations on 17,935 firms for 17 years (1985-2001), accounting for 62% of the total company debt in the original CBA database. Thus, our sample covers a significantly longer time period than usual (see, for example, Bunn and Redwood, 2003, and Corcóstegui *et al.*, 2003). Of those observations, 1,839 relate to firms defaulting the year after (2.3% of the total), with the number of companies failing each year ranging from 54 to 180.

To further clean up the data, we winsorise financial indicators, setting those observations above (below) the 99th (1st) percentile at the value of the 99th (1st) percentile. Also, the borrowing ratio is constrained to take values between 0 and 1, and real sales growth (measured by the first difference in the log of real sales) is constrained to values between -0.5

5. Currently, it is set at six thousand euros.
6. Specifically, we consider as defaulted those loans that are non-performing (more than three months in arrears) or that, for several reasons, the lender considers as doubtful in spite of being performing.
7. We considered alternative thresholds. A lower limit generates more defaults but some of these may be false defaults resulting from legal disputes, unrelated to the health of the company, or simply mistakes. We chose the 10 per cent level because it gave slightly better estimation results in terms of pseudo-R2 and likelihood function values at the optimum, although the differences were not very significant.

and 1. Chart 1 and Table 1 show the behaviour and some descriptive statistics of the main explanatory variables used in this work[8].

For each variable, Chart 1 displays the median, mean and weighted mean values. This gives us an idea of the behaviour of that variable both for the average company and for the largest ones. A few comments are warranted in this respect. First, there is a clearly apparent cyclical behaviour of companies' profitability, with a marked trough in 1993. Second, there is a declining trend in the liquidity ratio, particularly clear in the largest firms. Third, the total debt ratio of the average firm is highest at 1985; it then declines until 1989 and holds relatively stable from then on. This contrasts with the recent growing trend of non-financial firms' debt ratios at the macroeconomic level, which is reflected in the behaviour of the weighted mean level of indebtedness. Therefore, it is clear from the chart that the increased non-financial firms' leverage in the second half of the nineties comes almost exclusively from the behaviour of the largest firms[9]. Fourth, the decline in the cost of debt since 1993 has led to historically low borrowing ratios at the end of the sample, even for large companies.

Turning to our main variable of interest, Chart 2 shows the default ratio, calculated as the number of companies defaulted at t normalised on the total number of companies existing at year t-1, both in our sample and in the whole Central Credit Register database[10]. The default frequency in our sample is five percentage points lower on average than that in the Central Credit Register, but the trends are the same, particularly from 1990 on. Certainly the difference in levels must be related to the bias towards large companies in the CBA database. But that is not the whole explanation. Looking at the relationship between default rates and firm's size, it is found that, contrary to what it is expected and with the exception of the smallest firms, there is a positive relationship between these two variables in our sample (see Chart 3)[11]. This counter-intuitive result is particularly evident in the eighties, when the coverage of medium to small firms in the CBA is particularly low (see Chart 4). Thus, it seems that, while the coverage of large firms by the CBA is relatively high, its coverage of small to medium firms is biased towards 'good' companies.

It is important also to make a distinction between total defaults and new defaults. As already mentioned, new defaults refer only to defaulting companies that were previously non-defaulters. The total default ratio is higher and more persistent than the new default ratio (see Chart 5). That is because when a company goes into default, it can stay in that status for more than a year. In fact, Table 2 shows that, in our sample, 62% of the companies in default at t are still in default at t+1, whereas only 1.1% of the non-defaulters at t are in default at t+1. In principle, the total default ratio should better reflect the health of the overall non-financial firms sector. However, it could happen that, once in default, the behaviour of a company differs from that in non-default status. For example, there might be a threshold effect, so that a defaulting company does not re-start payments until its financial condition is sufficiently better than when it entered into default. In that case, pooling the information on defaulted and non-defaulted firms might be misleading[12].

In any case, the aggregate default ratio shows a notably cyclical pattern. It was relatively high during the mid-1980s, as a result of the long aftermath of the oil crises in the late-1970s/early-1980s. It then fell to around 1%-1.5% during the expansionary 1988-1991 period and returned to historically high levels in the economic recession of 1993.

8. See the Appendix for definition of the variables.

9. See also Benito (2002).

10. Note that the sample period in Chart 2 is from 1986 to 2002. This is because we are looking at defaults the year after.

11. This is so regardless of the way we measure the firm's size.

12. It is also interesting to see that, particularly around the recession in 1993, the number of companies in the sample that turn out to be in default a year later tends to be higher than the number of effective defaults in the sample a year later. That could indicate that the attrition rate in the CBA is higher for stressed companies than for normal companies. To a large extent, our procedure corrects this problem.

Subsequently, there has been a continued decline to a rate of 0.5%-1% currently, against an empirical background of falling interest rates and sustained GDP growth rates.

4 DEFAULT PREDICTION

4.1 Basic results

Under the theoretical assumptions detailed in Section 2, we estimate various probit models for the probability of firm i being in default in December of the following year, based on accounting data for the current year. Initially, we restrict ourselves to linear models and to firm data, considering different alternative definitions of profitability, liquidity and so on. The main results are summarised in Table 3[13], where, for simplicity, only the results for the particular definitions of the financial indicators that we finally use are shown. In all cases, 15 sectoral dummies, defined in the same way as in Corcóstegui *et al.* (2003), are included as explanatory variables, being jointly significant at the 1% level.

When we look at total defaults (Model 1) a relatively high number of financial indicators turn out to be significant predictors of default. All of them have the correct sign apart from size (measured by the log of real sales), a result we have already explained above as being a consequence of the composition of the CBA database. The 'new firm' dummy variable, which picks up those companies that are five years old or less, is however non-significant, but this could be explained by the fact that this information is only available since 1992. In spite of many variables being significant, the fit of the model –as can be seen from the pseudo-R2– is not very high, although this is not unusual for probit models based on cross-sectional data and is in line with the results in other papers[14].

