Financial and Economic Determinants of Firm Default

Giulio Bottazzi*†, Marco Grazzi†, Angelo Secchi‡, and Federico Tamagni†

†LEM, Scuola Superiore Sant'Anna, Pisa, Italy
‡Università di Pisa, Pisa, Italy

January 8, 2009

Abstract

This paper investigates the relevance of financial and economic variables on firm defaults. Our analysis is not limited to publicly traded companies but extends to a large sample of limited liability firms. We consider size, growth, profitability and productivity together with a standard set of financial indicators. Non parametric tests allow to asses to what extent defaulting firms differ from the non-defaulting group. Bootstrap probit regressions confirm that economic variables play both a long and short term effect. Our findings are robust with respect to the inclusion of Distance to Deafult and risk ratings among the regressors.

JEL codes: C14, C25, D20, G30, L11.

Keywords: firm default, financial indicators, selection and growth dynamics, kernel densities, stochastic equality, bootstrap probit regressions, distance to default.

* *Corresponding Author*: Giulio Bottazzi, Scuola Superiore Sant'Anna, *E-mail*: bottazzi@sssup.it.

This paper presents an empirical analysis of firm default exploiting information on distress events occurring in a large panel of Italian firms. The fundamental motivation is to assess whether the inclusion of economic variables alongside traditional financial ones allows to better investigate the causes of firms' default, possibly improving the chance to correctly distinguish "healthy" firms from those at risk of distress.

Inside the broadly defined field of financial economics, and in particular in the analysis of firm default conducted in the context of credit ratings construction, firms' distress is typically conceived to be primarily determined by bad financial conditions, especially in the short run before default occurs. Purely industrial factors tend to receive less attention and sometimes turn completely left out of the analysis, possibly presuming that their effect is more relevant several periods before default and in any case already embedded into shorter run financial performances.[1] At the same time, it is well understood that the probability to stay in the market as well as the financial stability of a firm is deeply intertwined with the ability to perform well along the economic dimensions of firm operation. At least as long as market frictions or other institutional factors are affecting the speed and extent to which economic performances get perfectly reflected into financial structure and financial conditions, it is possible that looking exclusively at financial indicators cannot offer but a partial account of the main determinants of default. Starting from similar considerations Grunert et al. (2005) propose an "augmented" version of a standard financial model of default prediction which also includes two "soft" non-financial characteristics (managerial quality and market position) among the regressors. The aim of their exercise, asking whether non-financial indicators can improve upon default predictions based on banks' internal rating systems, is however different and to some extent narrower than what we are pursuing here. Yet, an empirical verification of whether economic variables contain any further explanatory power over financial indicators is largely lacking.

We believe that there is wide room for further improvements and we foresee financial literature can benefit from the inclusion in the default analysis of a sensible subset of economic indicators. Admittedly, the decision of which variables could play the most prominent role is difficult. However, modern theories of firm-industry dynamics offer a solid guidance to our attempt. Indeed, despite different schools of thought exist on the theory of the firm, a shared view is that survival and growth are eventually determined by the action of a selection mechanism which occurs through interaction and competition in the market, and operates on the economic characteristics of heterogeneous firms. Typically, one has models where a certain level of productivity/efficiency or, more generally, certain bundles of capabilities/competences represent the necessary conditions to remain in the market. Then, competition forces create a powerful market driven mechanism, so that the interplay between firm characteristics and the environment results into differential profitability levels and, ultimately, into exit or growth events. Whatever the specific theory one might discuss, there is strong agreement as to the identification of the suggested key levels of corporate performance: size-growth dynamics, profitability and productivity represent the crucial dimensions of performance along the selection process.[2]

These are the variables which we add to a set of standard financial indicators in our attempt to investigate the determinants of default events.[3]

A crucial aspect of the present analysis rests in its wide scope. While typical studies in firm default focus on large publicly traded companies, our studies cover almost 30,000 limited liabilities manufacturing firms very different in size and type of activity, which constitutes a representative sample of the Italian industry. In this respect the present analysis can also be seen as a contribution to the industrial economic literature concerned with the determinants of firm exit.[4]

We offer two specific contributions. First, we explore the heterogeneities possibly existing both within and across defaulting *vis á vis* non-defaulting firms along each dimension considered. We estimate the empirical distribution of their financial and economic characteristics and employ non-parametric tests for stochastic equality of the two groups, also looking at possible role played by time distance to default. Second, and in accordance to the main purpose of the paper, we estimate a series of probit models of default probability, allowing us to identify which are the main determinants of default once the effects of economic and financial factors are allowed to simultaneously interplay. Bootstrap techniques allow for robust estimates of the relevant coefficients, and a set of model evaluation criteria is also introduced, enabling to discern if default prediction accuracy is improved when economic characteristics are added to financial factors. The robustness of our findings is also checked against the inclusion of measures of distance to default (Merton, 1974) and risk ratings indexes among the regressors.

Our findings confirm the conjecture that explicitly adding economic indicators can enhance the understanding of the process leading to firms' default. The analysis of empirical distributions reveals that defaulting and non-defaulting firms display important differences, not only along financial characteristics, but along economic variables too. Further, results from bootstrap probit regressions reveal that economic characteristics exert a significant impact on the probability of default, complementary and additional with respect to the contribution of financial indicators. Notably, such an effect remains significant even near to default, when one would be tempted to assume that economic factors have been already embedded into financial conditions. These results do not depend from sectoral specificity at the level of 2-Digit industries, do not vary when we also include a variant of Merton's Distance to Default predictor among the regressors, and remain unchanged after a further extension of the models to include an official credit rating index.

The work is organized as follows. Section 1 presents a detailed description of the dataset. A first, descriptive comparison of defaulting *vs* non-defaulting firms is provided Section 2, based on kernel estimates of the empirical distribution of economic and financial variables in the two groups of firms. Section 3 further explores the issue by means of more formal statistical tests for equality of medians and for stochastic equality. In Section 4 we then tackle bootstrap probit estimates of default probability, focusing on whether the addition of economic variables can improve explanatory and predictive power of the models, as compared to a benchmark specification where only financial indicators are used. Robustness of results with respect to inclusion of Distance to Default and credit ratings is then tested in Section 5. Finally, Section 6 concludes suggesting some interpretations.

1 Data, variables and sample selection

We employ the database maintained by the Centrale dei Bilanci (CeBi), which contains financial statements and balance sheets of virtually all Italian *limited liability* firms. Italian Civil Law enforces the public availability of the annual accounting for this category of firms. CeBi collects and organizes this information, performing initial reliability checks. Included firms operates in all industrial sectors and no threshold is imposed on their size. This represents a remarkable advantage over other firm level panels, which typically cover only firms reporting more than a certain number of employees. The dataset as such is quite rich and detailed, and appears particularly suitable for the analysis of both large and small-medium sized firms.

For the sake of the present work we have access to Manufacturing data over the period 1998-2003. For each of the included firms, the following variables are available to us: Total Sales (S), Value Added (VA), Gross Operating Margins (GOM), Number of Employees (L), Cost of Labour, Gross Tangible Assets (K), Total Assets, Return on Investment (ROI), Return on Equity (ROE), Leverage (as the ratio of Assets over the sum of shareholders' equity plus annual income after taxes), Interest Expenses (IE), and Financial-Debt-to-Sales ratio (FD/S).

From this list, we select our indicators of firms' financial and economic characteristics, as follows. Concerning the financial side, although we can build less indicators than one typically finds in financial studies of bankruptcy prediction, we can anyway capture the "strands of intuition" (see Carey and Hrycay, 2001) lying behind the type of indicators usually employed. Interest Expenses (IE) provide a flow measure of the annual costs bore by firms to repay debt; Leverage is a standard indicator of the relative balance between external *vs* internal financing; finally, the Financial-Debt-to-Sales ratio (FD/S) gives a stock measure of overall exposure, scaled by size of the firm. On the other hand, concerning economic characteristics, we are able to include in the analysis measures of size, growth, profitability and productivity, that is, the four basic levels which theoretical models as well as empirical research in industrial economics suggest to use as reasonable measures of firm performances. Several proxies can be in principle adopted to measure each of these dimensions, each proxy capturing complementary aspects of the same phenomenon. Here we measure firm size in terms of Total Sales (S), and, accordingly, the log-difference of Total Sales (g^S) is used to measure firm growth. Next, we take the return on sales (ROS), given by the ratio between Gross Operating Margins and Total Sales, as a proxy for profitability performance. Finally, productive efficiency is captured by a standard index of labor productivity, measured in terms of value added per employee. Though limited, the list is sufficiently rich to give a relevant account of both the economic and the financial side of firm operation. In the robustness checks of Section 5 these variables are supplemented with a measure of distance to default, obtained from the balance sheet variables along the lines discussed in Bharath and Shumway (2008), and by a credit rating index produced by CeBi itself. The latter index enables us to indirectly include other dimensions which we might not directly capture through the available financial and economic variables (see Section 5 for details).

Accounting data from CeBi database are then matched with a dummy variable taking on value 1 when a firm incurs default at the end of the period (in either 2003 or 2004), and 0 otherwise. More precisely, default events are provided by an Italian bank only for those firms which were among its customers during the sample period. This implies that default status can be identified with certainty only for a subset of the available CeBi sample. It is therefore likely that our dataset understates distressed firms with respect to default frequency rates actually occurring in the population. Consequently, incorrect estimates might arise in regression analysis due to a "choice-based sample bias", which is a common problem faced by financial studies of distress prediction.[5] A basic strategy that we apply in order to overcome this potential drawback is to restrict the analysis only to those firms reporting at least 1 Million Euro of Total Sales in each year. The threshold is indeed a reasonable lower bound for our reference bank's customer size, so that excluding firms below this level of sales can enhance comparability between the default sub-sample and the rest of the dataset. On the top of this, a second cleaning step is to remove all those firms reporting only one employee. This cut allows to focus the study only on firms displaying at least a minimal level of structure and operation, and it is also intended to exclude self-employment, which is represented by single-employee businesses in the CeBi data.

Our final sample includes 23816 firms belonging to different manufacturing sectors. The first two columns of Table 1 reports the number of firms and default events by 2-Digit sectors, according to the NACE industrial classification.[6] The last two columns, instead, compare default rates in our data with default rates in the reference population of Italian firms in 2003, as officially reported by the association of the Italian Chambers of Commerce. As shown, underweighting of distressed sample is only partially solved by the implemented cleaning. Since this problem is likely to be particularly harmful for probit estimates, the analysis in Sections 4 and 5 also applies a bootstrap sampling procedure designed to make default frequencies equivalent to the actual default rates observed at the national level.

2 Descriptive analysis

This section analyzes if and to what extent the economic and financial characteristics of defaulting firms differ from the rest of the sample. We compare the empirical distribution of the relevant variables across the two groups of firms. To take account of the possible role of time, we present results at different time distance to default, comparing the estimates in the first available year, 1998, with the estimates obtained in the last year before default occurs, 2002. We apply non-parametric techniques, which do not impose any *a priori* structure to the data, thereby allowing to take a fresh look at the heterogeneities possibly existing both within and across the two groups of firms. The descriptive nature of this analysis is supplemented by formal statistical tests for distributional equality performed in the next Section.

2.1 Economic characteristics

We start with the comparison of firm size. In the two panels of Figure 1 we plot, on a double logarithmic scale, the kernel density of firm size (S) estimated for defaulting and non-defaulting firms in 1998 and in 2002. The actual values of S for each defaulting firm are depicted in the bottom part of each plot.[1]

First look at 1998. Somewhat contrary to what one might conjecture on the basis of theory and previous empirical studies, defaulting firms are neither less heterogeneous nor smaller with respect to the rest of the sample. The two densities are indeed very similar: supports are comparable, and the shapes are both right-skewed, an empirical result repeatedly found in the literature on firm size distribution. Actually, the weight on the right part of the support of defaulting firms density implies that default events are more frequent among medium-big sized firms rather than at small sizes. Estimates for 2002, in the right panel, show that these properties do not depend on time distance to default. The upper tail of the defaulting firms' distribution is indeed even heavier as compared to 1998. A formal non-parametric test of multi-modality (Silverman, 1986) cannot reject the presence of bimodality in the distributions of defaulting firms (with a p-score of 0.72 for 1998 and of 0.63 for 2002).