Compared with non-defaulting companies, those defaulting at t+1 are characterised, on average, by higher borrowing and debt ratios, lower return on assets, lower real sales growth, lower liquidity ratios and more dividend omissions. But there is wide dispersion in the data. For example, it can be seen from Table 1 that some companies default having very low (even zero) borrowing and/or debt ratios. On the contrary, some other companies survive despite having very high borrowing and debt ratios.

Another interesting result based on the last panel of Table 1 is that firms already in default at t are financially somewhat better than firms non-defaulting at t but defaulting at t+1. At least, this is the case in terms of return on assets, real sales growth and borrowing ratios. However, this latter variable is clearly affected by the process of default. Thus, if a firm is in arrears, it is not paying all its interest due and hence its actual borrowing ratio is lower. But in this case it is not a real sign of financial health.

Focusing on new defaults only (Model 2 in Table 3), the results are somewhat different, with the borrowing ratio being the most significant fragility indicator. But the rest of the variables are still significant in general, including now the 'new firm' dummy variable, which is positive, reflecting the higher probability of default of new companies compared with old established companies. The positive sign of the 'no age' dummy variable reflects the higher average default rate in the years prior to 1992, for which the firm's age is not available.

Given the different results for firms already in default at t and new defaulters at t+1, the preferred strategy should be to take into account the credit status of the firm at t to predict defaults at t+1. This is done in Model 3 in Table 3. In this case, all explanatory variables were included in the regression interacted with the firm's default status at t, although only a few interactions turned out to be significant (those with the borrowing ratio, dividend omission and new firm dummy). The fit of the model increases considerably (the pseudo-R2 increases from 0.15 in Model 1 to 0.42 in Model 3), but looking at the estimated coefficients,

13. The definition of the variables can be found in the Appendix.
14. See, for example, Bunn and Redwood (2003).

it is clear that this comes almost exclusively from the persistence of defaults. The probability of being in default at t+1 is 50 percentage points higher if the company is already in default at t than if it is not. Since the probability of default is generally very low, this means that Model 3 is basically equivalent to classifying all companies defaulted at t as predicted defaults a year later. The capacity of the model to distinguish those companies in default at t that return to a normal credit status at t+1 is very low and, with respect to those that go from non-default to default, the estimated marginal effects are very similar to those in Model 2[15].

Thus, when looking at micro firm data, it is important to take into account the credit status of the firm, since the information content of some of the more commonly used financial ratios differs depending on its credit status. In terms of our original aim of finding out the relative importance of the different financial indicators for the health of the non-financial corporate sector, Model 2 is more informative than Model 1, because the estimated marginal effects of the explanatory variables on the probability of default are not biased by the inclusion of firms already in default.

4.2 Some extensions

Focusing on Model 2 (new defaults), we tried two possible extensions of the basic model. Firstly, there are strong reasons to believe that the impact of financial ratios on the probability of default will not be linear, as has been supposed in the above models. For example, a fall in profitability from 6% of total assets to 4% is not expected to have the same impact, on a firm's financial health as a fall in profitability from 1% to -1%. Similarly, an increase in the liquidity ratio from 0% to 5% should not have the same impact as an increase in the liquidity ratio from 20% to 25%, and so on. Secondly, apart from the micro variables we have considered so far, there may be additional information contained in macro variables that could help predict firms' rate of failure.

Regarding possible non-linearities in the model, we applied the following procedure. For each financial ratio, we explored the form of its relationship with the firm's probability of default by using dummy variables for different values of the financial ratio instead of the actual value of that ratio. We also considered simple functional forms like the square, cubic or inverse of the explanatory variable. The best fit is obtained with the specification presented in model 4 in Table 4, in which the variables entering in a non-linear form are the cube of the borrowing ratio, a dummy variable for firms with negative profitability and a dummy variable for firms with a liquidity ratio below 2.5%. The pseudo-R2 of the model is somewhat better than in Model 2 in Table 3 and all the variables are significant.

As regards macro (or aggregate) variables, Model 5 in Table 4 exhibits the results of including year dummies in the equation. These dummies should reflect the impact of all possible relevant macro variables and are, in fact, jointly significant at the 1% confidence level. However, this model is not very informative about what the relevant macro variables are and it is not very useful for forecasting purposes. Model 6 presents an alternative specification in which the real GDP growth rate and the median cost of debt for the non-defaulted companies in each year are substituted for the year dummies[16]. Nonetheless, a dummy for the year 1987 is kept in the model to capture that year's spike in corporate defaults, apparent in our sample but not in the more comprehensive Central Credit Register data[17]. The two macro variables and the 1987 dummy are clearly significant, with higher GDP growth reducing the probability

15. Interestingly, the marginal effect of the borrowing ratio for firms already in default at t –which is equal to the sum of the marginal effects of the borrowing ratio interacted and un-interacted with default at t– is not significantly different from zero. This is clearly the result of the distinction between firms' interest payments and firms' interest obligations when they are in arrears.

16. We tried both with real and nominal aggregate cost of debt. Although both are significant, the latter is more informative and, in fact, when both rates are included, this is the only significant one.

17. Neither of these two models includes the new firm/no age dummies, because of the collinearity between the latter and the macro variables.

of a firm's default, all else held constant, and higher nominal aggregate cost of debt increasing it.

Chart 6 shows how the inclusion of the macro variables improves the fit of the model in terms of the temporal behaviour of the average predicted default rate. When the macro variables are not considered, the predicted rate has the same cyclical and trending behaviour as the final model. Thus, for example, the average predicted default rate at the end of the sample, in spite of having increased since 2000, is still below the lowest level reached in the previous business cycle of the 1980s/early-1990s. Nonetheless, there is significantly less time variation in the predicted series than in the observed series. Including GDP growth and the median cost of debt as explanatory variables helps to capture better both the high default ratios around 1993 and the low levels since 1998.

The contribution of these aggregate variables to explaining an individual firm's probability of default can be attributed to the existence of externalities in firms' failures, as well as to the impact of additional factors related to macroeconomic developments. Thus, for example, in a recessionary context, with many firms failing and banks less willing to assume new risks, it is more likely that a given level of profitability and indebtedness ends up in default than it would be in an expansionary context. Similarly, a background of sustained low aggregate nominal and real interest rates implies a more stable macroeconomic outlook that should impact favourably on the capacity and willingness of firms to assume more debt and of banks to grant credit. This latter effect, together with an improvement in the risk management of lenders and borrowers, could explain the historically low default ratios since 1998 and is captured in our model through the incorporation of the aggregate cost of debt. To give an idea of the importance of this effect, if we substitute the average of the median cost of debt between 1985-1993 (14.3%) for the observed value in 2001 (6.0%), the mean predicted probability of default for 2002 increases from 0.62% to 0.97%. Conversely, with the current (2001) level of the cost of debt, the expected probability of default in 1994, would have been 1.36%, instead of 2.08%.

The performance of the final model (Model 6) in terms of the classification accuracy of the different firms into future defaulters and non-defaulters can be seen in Table 5. Naturally, the higher the estimated probability of default above which a firm is classified as a failure, the lower the number of predicted failures and the percentage of non-failures incorrectly predicted as failure (Type II error). However, the higher the cut-off value, the higher the percentage of failures that are not correctly predicted (Type I error).

5 ANALYSIS OF THE ESTIMATED PROBABILITIES OF DEFAULT

Once we have a model to estimate the probability of failure of a firm in a particular year, we can analyse not just the behaviour of the average default rate, but also its distribution across firms. This is important since, as Chart 7 shows, this distribution is strongly positively skewed. Thus, for example, in 1988, half of the firms had an estimated probability of default between zero and 0.34%, meaning they had a very low probability of failing, but 10% of the firms had an estimated probability of default above 2.77%. From the point of view of macroeconomic and financial stability, it is more relevant to analyse the firms in the upper percentiles of the distribution. In this respect, it is interesting to see how the historically low average probabilities of default since the mid-1990s were accompanied by a noticeably lower dispersion across firms. This is reflected in the more marked fall in the 90th percentile since 1994 than in the mean or median of the distribution.

After the peak in 1994, the three measures of financial risk represented in Chart 7 show a clear downward trend, reaching a trough in 2000. Since then, all of them show a slight increase, which is once again more marked in the case of the 90th percentile. Nonetheless, importantly, the levels of risk at the end of the sample are still below the minimum levels reached in the boom years of 1988-90.

Although given the non-linear nature of the probit model, it is not possible to perform a standard analysis of the contribution of each explanatory variable to changes in the predicted probability of default, we can still get an idea of their relative importance by looking at the changes in the average values of the explanatory variables multiplied by the estimated coefficients. According to this procedure, the increased average probability of default in the last two years of the sample is related, to a similar extent, to the negative behaviour (see Chart 1) of the borrowing ratio, the debt to assets ratio, GDP growth and, somewhat less importantly, the median cost of debt. With respect to the more 'structural' difference between the estimated mean likelihood of failure in 2002 and in 1988-89, as Chart 6 makes clear, this is mainly explained by the macro variables, with the fall in the median cost of debt more than offsetting the lower GDP growth rate in 2001 compared with 1987-1988.

So far, the analysis has not taken into account the fact that firms are not equally important in terms of the systemic implications of their potential failure. A given distribution of default probabilities may have very different results depending on the size of the firms more likely to default. In this context, Benito *et al.* (2001) defined the concept of 'debt at risk' as the product of the probability of default by the amount of debt of each firm. Summing over all the firms leads to an aggregate measure of debt at risk, which reflects both the likelihood of failure and the systemic importance of that failure. When this aggregate debt at risk is expressed as a percentage of total debt, it can be interpreted as a weighted average of the individual probabilities of default, where the weights are the shares of each firm's debt in total debt. Thus:

$$\frac{DAR_t}{D_t} = \frac{1}{D_t}\sum_{i=1}^{N} D_{it}\,\hat{p}_{it} = \sum_{i=1}^{N}\left(\frac{D_{it}}{D_t}\right)\hat{p}_{it}$$

Using total non-equity liabilities as the measure of total debt, we calculated the weighted average predicted probability of default, as well as the 90th percentile[18], and compared them with their unweighted counterparts (see Chart 8). It can be seen that the weighted average is generally above the simple average, reflecting the higher default

18. This is the value of the probability of failure such that 90% of the total debt is in firms with equal or lower likelihood of failure. That is, 10% of the total debt is owed by firms with a higher probability of default. To calculate this and the weighted average, we excluded one big holding company which distorted the results for the years 1998-2002.

frequency of the largest firms in our sample. Differences in the first part of the sample should be at least partly related to the problem of sample selection, but, since 1998, the divergent behaviour of the two measures must also be related to the relatively worse performance of financial ratios in the largest Spanish firms (see Chart 1) compared with the average firm. In fact, in 2002, just five companies accounted for more than 50% of total debt at risk, up from 25% in 1998. Therefore, according to this measure, overall financial risk in the non-financial corporate sector was highly concentrated in a few very large firms, but not because of their high probability of failure but rather due to their size. In any case, the estimated default risk in the Spanish non-financial corporate sector in 2002 was historically low, however measured.

As regards the sectoral distribution of the 10% of firms more likely to default in 2002, 21% of them were in the Construction sector. However, this is due to the high number of firms belonging to that sector in the sample, so that there was no significant difference in the probability of being above the 90th percentile for firms in the Construction sector and in the whole sample. The sectors with the highest proportions of companies in the upper part of the distribution were: Agriculture, forestry and fishing; Paper; and Hotels and restaurants. On the contrary, those with the lowest proportions were: Telecommunications and R&D; and Wholesale and retail trade.