Such differences in the tail behavior is due to relatively few very big firms (see the dots at the bottom of the plots), but in the central part of the densities, where most of the observations are placed, the overlap is anyway almost perfect: if not bigger, defaulting firms are for sure not smaller than the others, at least on average. The evidence is therefore suggestive that there is a lacking clearcut relationship between size and the event of default: operating above a certain size threshold does not provide any relevant warranty in preventing default.

[1]Here, as well as in the following, estimates are performed applying an Epanenchnikov kernel, and the bandwidth is set following the "optimal rules" suggested in Silverman (1986), Section 3.4.

Next we focus on firms' growth rates. Figure 2 shows the kernel density of the log-difference of Total Sales, g^S for both defaulting and non-defaulting firms. The actual values for the growth rates of defaulting firms are reported below the estimated densities. Given the initial year of the sample is 1998, the first available data for growth is for 1999. This is shown in the left panel, while 2002 is depicted on the right graph.

Similarly to what emerged with size, defaulting firms do not seem to significantly differ from the rest of the sample. This is best understood by looking at the central part of the distributions (approximately between -1 and 1). In this part the distributions are crossing each other, and the estimated shapes are very similar, independently from the time distance to default. One difference emerges regarding the variability of growth episodes: in 2002, that is nearer to default, the width of the supports spanned by the defaulting group is sensibly lower. This gets also mirrored in the much less relevant presence of defaulting companies in the tails of the densities (outside the interval $[-1, 1]$). In both the years considered, extremely bad growth records are indeed exclusive prerogative of non-defaulting firms. Only few defaulting firms are instead responsible for the peaks present at the top extreme in 1999. These tail patterns are however too weak to conclude that one of the two groups is significantly outperforming the other, also because the different sizes of the two compared samples is likely to play a role in this respect.

We then repeat the same exercise with profitability performance. Figure 3 reports kernel density estimates of ROS in 1998 and 2002. The two groups of firms significantly differ: defaulting firms perform worse than the rest of the sample, especially for positive values of ROS. Indeed, in 1998, the two distributions are substantially overlapping in the negative half of the support, while the density of defaulting firms lies constantly below that of the other group in the positive half. The same ranking is reinforced in 2002. The distance between the two distributions in the right part of the support increases, and the density of defaulting firms is much concentrated at negative values. Overall, despite negative performance is experienced also by non-defaulting firms, there is sufficient evidence to suggest that some sort of selection on profitability seems to be at work: default events tend to associate with lower profitability levels. In addition, time plays an important role in the story, since profitability differentials across the two groups tend to becon wider in the very short run before default.

Finally, the densities of Labour Productivity, plotted in Figure 4, show that a similar selection mechanism is also acting upon productive efficiency. The estimates obtained for non-defaulting firms tend indeed to lie above the ones obtained for defaulting firms in the right part of the supports, especially if one nets out the effect of few outliers present at the extremes. The intertemporal comparison resembles the findings observed for profitability: the productivity advantage of non-defaulting firms increases over time. This suggests that Labour Productivity too represents a discriminatory factor telling apart defaulting firms from the rest of the sample. The relevance of this factor increases as the default event approaches.

2.2 Financial characteristics

We then ask if defaulting firms display any significant peculiarity as compared to non-defaulting firms when financial variables are considered. We rely on three financial indicators: Interest Expenses (IE), Leverage and Financial Debt-to-Sales ratio (FD/S). The analysis of the empirical densities can provide information not only on the central values of the two samples, but also on different characteristics such as shape, degree of heterogeneity among different classes of firms, skewness and so on, which are usually ignored by traditional approached based on the comparison of means or medians.

Figure 5 shows kernel densities of Interest Expenses over Sales IE/S, i.e. the proportion of annual revenues that goes to meet interest payments. The resulting estimates, reported in logs, suggest a clearcut difference between defaulting and non-defaulting firms. Both the average and the modal values of the former group are indeed larger than the ones of the latter. Also the shape of the distributions differ, with the defaulting firms much more concentrated in the right part of the support. A second noticeable feature is that, whereas the estimates for non-defaulting firms do not change over time, the density of defaulting firms displays a right-ward shift of probability mass between 1998 and 2002. This means that the burden of interest payments per unit of output sold becomes heavier as the default event approaches.

The densities of Leverage (Figure 6) and Financial Debt-to-Sales ratio (Figure 7) follow similar inter-temporal dynamics, even if the differences between defaulting and non-defaulting firms are smaller if compared to Interest Expenses. The shift in the Leverage distribution of defaulting firms means that the relative balance between self-financing and debt tends to increase over time, resulting into a disproportionate financial structure in proximity of the default event.

3 Non-parametric inferential analysis

In order to add statistical precision to the comparison between the two groups of firms, we now perform formal tests of distributional equality. A range of testing procedures is in principle available. There are however some specific features of our data which must be carefully considered in selecting the most appropriate alternative. First of all, given that default events are much less frequent than non-defaults, we need a test which can be applied in the case of two uneven samples. Second, as shown in the previous section, the distributions we are going to compare display clear non-normalities and unequal variances. Consequently, non-parametric tests should be preferred over parametric ones.

Based on the foregoing requirements, the first procedure we apply is a Wilcoxon-Mann-Witney (WMW) test. For each given financial or economic variable, X, the null hypothesis is that the two samples (defaulting, D, *vs* non-defaulting firms, ND) have equal median, $H_0 : m_D = m_{ND}$. We check the null against a two-sided alternative $H_1 : m_D \neq m_{ND}$. The exercise is performed separately for each year of the sample period before default occurs. Values of the WMW statistics and corresponding p-values are presented in Table 2. The general message is consistent with the foregoing descriptive analysis. The medians of the two groups display statistically significant differences with respect to all financial characteristics and also differ with respect to productivity and profitability performance. Size and growth, instead, do not seem able to always discriminate between the two groups, possibly recording some of the tail effects observed above in the shape of the kernel densities of these variables.

An implicit assumption of the WMW test is that the two compared samples only differ for a shift of location, while their distributions possess identical shapes. Given that the latter condition is in general violated by our data, it seems appropriate also to explore tests which abandon this hypothesis. However, when distributions with different shapes are compared, looking at the relative positions of median, modal or mean value can no longer be the most informative exercise, as the very meaning of these measures changes with the nature of the underlying distribution. A better measure of the relative position of the two samples is provided by the idea of stochastic (in)equality.

Let F_D and F_{ND} be the distributions of a given economic or financial variable, for the two samples respectively. Denote with $\mathbf{X}_D \sim F_D$ and $\mathbf{X}_{ND} \sim F_{ND}$ the associated random variables, and with X_D and X_{ND} two respective realizations. The distribution F_D is said to dominate F_{ND} if $\text{Prob}\{X_D > X_{ND}\} > 1/2$. That is, if one randomly selects two firms, one from the D group and one from the ND group, the probability that the latter displays a smaller value of X is more than 1/2, or, in other terms, it has a higher probability to have the smaller value. Now, since

$$\text{Prob}\{X_D > X_{ND}\} = \int dF_D(X)\, F_{ND}(X) \quad , \tag{1}$$

a statistical procedure to assess which of the two distributions dominates can be formulated as a test of

$$H_0 : \int dF_D\, F_{ND} = \frac{1}{2} \quad \text{vs} \quad H_1 : \int dF_D\, F_{ND} \neq \frac{1}{2} \quad . \tag{2}$$

The quantity $\hat{U}$ proposed in Fligner and Policello II (1981) provides a valid statistic for H_0. We apply their procedure exploiting the fact that, in case of rejection of the null, the sign of the Fligner-Policello (FP) statistic tells us which of the two groups of firms is dominant: a negative (positive) sign means that defaulting (non-defaulting) firms have a higher probability to take on smaller values of a given financial or economic variable.[2]

Table 3 presents the results obtained year by year. The high rate of rejection of H_0 supports the conclusions drawn from the WMW test, confirming that the two groups differ under many respects. First, looking at financial variables, the signs of the FP statistics are consistent with the idea that defaulting firms are suffering under all the dimensions considered. Second, as far as economic variables are concerned, defaulting firms tend to be less profitable and less productive than those in the other group, while the findings for size and growth are less clearcut. Possibly due to the already mentioned tail behavior observed in the empirical distribution of Total Sales, defaulting firms tend to be comparatively bigger in the second half of the period. Growth rates instead display statistically significant differences in 2002 only.

Overall, the findings broadly confirm the conclusions based on the kernel estimates. Notice also that differences in both economic and financial performances matter over both the shorter and the longer run. With the exception of growth, the null is already rejected at the beginning of the period, or at least some years before default.

4 Robust probit analysis of default probabilities

The analyses conducted so far tell us how defaulting firms compare with non-defaulting firms when each economic or financial dimension is considered on its own. Conversely, in this section we try to identify which are the main determinants of default once the effects of economic and financial factors are allowed to simultaneously interplay. Motivated by the attempt to test the commonly held presumption that default is mainly determined by poor financial conditions, especially in the short run before default occurs, the exercises we present are primarily meant to verify whether adding economic variables, in general, and looking at their effect at different time distances to default, in particular, might improve the chance to correctly distinguish "healthy" firms from those at risk of default. Our conjecture is that explicit consideration of economic variables should improve the understanding of default dynamics.

[2] Under the further assumption that the two compared distributions are symmetric, testing H_0 is equivalent to testing for equality of medians. This is what is usually referred to as the Fligner-Policello test.

To this end, we frame our research questions so as to single out the effects of financial and economic variables within a more standard parametric setting. As common in the literature, the response probability of observing the default event is modeled as a binary outcome Y (taking value 1 if default occurs, 0 otherwise), and then estimated conditional upon a set X of explanatory variables and controls. We employ a probit specification, where the default probability is assumed to depend upon the covariates X only through a linear combination of the latter, $X\beta$, which is in turn mapped into the response probability through

$$P(Y = 1 \mid X) = \Phi(X\beta) \quad , \tag{3}$$

where $\Phi(\cdot)$ is the cumulative distribution function of a standard normal variable, with associated density $\phi(\cdot)$. Due to the characteristics of the dataset, the covariates can be measured over the different years t of the window 1999-2002, while Y is measured after the end of the period only (at time labeled as T).[7]

Within this general setting, we consider two basic specifications of equation (3). In the first we include, among the regressors, only financial indicators together with a full set of 2-Digit sectoral dummies

$$P(Y_T = 1 \mid X_t) = \Phi(\beta_{0t} + \beta_{1t}\,\frac{IE_t}{S_t} + \beta_{2t}\,LEV_t + \beta_{3t}\,\frac{FD_t}{S_t} + \beta_{4t}\,\mathrm{Sector}_t) \quad , \tag{4}$$

where, as in the previous sections, IE/S stands for Interest Expenses scaled by Total Sales S, LEV is Leverage, and FD/S is the Financial-Debt-to-Sales ratio. The second specification is obtained adding the economic variables

$$\begin{aligned} P(Y_T = 1 \mid X_t) \;\; = \;\; & \Phi(\beta_{0t} + \beta_{1t}\,\frac{IE_t}{S_t} + \beta_{2t}\,LEV_t + \beta_{3t}\,\frac{FD_t}{S_t} + \beta_{4t}\,S_t + \\ & \beta_{5t}\,PROD_t + \beta_{6t}\,PROF_t + \beta_{7t}\,GROWTH_t + \beta_{8t}\,\mathrm{Sector}_t) \quad , \end{aligned} \tag{5}$$

where PROD is Labour Productivity (as Value Added per employee), PROF is profitability (in terms of Return on Sales), and GROWTH is the log-difference of Total Sales.

Several variations of equation (4) and (5) are estimated below. The estimation strategy is common, and goes as follows. As we already anticipated in Section 1, our database is underweighting the number of defaults as compared to distress rates observed in the reference population of Italian firms (see Table 1). This might give rise to a classical "choice-based sample" problem (Manski and McFadden, 1981), which is well known in the context of default probability models since Zmijevski (1984). There are in principle different ways to get rid of the potential bias, either by employing specific estimators designed for this situation (see Manski and Lerman, 1977; Imbens, 1992; Cosslet, 1993), or by performing bootstrap sampling. We follow the latter strategy, which has the advantage that it does not depend on specific assumptions about the distribution of the estimated parameters. The only requirement is that each bootstrap sample needs to be representative. Financial studies of distress prediction, where oversampling of default events is the typical situation, achieve this goal by performing randomized re-sampling of both defaulting and non defaulting firms in the desired, population-wide proportions (see, for instance Grunert et al., 2005). In our case, instead, the relatively low number of defaults suggests to take defaulting firms fixed, and randomly extract a subset of non-defaulting firms only. In order to reduce the bias as much as possible, randomization of non-defaulting firms is implemented within each 2-Digit industry, so that the ratio of defaulting over non-defaulting firms equals the population-wide default frequency reported in Table 1 at this level of sectoral disaggregation. This sampling procedure is repeated several times with replacement, and the different specifications of the probit equations (4) and (5) are then estimated on the sample obtained at each replication. In the following, discussion of results is based on the case when 200 independent replications, which turned out to be a large enough bootstrap sample.

It is also important to underline that all the regressions we present are performed after transforming each financial and economic variable in z-scores. This reduces them to have equal (zero) mean and equal (unitary) variance, allowing for a direct comparison of the magnitudes of the estimated effects across different models.[3] Notice that coefficient estimates associated with sectoral dummies will not be reported. We indeed find that only less than 5% of these coefficients turns statistically significant at the 5% confidence level, and the few significant sectors tend to differ across the different exercises considered. These results hold true throughout all the section, yielding strong support that sectoral specificities do not affect the link between the probability of default and the set of economic and financial characteristics included in our analysis.

4.1 Estimates with time averaged regressors

Our first exercise tries to achieve an overall understanding of the effects present in the data. We estimate regression (4) and regression (5) using the time average of each explanatory variable. For each firm these are obtained by averaging only for the number of years in which a given covariate is non-missing. In this way the time dimension is exploited in order to smooth the possible distortions of estimates due to outliers or missing observations. The z-scores are then taken after computing the time average of the variables.

Table 4 reports the estimation results (cfr. Panel A) computed over the 200 replications. Robust estimates of significance levels are built from confidence intervals based on bootstrap percentiles (see Efron and Tibshirani, 1993). That is, we first estimate the empirical probability distribution function (EDF) of the 200 coefficients obtained over the bootstrap replications. Then, statistical significance at the α% level is rejected if the zero falls within an interval

$$[\hat{q}(\alpha/2), \hat{q}(1-\alpha/2)] \quad , \tag{6}$$

where $\hat{q}(\alpha)$ stands for the estimate of α-th quantile of the bootstrap distribution estimated from the EDF.[8]

The results reported as Model I, corresponding to the "financial variable only" equation (4), shows that IE/S is overall the most relevant financial dimension, with an expected positive sign meaning that higher cost of debt service is increasing the likelihood of default. The findings for Model II, obtained from specification (5), strongly support the idea that economic characteristics do have a relevant effect, additional to financial indicators. In particular, Productivity and Profitability turn strongly significant and with an expected negative impact on the probability of default. Size shows weaker significance, and displays a positive effect which seems consistent with the foregoing evidence about kernel densities and stochastic dominance of defaulting firms, discussed in Section 2 and Section 3. Growth, instead, does not seem to have any significant effect. Also notice that the coefficient estimates obtained for the financial

[3] Another way to allow comparability of the magnitudes is to compute marginal (or partial) effect of each variable at the sample average of covariates. This is defined as the approximate change in $P(Y=1 \mid X)$ when x_j increases holding all the other variables constant, $\partial P(Y)/\partial x_j = \phi(X\beta)\beta_j$, evaluated at $\phi(\bar{X}\beta)$. Given the z-scoring, it is $\bar{X}=0$ and $\phi(\bar{X}\beta) = 1/\sqrt{2\pi}$, so that the marginal effect can be easily obtained from the coefficients reported in our tables.

indicators confirm the predominant role played by cost of debt. Leverage indeed displays a rather smaller coefficient, and weaker statistical significance as compared to IE/S.

Panel B then focuses on goodness of fit and prediction accuracy of the models. The first measure adopted is the Brier Score (Brier, 1950), which gives a standard indicator of model performance employed in the literature. This is computed as $1/N \sum_{i=1}^{N}(Y_i - P_i)^2$, where N is the number of firms, P_i is the estimated probability of default of firm i returned by the probit regression, and Y_i is the actual realization of default. We report the bootstrap mean of this measure over the 200 replications.

Prediction accuracy of the models is then evaluated building upon the concept of correctly classified observations. This is based on the idea of transforming the estimated default probability of a firm, P_i, into a 1 when the latter is bigger than a certain threshold value τ, while a firm is assigned a 0 otherwise. Such a classification obviously produces predictions which are distorted with respect to the true default or non-default status. A Type I error occurs when a firm which is actually defaulting in the sample (a true Y_i=1 in the data) is classified as non-defaulting, and thus is assigned a 0. Notice that this kind of mis-classifications represent the outcome which one is typically willing to avoid, since failing to predict a bankruptcy might be much more costly than mistakenly predicting a default, at least from the point of view of an investor. A missed chance of investing might instead be related to a Type II error, which is instead counted when a non-defaulting firm (a true Y_i=0) is assigned a 1 by the classification procedure. Then, the percentage of correctly predicted ones ("% Correct default" in the Table) gives the ratio of the correctly predicted number of defaults over the actual number of defaults present in the sample. Conversely, the percentage of correctly predicted zeros ("% Correct non default" in the Table) gives the fraction of correctly classified non-defaulting firms over the actual number of non-defaulting firms. Accuracy of predictions depends quite obviously on the specific value of the threshold τ, for the choice of which different criteria are in principle available. We consider an "optimal" τ^* so as to minimize the overall number of prediction errors (Type I plus Type II), weighted by the relative frequency of zeros and ones. In practice, this is obtained by picking the value of τ that solves the following minimization problem

$$\tau^* = \arg\min_{\tau} \left(\frac{1}{N_0} \sum_{i \in ND} \Theta(P_i - \tau) + \frac{1}{N_1} \sum_{i \in D} \Theta(\tau - P_i) \right) \quad , \tag{7}$$

where $\Theta(x)$ is the Heaviside step function, taking value $\Theta(x) = 0$ if $x < 0$ and $\Theta(x) = 1$ if $x > 0$, while N_0 and N_1 stand for the actual number of non-defaulting and defaulting firms in our sample, respectively, with ND and D the two corresponding sets.[9]

The figures in Panel B are obtained by repeating the minimization procedure for each of the 200 bootstrap replications, and then computing the bootstrap mean of the associated number of Type I and Type II errors, together with the average percentage of correctly predicted default and non default events.[10] What we observe is that Model II, the one including economic variables, tend to display better results, both in terms of lower number of errors and in terms of higher rates of correctly classified firms. However, a direct comparison of these numbers is not truly informative. The values of the accuracy measures reported are indeed computed for different values of τ^*, each optimal for its own model. A more reliable comparison would instead require to evaluate the performance of Model II when the optimal threshold of Model I is used: if the former performs better under the τ^* of the latter, this would imply a strong confirmation that including economic variables into the analysis is improving predictive power with respect to the benchmark "financial variables only" specification. This is done in Panel

C of the same Table 4, where we take the optimal τ^* of the "financial variables only" Model I, and use it to compute Type I errors, Type II errors and correctly classified observations of the corresponding "financial plus economic variables" Model II. It is clear that Model II is doing much better than the results obtained in Panel B for the benchmark: under all the considered measures, inclusion of economic variables reduces the number of both Type I and Type II errors, and it is also increasing the rates of correctly classified default and non-default events (from about 78% to about 85%, and from 68% to 69%, respectively).

4.2 Estimates with yearly regressors

By focusing on the average values of the dependent variables over time we neglected the dynamics possibly present in the effects of the covariates on the probability of default. Investigating the existence of time effects in the way financial or economic dimensions affect default probabilities is however a relevant issue, especially in understanding the extent to which financial conditions are indeed embedding the past history of economic dimensions of firm performance. With this question in mind, and within the limits of the relatively short time period covered by the data, we now repeat all the exercises by year. We again consider specification (4) and specification (5), but we now run separate regressions for each year t in the period 1999-2002. Table 5 shows estimation results as well as the analysis of model performance. As before, reported estimates are based on 200 bootstrap replications.

Panel A of the Table presents bootstrap means of coefficients, together with the non-parametric estimates of significance levels computed as explained above. Columns 1-4 show the findings concerning the probit regression (4), wherein financial factors alone are considered. The general picture is consistent with what observed employing the time average of the variables. We indeed obtain that IE/S retains the most relevant, and positive, effect on default probability over the entire period, while Leverage and FD/S display weaker statistical significance. This is connected to the finding that the estimates show some interesting variation over time. The stock of debt tends indeed to be more relevant at longer distance to default, then loosing significance in the shorter run, when the estimated impact of the flows of debt repayment is remarkably increased. Notice also that Leverage is turning significant only in the last year before default. This possibly captures part of the short run effect played by an excessive debt burden, thereby compensating for the disappearing significance of FD/S.

In Columns 5-8 we then add economic variables to the analysis, and repeat the same year by year exercise estimating the probit specification in (5). Overall, cost of debt is confirmed to play the crucial role among the financial indicators, but results also reveal that economic characteristics are relevant. Concerning the sign of their effect, estimates are broadly consistent with the probit analysis based on averaged variables, in turn reflecting the above discussion about the empirical distribution of the economic variables within defaulting and non defaulting firms. Size and growth tend indeed to exert a positive effect on the probability of default, while productivity and profitability display an opposite reducing impact. In addition, there is also evidence of intertemporal patterns which allow to identify interesting time effects, even over the relatively limited horizon allowed by the data. Statistical significance of economic variables is higher in the first two years, that is more distant from default, but it is also noticeable that only profitability and IE/S remain significant in 2002. The interpretation can be that, in the very short run, default is, not surprisingly, mainly determined by the balance between the adequacy of available internal resources generated by the operational activity of the firm, on the one hand, and the costs raised by the service of external financing, on the other hand. In other words, the two variables are to a certain extent summarizing the complementary effects of the two sets of dimensions – financial and economic – considered in the models, which both matter at longer as well as at shorter time distance to default. The bootstrap procedure with its random sampling of firms allows to safely conclude that the observed intertemporal variation cannot be simply attributed to outliers or missing observations affecting the estimates in each specific year.