6 CONCLUSIONS

In this paper, we have contributed to the quantitative analysis of the financial health of the Spanish non-financial corporate sector by constructing a synthetic leading indicator of the probability of a firm failing to meet its future financial obligations. The study is motivated by the implications of this analysis for the banking and financial systems, and potentially for the real investment and employment decisions of firms and thus for overall macroeconomic stability.

To this end, we matched firms' accounting data from the Central Balance Sheet Data Office of the Banco de España with credit data from the Spanish Central Credit Register. This resulted in a large data set (80,701 observations) covering a significantly longer time period (1985-2001) than is usual in the literature.

In the process we discovered the importance of distinguishing between firms that remain in default for more than one period and new defaulters, as well as the relevance of non-linearities to the relationship between the explanatory financial ratios and a firm's probability of default. Even the relatively simple treatment of non-linearities used in this paper is better than the more standard linear approach. Firms' measures of indebtedness, profitability, income leverage, liquidity, dividends and sales growth contribute to explaining corporate defaults. Nonetheless, purely micro variables turn out to be unable to accurately capture the temporal behaviour of the observed probabilities of default, probably due to externalities and other macro effects. Thus, in our model both the real GDP growth rate and the median interest cost of debt are significant additional predictors of a firm's probability of default.

The financial pressure indicator constructed is a potentially useful tool for detecting vulnerabilities in the non-financial corporate sector, both at the aggregate level and in particular groups of firms. In this regard, our results show a low level of pressure in the latter part of the sample. Since 2000, there is a slight deterioration in firms' overall credit quality, which is somewhat more marked in the large firms and in those firms in the upper percentiles of the default risk distribution. This deterioration appears to be explained mainly by moderate increases in the borrowing ratio (interest payments to ordinary profits before interest payments) and the debt to assets ratio, together with the observed deceleration in GDP growth rate. Nevertheless, this weakening of the financial health of Spanish non-financial firms was limited and it did not reverse the historical decline in the estimated probabilities of default underpinned by the fall in interest rates. Thus the level of ex-ante corporate default risk at 2002 was still below the minimum in the previous business cycle, regardless of whether we measure it in terms of simple average, debt-weighted average or upper percentiles.

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TABLE 1. DESCRIPTIVE STATISTICS

	Total sample (80721 obs.)					
	mean	**median**	**min**	**p10**	**p90**	**max**
Borrowing ratio	0.436	0.352	0.000	0.000	1.000	1.000
Return on assets	0.037	0.029	-0.225	-0.025	0.121	0.270
Liquid/total assets	0.056	0.027	0.000	0.000	0.150	0.418
Debt/total assets	0.237	0.209	0.000	0.005	0.505	0.787
Trade credit/total assets	0.322	0.291	0.008	0.097	0.598	0.865
Total non-equity liabilities/ total assets	0.560	0.571	0.072	0.245	0.857	0.990
Omit dividend	0.722					
Real sales growth	0.058	0.026	-0.500	-0.205	0.338	1.000
Real sales	35166	5114	1	858	47551	9178421

	Non-defaults at t and t+1 (78265 obs.)					
	mean	**median**	**min**	**p10**	**p90**	**max**
Borrowing ratio	0.426	0.333	0.000	0.000	1.000	1.000
Return on assets	0.039	0.030	-0.225	-0.021	0.122	0.270
Liquid/total assets	0.057	0.028	0.000	0.000	0.152	0.418
Debt/total assets	0.232	0.204	0.000	0.004	0.498	0.787
Trade credit/total assets	0.322	0.291	0.008	0.098	0.598	0.865
Total non-equity liabilities/ total assets	0.556	0.567	0.072	0.243	0.851	0.990
Omit dividend	0.715					
Real sales growth	0.059	0.027	-0.500	-0.200	0.337	1.000
Real sales	35340	5106	1	865	47335	9178421

	Defaults at t+1 but not at t (841 obs.)					
	mean	**median**	**min**	**p10**	**p90**	**max**
Borrowing ratio	0.818	1.000	0.000	0.294	1.000	1.000
Return on assets	-0.029	-0.008	-0.225	-0.145	0.045	0.268
Liquid/total assets	0.027	0.011	0.000	0.000	0.069	0.418
Debt/total assets	0.382	0.367	0.000	0.109	0.650	0.787
Trade credit/total assets	0.309	0.269	0.008	0.089	0.592	0.865
Total non-equity liabilities/ total assets	0.694	0.720	0.072	0.392	0.968	0.990
Omit dividend	0.901					
Real sales growth	0.003	-0.043	-0.500	-0.348	0.371	1.000
Real sales	24580	5078	6	643	46318	989579

	Defaults at t (1615 obs.)					
	mean	**median**	**min**	**p10**	**p90**	**max**
Borrowing ratio	0.708	0.974	0.000	0.056	1.000	1.000
Return on assets	-0.008	0.002	-0.225	-0.125	0.075	0.270
Liquid/total assets	0.028	0.012	0.000	0.000	0.073	0.418
Debt/total assets	0.384	0.369	0.000	0.112	0.682	0.787
Trade credit/total assets	0.307	0.273	0.008	0.080	0.593	0.865
Total non-equity liabilities/ total assets	0.695	0.716	0.072	0.406	0.979	0.990
Omit dividend	0.936					
Real sales growth	0.026	0.004	-0.500	-0.371	0.407	1.000
Real sales	32234	5794	6	662	55953	2764177

TABLE 2: CREDIT-STANDING PERSISTENCE

Credit status at t	Credit status at t+1: Non-default	Default	Total
Non-default	78,265	841	79,106
Default	617	998	1,615
Total	78,882	1,839	80,721

TABLE 3. PROBIT RESULTS: LINEAR MODELS (a)