A further test of the contribution offered by economic variables is conducted in Panel B of the same Table 5, where we show Brier Scores and prediction accuracy measures, these latter computed with their own optimal τ^*. Comparisons of Brier Scores between pairs of corresponding specification in each year – i.e. looking at each "financial variables only" model versus the "financial plus economic variables" model estimated in the same year – highlight that inclusion of economic variables results into improved model performance in 1999 and in 2002. The results in terms of prediction accuracy are even more suggestive of the significant role played by economic dimensions, as the models including the set of economic characteristics are always displaying a lower number of both Type I and Type II errors, as well as a higher percentage of correctly classified observations. More importantly, Panel C shows that a similar conclusion can be drawn even when prediction accuracy of the "financial plus economic variables" specifications is computed taking the optimal threshold τ^* of the "financial variables only" model in the same year. Indeed, as compared to the benchmarks figures of Panel B, the number of Type II errors is lower in two out of four years (1999 and 2002), while the number of Type I errors turns always lower. Finally, Panel D explores the performance of the different "financial plus economic variables" models against one single "financial variables only" benchmark specification. We take the τ^* of the "financial variables only" model of 2002, which is the best performing according to all the criteria (see Panel B), and we use it to re-compute all the prediction accuracy measures for the specifications including our set of economic variables. The result is that, once again, inclusion of economic covariates is able to generate significant improvements. Irrespective of the year considered, indeed, the "economic plus financial variables" specifications perform always better than the benchmark in terms of Type I errors and correctly classified defaults. Moreover, both Type II errors and the percentage of correctly classified non-defaulting firms turn also improved in 2002: consistently with suggestions derived from estimation results and Brier Scores, the contribution of economic variables is important even in the very proximity of the default event.

5 Including distance to default and credit ratings

Following the literature on corporate default prediction, there are two further measures which one should consider in the analysis of default probability, distance to default and credit ratings. In this section we investigate the robustness of foregoing bootstrap probit estimates with respect to inclusion of these further explanatory variables.

Distance to default is at the core of the last generation of empirical models of default prediction, adopted by both scholars and practitioners.[11] The theoretical foundation of this measure derives from an application of classical finance theory (Black and Scholes, 1973; Merton, 1974), modeling the market value of firm equity as a call option on the value of the firm, with strike price given by the face value of its liabilities. Distance to deafult (DD) is defined as a function of firms' underlying value of assets, of the volatility of the latter and of the face value of debt. Under the assumptions of the models, the probability of default is completely determined as the value of the density of a normal variable computed in DD, which is therefore considered as a sufficient statistic to predict default. Despite theoretically appealing, DD has two major limitations. First, computation of the measure is in practice rather complicated, essentially related to the non trivial estimates required to get a numerical solution of the models. Second, and relatedly, DD applies to publicly traded firms only, because computation of the underlying values of firms, not observable in practice, is based on the market value of equity, essentially exploiting the standard hypothesis that markets are fully informed and stock prices instantaneously incorporate all information on the underlying value of the firm. A solution to the first problem is to adopt a *naive DD* measure, which is much easier to compute than the original DD and ensures, at the same time, equivalent results in terms of default prediction accuracy (see Bharath and Shumway (2008) where this variant of DD is originally proposed). Yet, the *naive DD* still requires data on market values of firms' equity and assets, so that it is not obvious how it is possible to include this measure in the context of our study, where the scope of analysis goes beyond the limited subset of publicly traded firms, and, consequently, only accounting data are available.

Motivated by the widespread use and the solid theoretical basis of DD, we nevertheless attempt to include such a potentially important explanatory variable in the analysis. We start from the *naive DD* estimator of Bharath and Shumway (2008) and try to build an equivalent measure, denoted $BookDD$, based on accounting data on value of shares and value of debt, which we can derive from available figures on Leverage and Total Assets. Appendix I shows details on construction of this proxy and also shows that the inclusion of this further regressor does not affect any of the results achieved in the foregoing section. Bootstrap estimates indeed reveal that our $BookDD$ is never statistically significant, not even when it is used as unique regressor against the default indicator. Moreover, statistical significance and sign of the effects of financial and economic variables remain in practice unchanged, both on average and over year by year estimates.

The discussion of the results originated from the inclusion of credit ratings is more interesting. The motivation for this further check is twofold. First, credit ratings represent synthetic measures of some dimensions which our set of financial and economic regressors might have only partially captured. Rating procedure are indeed designed to embrace a wide range of firms' characteristics, together with qualitative and quantitative assessment of industry as well as national scenarios, technological changes, regulatory framework, and so on.[4] Second, credit ratings seem also a natural candidate to validate the statistical consistence of the timing effects discovered so far. Indeed, another intrinsic characteristic of credit ratings is their nature of a short-run forecast of default probability, evaluating firms' ability to meet their debt positions typically over one year period, or less.

The analysis is performed using the credit rating index developed by CeBi. The analysis can be replicated taking credit ratings from international agencies, such as Moody's or Standard & Poor's indexes, but a first obvious advantage of the CeBi index is that it is available for all the firms included in our dataset. On the contrary, international agencies are mainly concerned with bigger Italian firms, those who have either reached an international relevance, or are listed on stock exchanges around the world. As a result, using credit files from these well known institutions would have limited our robustness check of results towards a sub-sample of firms, not fully representative of the Italian system. Another peculiar characteristic of the

[4]This is typically the case with credit ratings issued by international agencies (see the "prototype risk rating system" described in Crouhy et al., 2001). This tendency has been more recently confirmed, by the effect of the provisions of the Basel II process, encouraging banks and financial institutions to also introduce ratings-based internal systems of risk assessment which consider a broad and multidimensional evaluation of their exposure (see BIS, 2001).

CeBi index is that it is an official credit rating, which allow us to safely assume that it is reliable and maintained up to international standards. Indeed, founded as an agency of the Bank of Italy in the early 80's, CeBi has a long-standing role as an institutional player within the Italian financial system. Credit rating construction is one of the core activity within its institutional tasks of providing assistance in banking system supervision. Nowadays a private company, CeBi is still carrying out an institutional mandate, as the Italian member within the European Committee of Central Balance Sheet Data Offices (ECCBSO), operating in close relationships with Italian Statistical Office and the major commercial banks.

On a more detailed level ground, the CeBi index is a "issuer credit rating", meaning that it gives an assessment of the obligors' overall capacity to meet its obligations, without implying any specific judgment about the quality of a particular liability of the company. It is updated at the end of each year, and thus allowed to change over time. The method employed for the computation of the index is exclusive property of CeBi. There is however no reasons to expect that the procedure is dramatically different from the methods applied by other rating agencies, both in terms of being targeted over the very short run (as said, one year ahead) and in terms of embracing a wide range of firms' characteristics. The firms included in the database, no matter whether defaulting or non-defaulting at the end of the period, are ranked with a score ranging from 1 to 9, in increasing order of default probability: 1 is attributed to highly solvable firms, while 9 identifies firms displaying a serious risk of default. Notice that the ranking is an ordinal one: firms rated as 9 are not implied to have 9 times the probability of going default as compared to firms rated with a 1. For the purpose of the present section, we build three classes only, which we label Low Rate firms (having lower probability of default, with credit ratings 1-6), Mid Rate firms (rated 7) and High Rate firms (rated 8-9).

The transition matrices among the three groups, displayed in Table 6, summarize the salient properties of the rating index in the sample. Over the longer-run transition 1998-2003, the Low Rate class is very stable, while both Mid and High Rate firms have an higher probability to jump back to better ratings, as compared to the likelihood of remaining in the same class. This gets reflected in the transition probability to end up defaulting (last column), which is higher for Mid Rate firms than for High Rate firms. Similar patterns persist in the 1-year transition 2002-2003. The numbers on the diagonal suggest higher stability within-class, as compared to the longer-run transition, but the "reversion to the mean" property – towards improved ratings – is still present, even in the High Rate group. The transition probabilities to default (last column) are more in accordance with what one would expect: probability of default increases with the value of the CeBi index, confirming that credit ratings are much better predictors of default in the very short run than over a longer distance to the event. In turn, the fact that the CeBi index displays variation over time is important, allowing to test the time effects of financial and economic variables observed in the foregoing probit regressions.[12]

According to the classification in three rating classes, we build three dummy variables taking on value 1 when a firm is belonging to one of the classes, and zero otherwise. These are then employed in order to investigate to what extent the estimates of default probability presented in the previous section turns affected by the inclusion of different credit rating conditions. The estimation strategy goes exactly as before. We specify default probability in terms of probit models, resort to bootstrap techniques intended to cure under-weighting of default event, and evaluate significance levels of the coefficient estimates via confidence intervals based on bootstrap percentiles.

We again start by considering the overall effects present over the entire sample period. In parallel with the above analysis, this can be done by averaging the relevant financial and economic variables over time. However taking the intertemporal average of the original values of the CeBi index would give a meaningless classification, due to the ordinal nature of this measure. Instead, the firms are assigned to our 3 rating classes according to two different criteria, taking either (a) the maximum value of the CeBi index (MAX, hereafter) received by the firm during the sample period, or (b) the value of the CeBi index as of 2002. Choosing the MAX corresponds to assign the firms to the worst rating class in the period. Taking the value of 2002 is instead meant to include the effect of credit ratings in the last available year before default is measured in our data, consistently with the nature of short run (1-year ahead) forecast of default which is embedded in the CeBi index. The two classification are likely to differ, due to the "reversion to the mean" property observed in the transition matrices (c.f. Table 6). In particular, classification according to the MAX value of the index is very likely to give a better account of past rating history of each firm.

The specifications attempted are as follows. We first estimate a "rating only" model

$$P(Y_T = 1 \mid X) = \Phi(\beta_0 + \delta_1\, LOW_\gamma + \delta_2\, MID_\gamma + \delta_3\, HIGH_\gamma) \quad , \tag{8}$$

where we alternatively consider $\gamma = MAX$ or $\gamma = 2002$, depending on the type of credit rating classification. Secondly, we add the other covariates, and estimate

$$\begin{aligned} P(Y_T = 1 \mid X) \;=\; & \Phi(\beta_0 + \delta_1\, LOW_\gamma + \delta_2\, MID_\gamma + \delta_3\, HIGH_\gamma + \\ & \beta_1\, \frac{IE}{S} + \beta_2\, LEV + \beta_3\, \frac{FD}{S} + \beta_4\, S + \\ & \beta_5\, PROD + \beta_6\, PROF + \beta_7\, GROWTH) \quad . \end{aligned} \tag{9}$$

As it was done in the previous section, z-scores of financial and economic variables are taken after computing their time average over the period 1999-2002. Statistical irrelevance of sectoral dynamics motivate the exclusion of 2-Digit dummies from the exercise.

Table 7 presents the results. Due to obvious collinearity between the rating dummies and the overall constant term, we present coefficient estimates of regressions where only the Mid Rate and the High Rate class are considered. Coefficients of the associated dummy variables are therefore capturing the effect of belonging to the two classes "in deviation" from a baseline Low Rate firm.

Model IA and Model IB report the coefficients for the benchmark case when credit ratings are considered alone, taking either the MAX or the 2002 value, respectively. The positive sign of the estimates suggests the expected increase in default probabilities of firms with higher ratings with respect to the baseline group. Still, we also see the influence of the reversion to the mean property observed above. High rate firms indeed display lower coefficients as compared to the Mid category. Such an effect is reduced, albeit still present, when the assignment of firms to rating classes is done according to the MAX rating over the period. Model performance measures (cfr. Panel B) agree with this description. Very low Brier Scores confirm the tight link between ratings and default events which is suggested by the strong significance of the estimated coefficients. Further, lower number of Type I errors obtained for the case where MAX rate is used are again suggesting that the worst rating does not need to coincide with the 2002 rating: due to reversion toward better ratings, the MAX is more able to correctly predict default events.

The estimates of specification (9), labeled as Model IIA and Model IIB, display very similar effect of credit ratings. More importantly, they also confirm much of the conclusions drawn in Section 4 about the role played by both financial and economic characteristics of firms. Credit ratings are indeed absorbing some of the variables, as compared to Table 4 of the previous section, but do not completely destroy the statistical significance of the other covariates. In particular, our findings are also consistent with the time effects suggested by the foregoing analysis. Indeed, cost of debt, captured by IE/S, turns out to be the only significant financial variable in the case we take the 2002 credit ratings, that is in the very short run to default. Conversely, the stock of debt is confirmed to be more important in the past, since statistical significance of FD/S does not disappear when we consider the MAX rating, that is when it is likely that we give more weight to past values of the CeBi index. The effect of industrial characteristics is instead summarized by Productivity, which is significant irrespectively of the type of rating employed to assign firms to the three rating classes. Panel B of Table 7 explores Brier Scores and accuracy prediction measures, the latter computed with the own optimal τ^* of each model. Brier Scores allow to conclude that credit ratings are clearly relevant. These are indeed lower as compared to the Brier Scores of the "financial plus economic variables" specifications investigated in Table 4 of Section 4. Still, computation of prediction accuracy against the τ^* of the "rating only" models (in Panel C) is yielding strong support that financial and economic factors are able to exert an additional effect. Both Type I and Type II errors are indeed less frequent as compared to the number reported in Panel B for the corresponding "rating only models". This holds irrespective of the type of rating employed. Model IIA is however outperforming Model IIB in terms of a lower number of Type I errors and also in terms of a higher number of correctly classified defaults. The interpretation is again that using the MAX value of rating provides a more accurate account of "past history" of the CeBi index, as compared to taking the 2002 value of the rating.

In Table 8 we present robustness checks of year by year probit regressions. That is, we measure rating class dummies and other covariates in each year t of the considered period 1999-2002, and run separate estimates by year. Once again, we compare a "rating only" specification

$$P(Y_T = 1 \mid X_t) = \Phi(\beta_{0t} + \delta_{1t}\, LOW_t + \delta_{2t}\, MID_t + \delta_{3t}\, HIGH_t) \quad , \tag{10}$$

with a second model where financial and economic characteristics are also included

$$\begin{aligned} P(Y_T = 1 \mid X) \;=\; & \Phi(\beta_{0t} + \delta_{1t}\, LOW_t + \delta_{2t}\, MID_t + \delta_{3t}\, HIGH_t + \\ & \beta_{1t}\, \frac{IE_t}{S_t} + \beta_{2t}\, LEV_t + \beta_{3t}\, \frac{FD_t}{S_t} + \beta_{4t}\, S_t + \\ & \beta_{5t}\, PROD_t + \beta_{6t}\, PROF_t + \beta_{7t}\, GROWTH_t) \quad . \end{aligned} \tag{11}$$

Columns 1-4 consider the estimates of regression (10). Results are still using Low Rate firms as the baseline. Therefore, the positive sign of the Mid Rate dummy must be interpreted as revealing that belonging to this class entails a higher probability of default relative to Low Rate firms. The effect is constantly significant over time. The sign of the High Rate class dummy is instead changing from negative to positive in 2002. This seems to suggest a further qualification of the "reversion to the mean" property of the CeBi index. Switching signs indeed signal the coexistence of two types of High Rate firms. A first group for which high ratings are persistent, but do not default at the end of the period, and a second group for which high ratings instead translate into default over the one year time period foreseen by the rating index. The existence of the latter group can indeed be responsible for the positive impact found in 2002, just before the time in which default is measured in our dataset. The former group can instead explain the negative sign for the years 1999-2001, implying a reduction of the probability to default with respect to the baseline Low Rate firm. This kind of dynamics might also affect model performance, in Panel B. As compared to the very short run model of 2002, the model of 2001 present lower number of Type I errors and higher rates of correctly predicted defaults (with own optimal τ^*), and a lower Brier Score. Also notice that the values of this latter measure are generally lower than the ones associated with the corresponding specifications without rating dummies investigated in Section 4 (cfr. Table 5), confirming that credit ratings retain the capacity to capture relevant dimensions omitted in the foregoing analysis.

The estimates of regression (10), obtained through adding financial and economic variables, are presented in the last four columns (5-8) of the Table 8. Rating dummies coefficients corroborate the results of the corresponding "rating only" models. The Mid Rate class displays the expected positive sign, and the switching sign observed for High Rate firms is also preserved. What is more, the previous effects of financial and economic variables are all surviving the inclusion of credit ratings. Indeed, we are able to confirm the estimates obtained for each corresponding model without rating dummies (cfr. Table 5). First, the cost of debt plays the main role among financial characteristics, also displaying the expected positive coefficient, increasing over time. Second, economic factors retain their signs: the estimates exhibit a negative impact of productivity and profitability on the probability of default, while size and growth tend to display a positive effect. Third, and last, we confirm the interesting time effects exerted by the interplay between the different dimensions considered. Economic variables, as a whole, tend indeed to be more important at longer distances to default, but there is evidence that they are retaining a relevant role also in the very short run to default. As in Table 5, this conclusion is supported by the strong significance of profitability in 2002, which is once again acting as a sort of summary variable of the dimensions connected with the strict operational activity of the firm. Overall, the main effect exerted by including credit ratings seems to be on model performance. As already noted for the specifications on averaged variables, Brier Scores are indeed lower for "rating only" models (cfr. Panel B). However, the inclusion of economic and financial variables improves the ability to correctly predict the default event: when they enter the regressions, the number of Type I errors decreases, and the number of correctly classified defaults increases. The same holds no matter whether we take the optimal τ^* of the corresponding "rating only" models in the same year (see Panel C), or we draw a comparison against the τ^* of the "rating only" model of 2001 (Panel D).

Summarizing, the analyses performed in this Section validate the robustness of the findings presented in the previous parts of the work. Strong significance of rating dummies, together with a steady reduction of Brier Scores, signal that credit ratings can surely complement for some of the relevant dimensions which are not considered in the previous exercises. Nevertheless, the conclusions drawn about the effect exerted by the set of financial and economic characteristics remain valid. The signs remain unchanged, and we can confirm their different statistical significance over the different (shorter *vs* longer) time distance to default allowed by the dataset.

6 Conclusions

Firms' distress is, in its essence, a financial phenomenon due to firm's inability to generate enough resources to repay commercial and financial debts. As a consequence it is commonly accepted that financial factors should be able, at least to a major extent, to capture the main determinants of default, in particular when the time of the event is approaching. In this paper we show, on the contrary, that the inclusion in the analyses of industrial or economic factors, like size, growth, productivity and profitability, turns out to be important.

Directly comparing the empirical distribution of a sample of economic and financial variables, we show that firms experiencing default are more financially exposed, less productive and less profitable in all the years before the default occurs, while differences in size and growth tend to be less significant. Our preliminary findings are statistically validated by means of formal tests of distributional equality. These tests allow us to safely conclude that it is possible to discriminate will-be defaulting from non-defaulting firms not only on the grounds of their financial situation, but also with respect to their industrial performances, at different time distances to default.

We then show that financial and economic dimensions do not explain the same aspects of default, but, rather, the two sets of variables capture diverse, albeit complementary, determinants of the process leading to firms' distress. Indeed, analyzing their respective effects within a set of probit models of default probabilities, we find that cost of debt exerts the most important effect among the financial variables, but economic characteristics also play a statistically significant role, remarkably over the entire time horizon covered by our data. The sign of the estimated effects turns as expected negative for productivity and profitability, which both reduce the likelihood of default, while size and growth tend to display a positive impact. This latter result, less intuitive at first, can be partially due to the fact that we record default events only for firms having established a formal credit relationship with a large commercial bank: these might be relatively bigger firms as compared to the other present in the reference population, but this is an issue which remains of course out of our direct control. Instead, we do not observe any significant over-representation of small firms in the non-defaulting group, suggesting that the threshold imposed on sales to clean the initial sample is not distorting the results.

What is more, probit regressions also provide evidence of interesting time effects. Indeed, economic variables tend to exhibit stronger statistical significance in the first part of the sample period, that is further away from the default event. However, their role remains relevant even in the very short run before default, when financial variables are usually conceived to be more important. Profitability, in particular, is displaying a strong effect in the last year before default, somewhat absorbing the other dimensions strictly related to the operational activity of the firm. As a consequence, the increase in the explanatory and predictive power of the model due to the inclusion of economic variables do not vanishes in the short run.

Robustness of findings is overall very strong. First, the bootstrap procedure employed should warrant us that probit estimates are not affected by choice-based sampling bias possibly due to under-weighting of defaulting firms as compared to the actual default at the national level. Second, coefficient estimates and time effects survive to inclusion of a credit rating index in the models. This is quite remarkable, since credit ratings represent, by construction, a short-run prediction of default, plausibly embedding many dimensions which are not completely measured by our set of financial and economic regressors. Finally, we find that sectoral dynamics do not display any impact: firms in 2-Digit sectors are certainly heterogeneous with respect to both financial and economic characteristics, but sectoral specificities do not affect the link between such characteristics and the default probability.

Overall, the findings yield empirical validation to the intuition, so far untested, that default cannot be regarded as a mere financial phenomenon. Rather, our evidence points towards the possible existence of frictions which prevent financial conditions from completely reflecting the industrial characteristics of the firms, both over the longer and the shorter run. This result, besides confirming our attempt to link financial and industrial economic research, might have important policy implications. One can indeed suggest that the accuracy of standard risk assessment devices – such as official credit ratings or risk management procedures internally maintained by financial institutions – might possibly devote too few attention to some important, economic rather than financial, factors. This suggests the necessity to develop broader, multidimensional assessments of corporate default risk, placing specific concern to the dimensions included and to the different time horizons considered. At the same time, this also has implications for the way one views the interaction between firms and financial markets, providing evidence in favor of the principles underlying the Basel II process, which is indeed encouraging the diffusion of an objective and comprehensive approach to evaluate investment decisions and exposure of financial institutions.

Appendix: Distance to Default

As explained in the text, we start from the *naive DD* of Bharath and Shumway (2008). For each firm, this is defined as

$$\text{naive DD} = \frac{\ln[(E+F)/F] + (r_{i,t-1} - 0.5 \text{ naive } \sigma_V^2)T}{\text{naive } \sigma_V \sqrt{T}} \quad , \tag{12}$$

where E is market value of equity, F is face value of debt, T is the time-to-maturity assuming each firm has issued just one bond maturing in T periods, $r_{i,t-1}$ is the firm's stock return over the previous year, and σ_V is the volatility of the value of the firms, computed as

$$\text{naive } \sigma_V = \frac{E}{E+F}\sigma_E + \frac{F}{E+F}(0.05 + 0.25\sigma_E) \quad , \tag{13}$$

with the last term in parenthesis being a naive estimate of the volatility of firm debt

$$\text{naive } \sigma_F = 0.05 + 0.25\sigma_E \quad . \tag{14}$$

This default predictor involves a computationally easier estimate of the underlying value of a firm as compared to numerical solution of Black-Scholes-Merton's equations, and its predictive power of default has been found to be comparable to that of the original DD measure.