Model	Model 1		Model 2		Model 3	
Dependent variable:	Total defaults		New defaults		Total defaults	
Explanatory variables	**dF/dx** (b)	**t-ratio**	**dF/dx** (b)	**t-ratio**	**dF/dx** (b)	**t-ratio**
Borrowing ratio	0.0110	10.07	0.0091	11.47	0.0105	11.89
Return on assets	-0.0545	-10.93	-0.0287	-8.57	-0.0310	-9.02
Liquid over total assets	-0.0502	-7.45	-0.0185	-4.19	-0.0211	-4.51
Debt over total assets	0.0345	18.26	0.0103	8.18	0.0129	9.80
Trade credit / total assets	0.0165	8.79	0.0049	3.94	0.0062	4.76
Omit dividend	0.0093	10.54	0.0018	3.14	0.0021	3.17
Real sales growth	-0.0063	-5.63	-0.0020	-2.62	-0.0028	-3.63
Log of real sales	0.0012	6.15	0.0004	3.13	0.0004	3.38
New firm (c)	0.0003	0.22	0.0027	2.64	0.0029	2.54
No age (c)	-0.0004	-0.64	0.0015	3.43	0.0018	3.44
Default at t					0.5056	16.95
Default at t*Borrowing ratio					-0.0140	-8.27
Default at t*Omit dividend					0.0230	4.29
Default at t*New firm (c)					-0.0044	-3.35
Default at t*No age (c)					-0.0043	-6.12
Number of obs	76897		75373		76897	
Log likelihood	-7045.54		-3829.14		-4771.67	
Pseudo R2	0.1493		0.1325		0.4239	

(a) All models include sectoral dummies.

(b) dF/dx for continuous variables is the marginal effect (in percentage points) of a 1 p.p. increase in the explanatory variable on the probability of default, evaluated at the sample mean of the variable. For dummy variables, it is the increase in the probability of default resulting from a change from 0 to 1 in the dummy variable.

(c) New firm is a dummy variable that takes the value one if the firm was created five or less years before. Since this information is only available from 1992 on, an additional dummy variable (no age) is added, with value equal to one when the age of the firm is not known.

TABLE 4. PROBIT RESULTS: NON-LINEAR MODELS (a)

Model	Model 4		Model 5		Model 6	
Explanatory variables	**dF/dx** (b)	**t-ratio**	**dF/dx** (b)	**t-ratio**	**dF/dx** (b)	**t-ratio**
(Borrowing ratio)^3	0.0078	11.32	0.0068	10.53	0.0071	10.57
Return on assets < 0	0.0056	7.53	0.0048	7.04	0.0050	7.10
Liquid over total assets < 2.5%	0.0032	6.57	0.0030	6.78	0.0032	6.86
Debt over total assets	0.0136	10.46	0.0132	11.04	0.0135	10.87
Trade credit / total assets	0.0068	5.24	0.0071	5.87	0.0071	5.66
Omit dividend	0.0020	3.24	0.0020	3.48	0.0021	3.45
Real sales growth	-0.0020	-2.57	-0.0012	-1.66	-0.0013	-1.68
Log of real sales	0.0004	2.77	0.0003	2.08	0.0003	2.16
New firm (c)	0.0024	2.32				
No age (c)	0.0016	3.31				
Real GDP growth					-0.0283	-2.17
Median nominal cost of debt					0.0301	4.33
Dummy 1987					0.0080	6.59
Time dummies	No		Yes		No	
Number of obs	75373		75373		75373	
Log likelihood	-3790.35		-3727.21		-3759.49	
Pseudo R2	0.1413		0.1556		0.1483	

(a) All models include sectoral dummies.

(b) dF/dx for continuous variables is the marginal effect (in percentage points) of a 1 p.p. increase in the explanatory variable on the probability of default, evaluated at the sample mean of the variable. For dummy variables, it is the increase in the probability of default resulting from a change from 0 to 1 in the dummy variable.

(c) New firm is a dummy variable that takes the value one if the firm was created five or less years before. Since this information is only available from 1992 on, an additional dummy variable (no age) is added, with value equal to one when the age of the firm is not known.

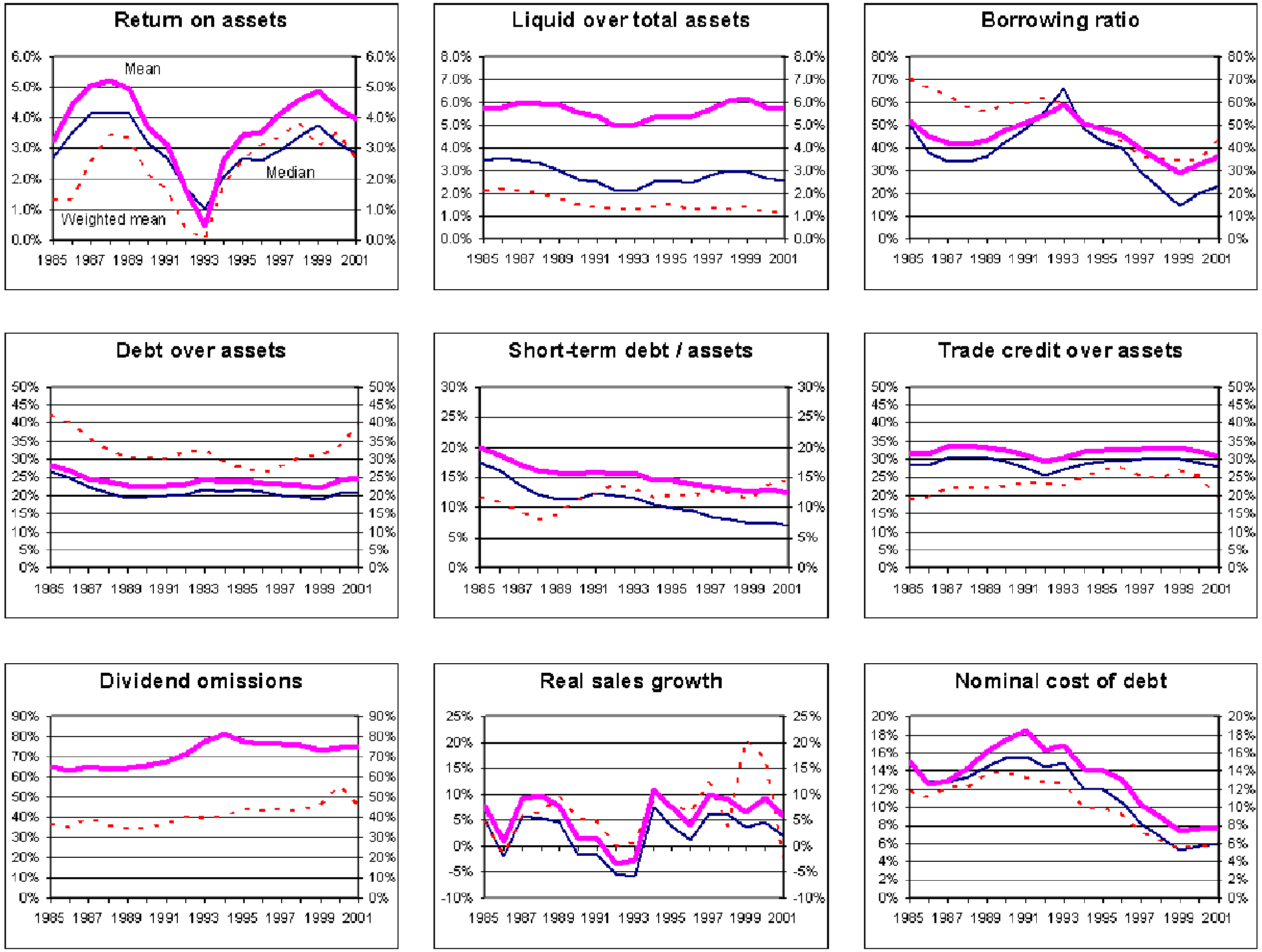
TABLE 5: PERFORMANCE OF THE FINAL MODEL (MODEL 6)