To make this definition operational in the context of our dataset, where most of the firms are not publicly traded, we make the following choices, based on available accounting book variables. First, we place the time of computation in 2002, the last year before default is measured in our data, so that T=1. Second, E is proxied with the sum of annual income after taxes plus face value of outstanding shares, which we define Book Equity, BE. This is simply the denominator of our measure of Leverage, and therefore we can compute it by

$$BE = \text{Leverage} * \text{Total Assets} \quad . \tag{15}$$

Third, since Total Assets equals the sum of BE plus the stock of outstanding debt, due to Italian accounting practises, we can proxy F via

$$D = \text{Total Assets} - BE \quad . \tag{16}$$

Fourth, in place of $r_{i,t-1}$, we take the average of the growth rates of Book Equity, μ_{BE}, which we compute over each year of the sample period before default occurs (1999-2002). This smoothing is done to incorporate all available past information, which is what the *naive DD* assumes to be entirely captured by stock returns over the previous year, due to efficient and fully informed stock markets. Fifth, in place of the approximation of debt volatility contained in Equation (14), we directly compute the volatility of D, as the standard deviation of the growth rates of D in each of the years 1999-2002. Finally, the same is done for σ_{BE}, the volatility of Book Equity. Therefore, our "accounting book version" of the *naive DD* becomes

$$\text{BookDD} = \frac{\ln[(BE_{2002} + D_{2002})/D_{2002}] + (\mu_{BE} - 0.5 \text{ naive } \sigma_V^2)}{\text{naive } \sigma_V} \quad , \tag{17}$$

with

$$\text{naive } \sigma_V = \frac{BE}{BE+D}\sigma_{BE} + \frac{D}{BE+D}\sigma_D \quad . \tag{18}$$

Table 9 and Table 10 show results of bootstrap probit estimates of default probability where $BookDD$ is included as regressor. Model 0 refer to estimates of a simple model where $BookDD$ enters as the sole covariate, together with 2-Digit industry dummies

$$P(Y_T = 1 \mid X_t) = \Phi(\delta\ BookDD + \beta_0 + \beta_1 \text{ Sector}) \quad . \tag{19}$$

Model I adds financial indicators

$$P(Y_T = 1 \mid X_t) = \Phi(\delta\ BookDD + \beta_{0t} + \beta_{1t} \frac{IE_t}{S_t} + \beta_{2t}\ LEV_t + \beta_{3t} \frac{FD_t}{S_t} + \beta_{4t} \text{ Sector}_t) \quad , \tag{20}$$

while Model II includes the full set of financial and economic variables considered in the work

$$\begin{aligned} P(Y_T = 1 \mid X_t) \quad = \quad & \Phi(\delta\ BookDD + \beta_{0t} + \beta_{1t} \frac{IE_t}{S_t} + \beta_{2t}\ LEV_t + \beta_{3t} \frac{FD_t}{S_t} + \beta_{4t}\ S_t + \\ & \beta_{5t}\ PROD_t + \beta_{6t}\ PROF_t + \beta_{7t}\ GROWTH_t + \beta_{8t} \text{ Sector}_t) \quad . \end{aligned} \tag{21}$$

As before, we take z-scores of relevant variables, and we also perform estimates (of Model I and Model II) over averaged values of covariates as well as separately for each year over the period 1999-2002.

References

Agarwal, R. and D. B. Audretsch (2001, March). Does entry size matter? the impact of the life cycle and technology on firm survival. *Journal of Industrial Economics 49*(1), 21–43.

Altman, E. I. (1968, Sept.). Financial ratios, discriminant analysis and the prediction of corporate bankruptcy. *Journal of Finance 23*(4), 589–609.

Altman, E. I. and A. Saunders (1997, December). Credit risk measurement: Developments over the last 20 years. *Journal of Banking & Finance 21*(11-12), 1721–1742.

Beaver, W. H. (1966). Financial ratios as predictor of failure. *Journal of Accounting Research 4*, 71–111. Empirical Research in Accounting: Selected Studies 1966.

Bharath, S. T. and T. Shumway (2008). Forecasting default with the merton distance to default model. *The Review of Financial Studies 21*, 1339–1369.

BIS (2001). The internal ratings-based approach. Supporting document to the new basel capital accord, Basel Committee on Banking Supervision.

Black, F. and M. Scholes (1973). The pricing of options and corporate liabilities. *Journal of Political Economy 81*, 637–654.

Brier, G. W. (1950, January). Verification of forecasts expressed in terms of probability. *Montly Weather Review 78*(1), 1–3.

Carey, M. and M. Hrycay (2001, January). Parameterizing credit risk models with rating data. *Journal of Banking & Finance 25*(1), 197–270.

Cosslet, S. R. (1993). Estimation from endogenously stratified samples. In C. R. Maddala G.S. and H. Vinod (Eds.), *Handbook of Statistics*, pp. 1–43. North Holland: Amsterdam.

Crosbie, P. and J. Bohn (2003). Modelling default risk. Kmv technical document, Moody's.

Crouhy, M., D. Galai, and R. Mark (2000, January). A comparative analysis of current credit risk models. *Journal of Banking & Finance 24*(1-2), 59–117.

Crouhy, M., D. Galai, and R. Mark (2001, January). Prototype risk rating system. *Journal of Banking & Finance 25*(1), 47–95.

Duffie, D., L. Saita, and K. Wang (2007). Multi-period corporate default prediction with stochastic covariates. *Journal of Financial Economics 83*, 635–665.

Efron, B. and R. J. Tibshirani (1993). *An Introduction to the Bootstrap*. Chapman & Hall.

Ericson, R. and A. Pakes (1995, January). Markov-perfect industry dynamics: A framework for empirical work. *Review of Economic Studies 62*(1), 53–82.

Fligner, M. A. and G. E. Policello II (1981, March). Robust rank procedures for the behrens-fisher problem. *Journal of the American Statistical Association 76*(373), 141–206.

Grunert, J., L. Norden, and M. Weber (2005, February). The role of non-financial factors in internal credit ratings. *Journal of Banking & Finance 29*(2), 509–531.

Imbens, G. W. (1992, September). An efficient method of moments estimator for discrete choice models with choice-based sampling. *Econometrica 60*(5), 1187–1214.

Jovanovic, B. (1982, May). Selection and the evolution of industry. *Econometrica 50*(3), 649–70.

Manski, C. F. and S. R. Lerman (1977, November). The estimation of choice probabilities from choice based samples. *Econometrica 45*(8), 1977–1988.

Manski, C. F. and D. McFadden (Eds.) (1981). *Structural Analysis of Discrete Data with Econometric Applications*. MIT Press: Cambridge, Mass.

Melitz, M. J. (2003, November). The impact of trade on intra-industry reallocations and aggregate industry productivity. *Econometrica 71*(6), 1695–1725.

Merton, R. C. (1974). On the pricing of corporate debt: The risk structure of interest rates. *Journal of Finance 29*, 449–470.

Nelson, R. R. and S. G. Winter (1982). *An Evolutionary Theory of Economic Change*. The Belknap Press of Harvard University Press: Cambridge, MA.

Silverman, B. W. (1986). *Density Estimation for Statistics and Data Analysis*. London: Chapman & Hall/CRC.

Winter, S. G. (1971, May). Satisficing, selection, and the innovating remnant. *The Quarterly Journal of Economics 85*(2), 237–61.

Zmijevski, M. E. (1984). Methodological issues related to the estimation of financial distress prediction. *Journal of Accounting Research 22*, 59–82. Supplement 1984.

Notes

[1]This is a tradition of analysis followed since the classical studies by Beaver (1966) and Altman (1968). See Altman and Saunders (1997) and Crouhy et al. (2000) for a more complete review of the literature.

[2]The same message is consistent with broad sense neoclassical models of firm-industry dynamics (see, for instance, Jovanovic, 1982; Ericson and Pakes, 1995; Melitz, 2003), as well with models originating from the evolutionary tradition (see Winter, 1971; Nelson and Winter, 1982).

[3]A huge empirical literature has highlighted the positive effect exerted on survival by the technological characteristics of the firms (see Agarwal and Audretsch, 2001, for a review), like R&D expenditures or patents. However we lack the necessary data to include these further dimensions in our analysis (see details in Section 1).

[4]In our case the “exit” of a firm is a truly economic event. This should be confronted with a large part of empirical studies in industrial dynamics where the “exit” of a firm is merely its disappearance from a given sample, typically due to a reduction in the number of employees or annual turnover.

[5]Zmijevski (1984) analyzes this point in depth. It is however noticeable that financial studies are usually confronted with an opposite problem as compared to ours, since default events tend to be over-represented in the samples typically employed in that literature.

[6]Nomenclature génerale des Activités économiques dans les Communautés Europénnes, NACE, is the standard at European level, and perfectly matches with the International Standard Industrial Classification, ISIC, at the 2-Digit level.

[7]Once again, 1998 is excluded simply because growth rates cannot be computed for that year.

[8]Several refinements of the bootstrap estimates of confidence intervals are discussed in the literature, most notably the BC_a and ABC corrections. These methods require an estimate of the bias, which we can only obtain by performing a “first step” probit regression on the overall original sample. This is however exactly what we want to avoid, in order to overcome under-sampling of defaulting firms. Alternatively, one could try to estimate the bias by re-sampling from each random sample. This second order bootstrap seems to us unnecessary due to the relatively large size of the sample considered.

[9]Minimizing the overall number of errors is equivalent to maximizing the total sum of correctly predicted observations. The weighting is instead introduced to address the specific characteristics of our exercise. True zeros are indeed much more frequent than true ones, simply because default rates in each bootstrapped sample equal the population-wide frequencies presented in Table 1.

[10]The application of the bootstrap to compute model performance measures is particularly important. Zmijevski (1984) indeed shows that classification and prediction errors of the defaulting group are generally overstated without an appropriate treatment of the “choice-based sample” problem.

[11]See Duffie et al. (2007), for the most recent advance in financial literature, and the works cited therein for a review of duration models based on Distance to Default. Crosbie and Bohn (2003) offer an extensive introduction to Moody’s KMV model, which is also based on Distance to Default theory.

[12]Notice that firms’ “ability” to improve their rating does not depend on the exit of better firms from the sample. The matrices are indeed computed taking all the firms which are still in the sample in the last year, when default is measured, and then tracing back their credit rating history.

Sectors	Number of firms	Number of defaults	Default rate in the Sample	Default rate in the population
15 - Food products & beverages	2392	10	0.0042	0.0543
17 - Manufacture of textiles	1774	14	0.0079	0.0833
18 - Wearing apparel; dressing; dyeing of fur	895	9	0.0101	0.0904
19 - Leather; luggage, & footwear	889	15	0.0169	0.0718
20 - Manufacture of wood	505	2	0.0040	0.0566
21 - Pulp & paper products	616	2	0.0032	0.0508
22 - Publishing, printing & recorded media	1047	7	0.0067	0.0516
23 - Coke & refined petroleum product	110	1	0.0091	0.0357
24 - Chemical products	1266	2	0.0016	0.0449
25 - Rubber and plastic products	1377	6	0.0044	0.0526
26 - Other non-metallic mineral products	1355	5	0.0037	0.0490
27 - Manufacture of basic metals	740	2	0.0027	0.0474
28 - Metal products (except machinery & equip.)	3077	15	0.0049	0.0510
29 - Machinery and equipment n.e.c.	3396	24	0.0071	0.0517
30 - Office machinery and computers	118	1	0.0085	0.0643
31 - Electrical machinery and apparatus n.e.c.	1007	8	0.0079	0.0573
32 - Radio, TV & communication equip.	340	5	0.0147	0.0581
33 - Medical, precision & optical instruments	607	2	0.0033	0.0449
34 - Motor vehicles, trailers & semi-trailers	499	8	0.0160	0.0437
35 - Other transport equipment	294	6	0.0204	0.0588
36 - Furniture; manufacturing n.e.c.	1500	11	0.0073	0.0571
Total	23816	155	0.0065	0.0581

Table 1: The first three columns report respectively the number of firms, the occurrences of default events and the default rate in our sample, computed at 2-Digit sectoral level. The last column displays the corresponding default rates in 2003 as provided by the association of the Italian Chambers of Commerce.