Cut-off pd>	Type I error % (a)	Type II error % (b)
0.7%	15.5	33.1
0.9%	19.5	27.8
1.1%	22.9	24.0
1.3%	24.6	21.2
1.5%	28.3	18.9
1.7%	30.9	17.1
1.9%	34.2	15.5
2.1%	37.3	14.1
2.3%	39.9	13.0

(a) Percentage of failures that are not correctly predicted.

(b) Percentage of non-failures that are predicted as failures.

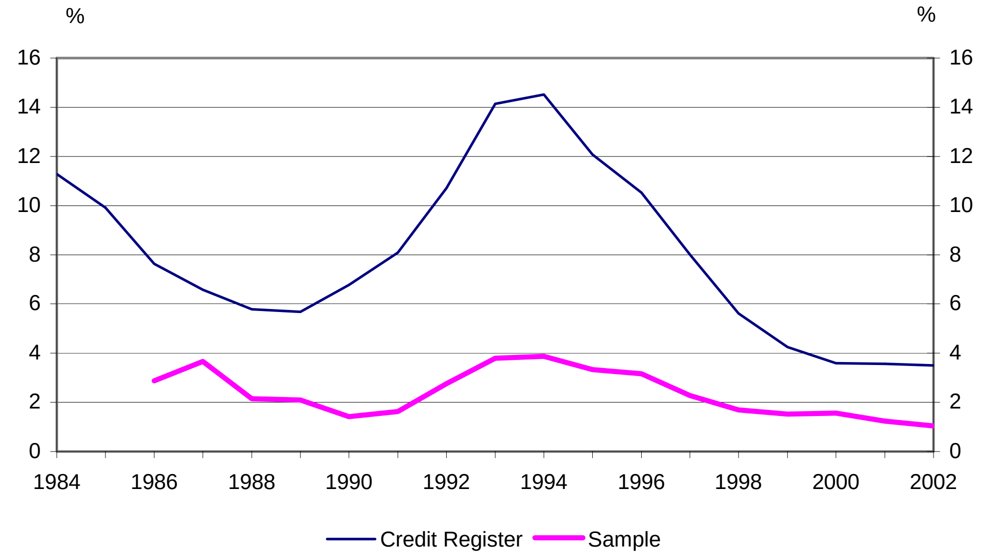
CHART 1. FINANCIAL INDICATORS OF SPANISH NON-FINANCIAL FIRMS



Note: The weighted mean is the average firm value weighted by total non-equity liabilities of each firm.

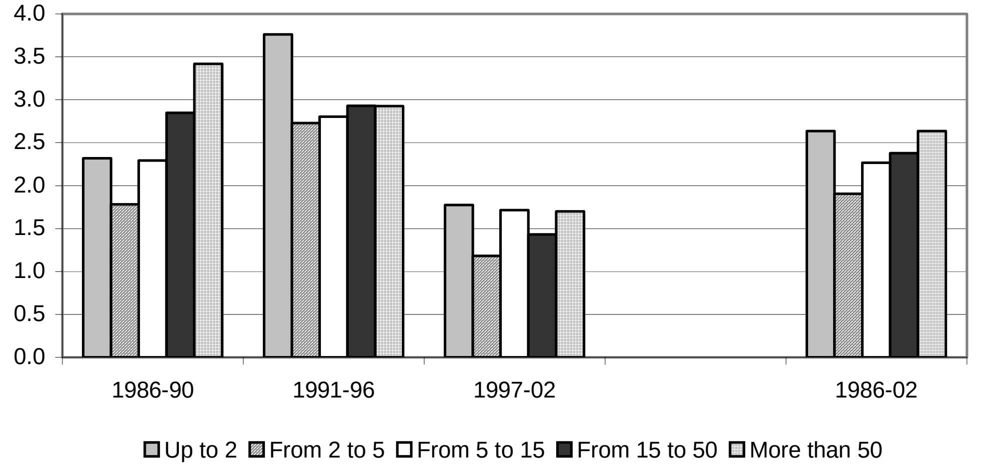
Source: Central Balance Sheet Data Office and own calculations.