Variable	Test	Test of Differences in Median 1998	1999	2000	2001	2002
IE/S	WMW stat	**1300831**	**1368752**	**1726736**	**1847061**	**1831014**
	p-value	0.0000	0.0000	0.0000	0.0000	0.0000
LEV	WMW stat	**1307497**	**1357716**	**1619228**	**1663846**	**1623066**
	p-value	0.0000	0.0000	0.0000	0.0000	0.0000
FD/S	WMW stat	**1304422**	**1400820**	**1769240**	**1800796**	**1726080**
	p-value	0.0000	0.0000	0.0000	0.0000	0.0000
SIZE	WMW stat	1005136	1072391	**1387314**	**1350906**	1224269
	p-value	0.8136	0.1524	0.0004	0.0022	0.0279
GROWTH	WMW stat		962364	922720	1066580	**831404**
	p-value		0.2901	0.4202	0.2293	0.0000
PROF	WMW stat	**789754**	**706489**	**831141**	**803633**	**586242**
	p-value	0.0001	0.0000	0.0000	0.0000	0.0000
PROD	WMW stat	**750596**	**706164**	**841545**	**835631**	**668137**
	p-value	0.0000	0.0000	0.0000	0.0000	0.0000

Table 2: Wilcoxon-Mann-Whitney Test of differences in medians, Defaulting *vs* Non-Defaulting firms. Value of the observed statistic (WMW) and associated p-value. Rejection of the null means that the two distributions have different medians, at 1% confidence level (in bold).

Test of Stochastic Equality						
Variable	**Test**	1998	1999	2000	2001	2002
IE/S	FP stat	**7.3860**	**9.1530**	**12.9900**	**17.8490**	**24.1740**
	p-value	0.0000	0.0000	0.0000	0.0000	0.0000
LEV	FP stat	**8.1390**	**10.6350**	**12.2380**	**13.7040**	**15.1520**
	p-value	0.0000	0.0000	0.0000	0.0000	0.0000
FD/S	FP stat	**7.3648**	**10.3543**	**14.2933**	**15.9266**	**17.0851**
	p-value	0.0000	0.0000	0.0000	0.0000	0.0000
SIZE	FP stat	0.2297	1.4295	**3.8616**	**3.3450**	2.3058
	p-value	0.8183	0.1529	0.0001	0.0008	0.0211
GROWTH	FP stat		0.9511	-0.7411	-1.0191	**-3.8527**
	p-value		0.3415	0.4587	0.3081	0.0001
PROF	FP stat	**-4.6137**	**-7.1738**	**-7.2601**	**-7.3563**	**-11.0602**
	p-value	0.0000	0.0000	0.0000	0.0000	0.0000
PROD	FP stat	**-5.2211**	**-7.0737**	**-7.1071**	**-6.7352**	**-8.7490**
	p-value	0.0000	0.0000	0.0000	0.0000	0.0000

Table 3: Fligner-Policello Test of stochastic equality, Defaulting *vs* Non-Defaulting firms. Observed value of the statistic (FP) and associated *p*-value. Rejection of the null means that the two distributions are different in probability, at 1% confidence level (in bold).

Bootstrapped Probit - average over time							
Panel A: Estimates	IE/S	LEV	FD/S	SIZE	PROD	PROF	GROWTH
Model I	**0.14065***	0.04850	0.13212				
Model II	**0.18708***	**0.11171****	0.15670	**0.04126****	**-0.16928***	**-0.11239****	-0.01967
Panel B: Model performance						Model I	Model II
Brier Score						0.04985	0.05016
Type I error						26.6529	20.1088
Type II error						682.0725	561.0104
% Correct default						0.7815	0.8251
% Correct non default						0.6861	0.7233
Panel C: Prediction performance against optimal t^* of Model I							
Type I error							16.9896
Type II error							618.8083
% Correct default							0.8523
% Correct non default							0.6948

Table 4: Probit estimates of default probabilities - regressions performed on the z-scored averages of the explanatory variables over time, computed for the period 1999-2002. Controls include a full set of 2-Digit sectoral dummies. Bootstrap mean of coefficients are reported, averaged over 200 replications. Significant coefficients in bold. * Significant at 5% level; ** Significant at 10% level.

Bootstrapped Probit Regressions - estimates by year								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	1999	**2000**	**2001**	**2002**	**1999**	**2000**	**2001**	**2002**
Panel A: Estimation results								
IE/S	**0.10635***	**0.12240***	**0.20988***	**0.33793***	**0.13766***	**0.15004***	**0.19617****	**0.34713***
LEV	0.06090	0.03059	0.07068	**0.12373***	0.00549	0.06029	0.08462	0.11519
FD/S	**0.14376***	**0.17293****	0.10637	0.08594	0.12420	0.18019	0.12294	0.03895
SIZE					**0.08776***	**0.10589***	**0.16006***	0.19977
PROD					**-0.19364***	**-0.09790***	**-0.17524***	0.01186
PROF					-0.10024	**-0.13497***	-0.08973	**-0.21707***
GROWTH					**0.15172***	**0.04408***	-0.03169	-0.01775
Panel B: Model performance								
Brier Score	0.05819	0.05293	0.05401	0.05134	0.05719	0.05921	0.05466	0.05072
Type I error	25.8135	25.0207	25.5026	18.7098	20.1813	19.9067	22.6632	15.6425
Type II error	672.9689	701.6114	599.1710	475.1865	532.8342	573.0363	546.7254	440.1503
% Correct default	0.7674	0.7786	0.7782	0.8299	0.8078	0.8190	0.8012	0.8538
% Correct non default	0.5900	0.6248	0.6737	0.7364	0.6552	0.6360	0.6937	0.7488
Panel C: Comparisons of prediction performance by year								
Type I error					15.6010	11.9326	19.6425	15.2435
Type II error					614.3990	711.7254	602.1140	446.2746
% Correct default					0.8514	0.8915	0.8277	0.8575
% Correct non default					0.6025	0.5479	0.6626	0.7453
Panel D: Comparisons of prediction performance against the "financial variable only" model of 2002								
Type I error					14.1554	14.9275	18.9223	15.2435
Type II error					648.1295	649.9585	616.4611	446.2746
% Correct default					0.8652	0.8643	0.8340	0.8575
% Correct non default					0.5806	0.5871	0.6546	0.7453

Table 5: Probit estimates of default probabilities by year. Bootstrap mean of coefficients are reported, computed over 200 replications. Variables in z-scores. Controls include a full set of 2-Digit sectoral dummies. Significant coefficients in bold. * Significant at 5% level; ** Significant at 10% level.

		2003			
		Low	**Mid**	**High**	**Default**
1998	**Low**	0.8947	0.0825	0.0176	0.0052
	Mid	0.5406	0.3647	0.0743	0.0204
	High	0.4589	0.3290	0.1991	0.0130
2002	**Low**	0.9308	0.0583	0.0077	0.0032
	Mid	0.3377	0.5444	0.0987	0.0192
	High	0.1502	0.3519	0.4742	0.0236

Table 6: Credit ratings transition matrices.

Bootstrap Probit with Credit Ratings - average over time				
	Rating only		Rating, Fin and Econ	
	Model IA	Model IB	Model IIA	Model IIB
Panel A: Estimates				
MID_{γ}	**1.03891***	**0.97368***	**1.08566***	**0.79375***
$HIGH_{\gamma}$	**0.83534***	**0.12538***	**1.38201***	**0.25926***
IE/S			0.05532	**0.13403***
LEV			-0.01597	0.03334
FD/S			**0.10762***	0.13116
SIZE			0.03458	0.02766
PROD			**-0.13665***	**-0.16283***
PROF			0.00111	-0.09323
GROWTH			-0.04525	-0.01615
Panel B: Model Performance				
Brier Score	0.04282	0.04225	0.04618	0.04765
Type I error	15.1554	78.0000	14.5855	15.3420
Type II error	2034.3830	248.1813	600.8549	630.0311
% Correct default	0.8843	0.4000	0.8732	0.8654
% Correct non default	0.2432	0.9072	0.7080	0.6919
Panel C: Comparisons against the corresponding "Rating only" model				
Type I error			8.0933	20.7409
Type II error			763.2591	555.5130
% Correct default			0.9296	0.8181
% Correct non default			0.6291	0.7283

Table 7: Probit estimates of default probabilities, robustness check with respect to inclusion of the CeBi credit rating - estimates performed on the z-scored average values of economic and financial variables over time, computed for the period 1999-2002. Models IA and IIA assign rating classes as the more risky situation experienced in the sample period (γ=MAX in Equation 8 and Equation 9). Models IB and IIB take rating classes as of 2002 (γ=2002 in Equation 8 and Equation 9). Bootstrap mean of coefficients are reported, averaged over 200 replications. Significant coefficients in bold. * Significant at 5% confidence level, ** Significant at 10% confidence level.

Bootstrap Probit with Credit Ratings - estimates by year								
	Rating only				**Rating, Financial and Economic**			
	(1) **1999**	(2) **2000**	(3) **2001**	(4) **2002**	(5) **1999**	(6) **2000**	(7) **2001**	(8) **2002**
Panel A: Estimates								
MID	**0.68284***	**0.78754***	**0.95278***	**0.97368***	**0.45669***	**0.59013***	**0.78172***	**0.69804***
HIGH	**-0.32325***	**-0.21789***	**-0.14440***	**0.12538***	0.06631	**-0.57439***	0.22175	**0.65828***
IE/S					**0.10282***	**0.12628****	**0.14680****	**0.24355***
LEV					-0.06887	-0.01718	-0.09133	0.04004
FD/S					0.11410	0.15692	0.08676	0.04719
SIZE					0.02605	**0.04377***	**0.08101***	0.02533
PROD					**-0.18537***	**-0.08811***	**-0.16003***	0.01581
PROF					-0.07994	**-0.13070***	-0.06378	**-0.16138***
GROWTH					**0.13030***	0.03362	**-0.06448****	-0.01064
Panel B: Model performance								
Brier Score	0.04291	0.04233	0.04189	0.04225	0.05515	0.05710	0.05199	0.04886
Type I error	80.7927	76.0000	72.0000	78.0000	21.8290	19.6062	21.2591	13.3886
Type II error	391.0777	289.0674	256.0881	248.1813	590.8135	502.9585	528.3316	499.0933
% Correct default	0.3785	0.4109	0.4462	0.4000	0.7921	0.8218	0.8135	0.8749
% Correct non default	0.8536	0.8916	0.9039	0.9072	0.6284	0.6849	0.7081	0.7179
Panel C: Comparisons of prediction performance against the "Rating only" model of the same year								
Type I error					18.6218	7.8601	13.5026	18.9067
Type II error					646.7824	771.5751	718.5337	417.7306
% Correct default					0.8226	0.9285	0.8816	0.8233
% Correct non default					0.5932	0.5167	0.6030	0.7639
Panel D: Comparisons of prediction performance against the "Rating only" model of 2001								
Type I error					4.1347	5.1244	13.5026	13.4300
Type II error					1058.0570	911.8187	718.5337	498.4922
% Correct default					0.9606	0.9534	0.8816	0.8745
% Correct non default					0.3346	0.4288	0.6030	0.7182

Table 8: Probit estimates of default probabilities, robustness check with respect to inclusion of the CeBi credit rating - estimates by year. Economic and financial variables are in z-scores. Bootstrap mean of coefficients are reported, averaged over 200 replications. Significant coefficients in bold. * Significant at 5% confidence level; ** Significant at 10% confidence level.