CHART 2. OBSERVED DEFAULT RATIOS(a)

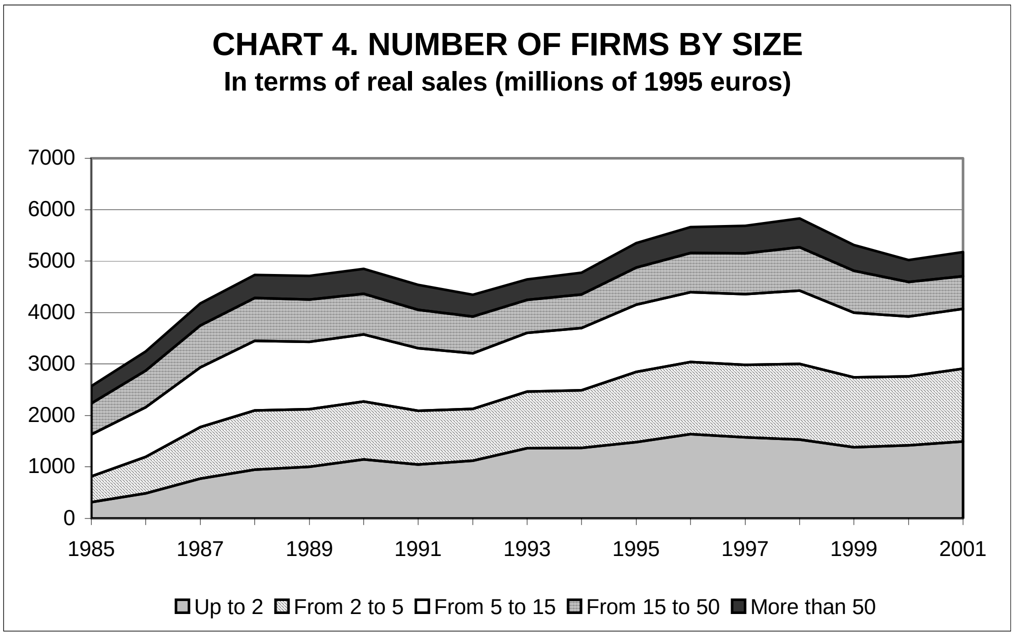


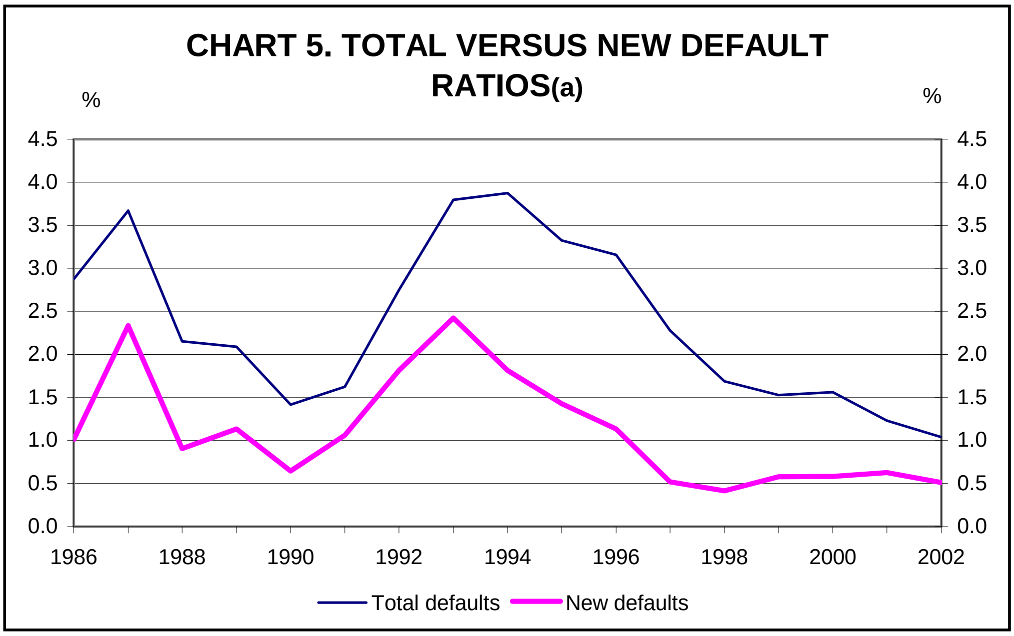
(a) Number of defaulted companies at t over total companies with data for t-1.

CHART 3. TOTAL DEFAULT RATIO (%) BY SIZE(a)



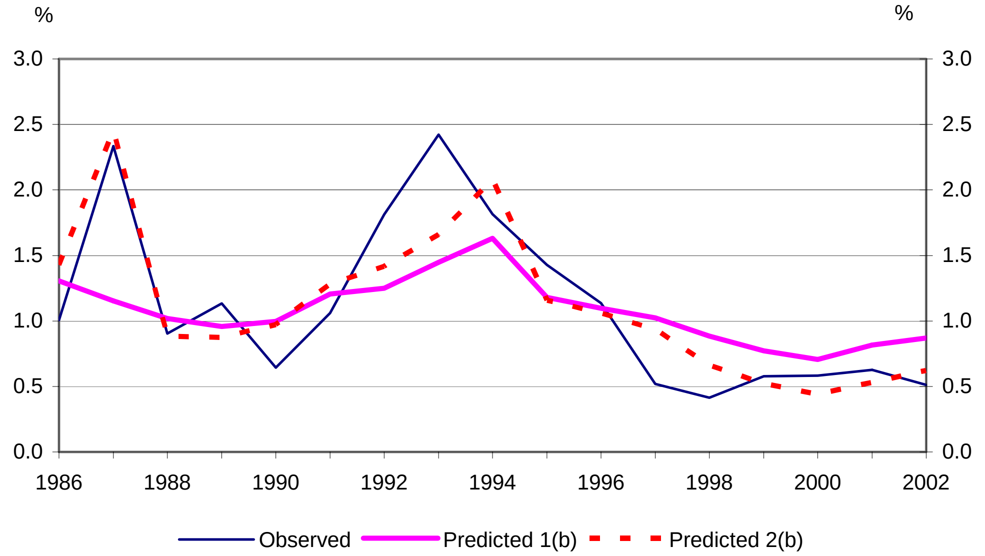
(a) In terms of real sales (millions of 1995 euros).





(a) Number of defaulted companies at t over total companies with data for t-1.

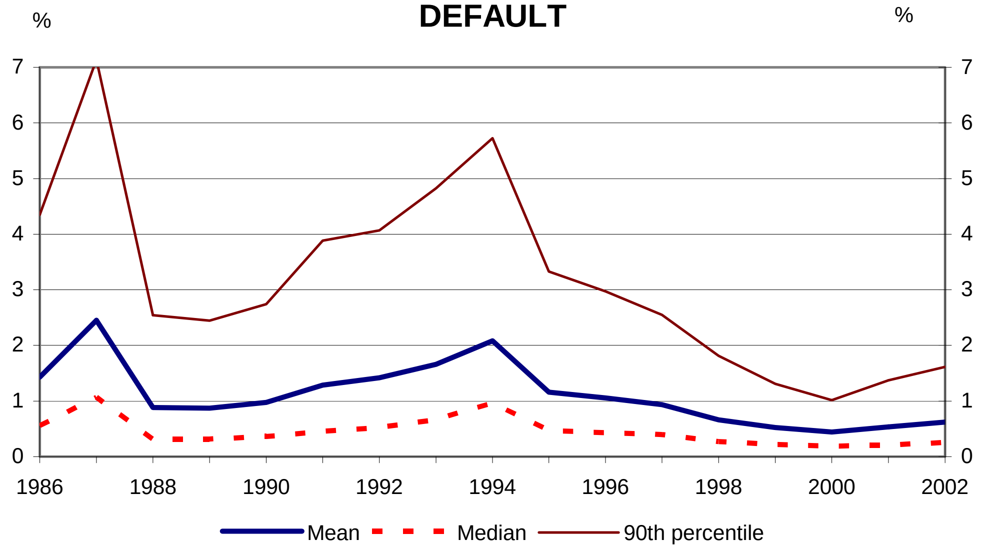
CHART 6. NEW-DEFAULT RATIOS(a)

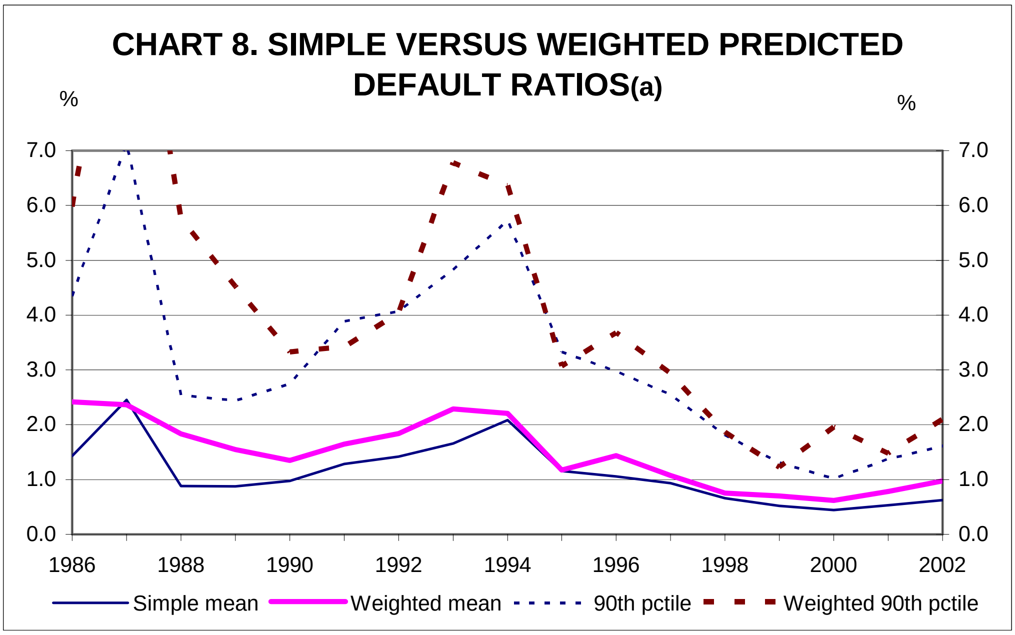


(a) Number of defaulted companies over total number of firms.

(b) Predicted 1 is according to the model without macro variables (Model 4 in Table 4). Predicted 2 includes also the effect of GDP growth, 1987 dummy and median nominal cost of debt (Model 6 in Table 4).

CHART 7. DISTRIBUTION OF THE PROBABILITY OF DEFAULT





(a) Total non-equity liabilities (number) of defaulted companies over total non-equity liabilities (number) of firms.

APPENDIX: VARIABLE DEFINITIONS

We have made use of different alternative definitions for each financial ratio. Those described below are the ones that were found to be more significant in the estimates and were consequently included in the final model or in the Tables or Charts.

Borrowing ratio: Interest payments / Ordinary profit plus interest payments.

Return on assets: Net profit / Average total assets (between t-1 and t).

Liquid assets: Cash and bank deposits.

Debt: All borrowing with an explicit cost (loans, bonds, etc.).

Short-term debt: Debt with less than one year to maturity.

Trade credit: borrowing from firms' suppliers.

Real sales: Sales deflated by GDP deflator.

Cost of debt: Interest payments / Average debt (between t-1 and t).

New firm dummy: equal to one if the firm was set up five or less year before.

No age dummy: equal to one if there is no information on firm's date of setting up.