Bootstrapped Probit with Distance to Deafult								
Panel A: Estimates								
	BookDD alone							
	BookDD	IE/S	LEV	FD/S	SIZE	PROD	PROF	GROWTH
Model 0	0.07535							
	BookDD and ohter covariates, average over time							
	DD Book	IE/S	LEV	FD/S	SIZE	PROD	PROF	GROWTH
Model I	0.11170	**0.40046***	**0.47961***	**0.19018***				
Model II	0.13368	**0.42419***	0.34241	**0.15492***	**0.07589****	**-0.25634***	**-0.36121***	0.07642
Panel B: Model performance						Model 0	Model I	Model II
Brier Score						0.07255	0.06914	0.06715
Type I error						24.3200	20.8850	15.9750
Type II error						851.9200	375.6150	340.2800
% Correct default						0.7543	0.7890	0.8386
% Correct non default						0.2643	0.6756	0.7062
Panel C: Prediction performance against optimal t^* of Model 0								
Type I error							26.9500	19.2000
Type II error							311.5250	305.0350
% Correct default							0.7278	0.8061
% Correct non default							0.7310	0.7366
Panel D: Prediction performance against optimal t^* of Model I								
Type I error								19.0350
Type II error								588.3100
% Correct default								0.8077
% Correct non default								0.4920

Table 9: Probit estimates of default probabilities - regressions performed on the z-scored averages of the explanatory variables over time, computed for the period 1999-2002. Controls include a full set of 2-Digit sectoral dummies. Bootstrap mean of coefficients are reported, averaged over 200 replications. Significant coefficients in bold. * Significant at 5% level; ** Significant at 10% level.

Bootstrap Probit with Distance to Default - estimates by year								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	1999	**2000**	**2001**	**2002**	**1999**	**2000**	**2001**	**2002**
Panel A: Estimation results								
DD Book	0.08923	0.09061	0.11255	0.11101	0.09161	0.10217	0.12827	0.13604
IE/S	**0.20842***	**0.19455***	**0.44003***	**0.38311***	**0.23123***	**0.24193***	**0.45443***	**0.38549**
LEV	0.22921	0.18360	**0.24550****	**0.40037***	0.14205	0.12568	0.19069	0.29924
FD/S	0.15881	**0.23693***	0.11432	0.07803	0.12976	**0.20230***	0.09483	0.05218
SIZE					0.03062	**0.03713***	**0.08611***	**0.05855***
PROD					**-0.21968***	**-0.10028***	-0.23321	0.03078
PROF					**-0.15218***	**-0.21541***	**-0.17011****	**-0.32905***
GROWTH					**0.15300***	**0.09827***	0.00031	0.04992
Panel B: Model performance								
Brier Score	0.07084	0.07047	0.06960	0.06758	0.06883	0.06983	0.06882	0.06592
Type I error	35.1000	27.0350	24.7100	20.0150	24.4850	23.2050	19.5800	16.0700
Type II error	372.3350	382.8950	357.8500	309.3000	429.0250	363.8100	357.6850	289.6450
% Correct default	0.6455	0.7269	0.7504	0.7958	0.7527	0.7656	0.8022	0.8360
% Correct non default	0.6782	0.6692	0.6882	0.7312	0.6292	0.6857	0.6883	0.7468
Panel C: Comparisons of prediction performance against t^* of Model 0								
Type I error	36.7000	31.2600	30.0650	24.0250	32.0100	24.6550	23.1750	19.4750
Type II error	354.7250	342.0750	313.2650	270.2950	348.5900	348.2550	319.8750	253.2450
% Correct default	0.6293	0.6842	0.6963	0.7548	0.6767	0.7510	0.7659	0.8013
% Correct non default	0.6935	0.7045	0.7270	0.7651	0.6988	0.6992	0.7213	0.7786
Panel D: Comparisons of prediction performance by year								
Type I error					29.0900	21.6450	22.4700	26.9250
Type II error					523.1300	632.8050	638.7500	533.2600
% Correct default					0.7062	0.7814	0.7730	0.7253
% Correct non default					0.5479	0.4534	0.4434	0.5338
Panel E: Comparisons of prediction performance against t^* of the "DD Book+financial variable model" of 2002								
Type I error					25.5250	19.4250	18.6650	15.9050
Type II error					418.4950	414.6800	367.8650	291.3450
% Correct default					0.7422	0.8038	0.8115	0.8377
% Correct non default					0.6383	0.6418	0.6794	0.7453

Table 10: Probit estimates of default probabilities by year. Bootstrap mean of coefficients are reported, computed over 200 replications. Variables in z-scores. Controls include a full set of 2-Digit sectoral dummies. Significant coefficients in bold. * Significant at 5% level; ** Significant at 10% level.

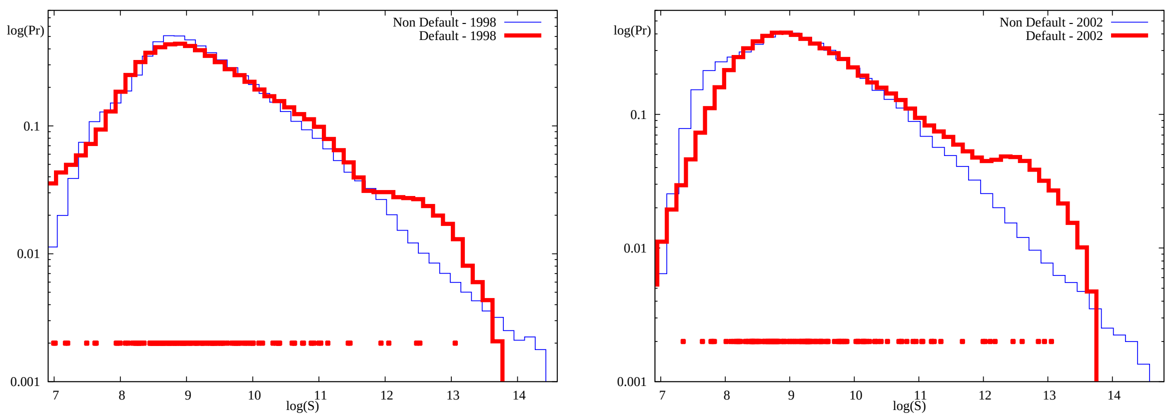


Figure 1: Empirical density of Total Sales (S) in 1998 (**left**) and 2002 (**right**): Defaulting *vs* Non-Defaulting firms.

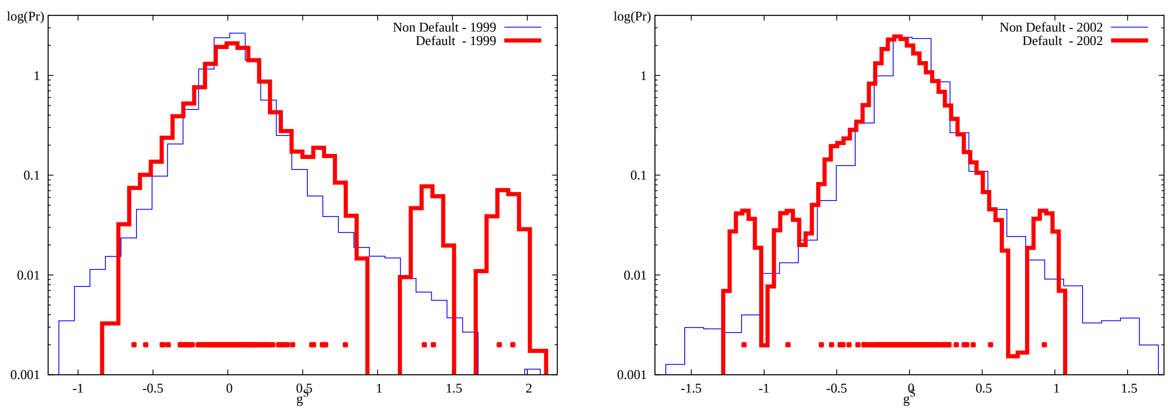


Figure 2: Empirical density of Total Sales Growth (g^S) in 1999 (**left**) and 2002 (**right**): Defaulting *vs* Non-Defaulting firms.

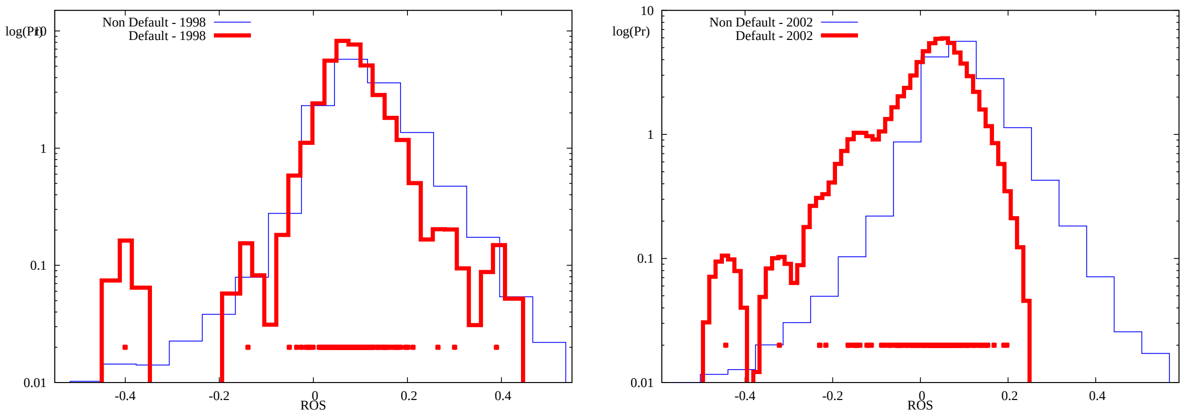


Figure 3: Empirical density of Profitability (ROS) in 1998 (**left**) and 2002 (**right**): Defaulting *vs* Non Defaulting Firms.

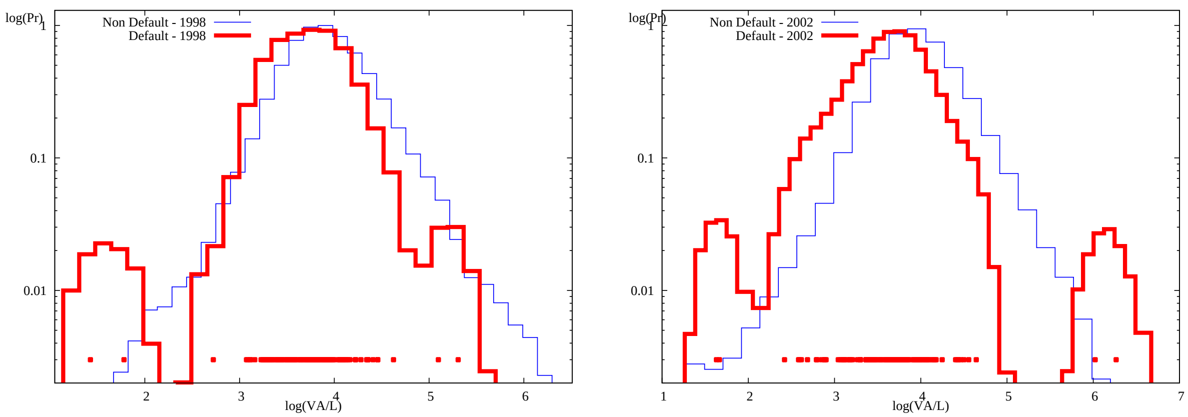
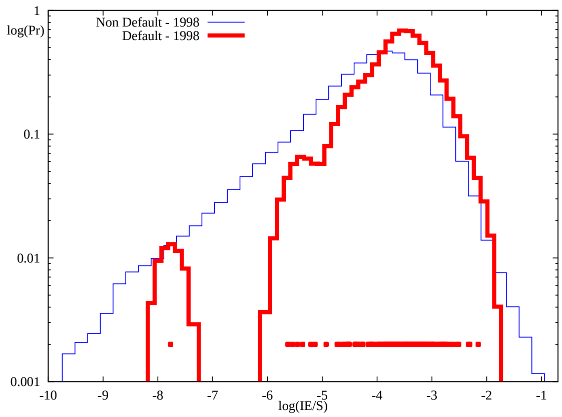


Figure 4: Empirical density of Labour Productivity (VA/L) in 1998 (**left**) and 2002 (**right**): Defaulting *vs* Non Defaulting firms.



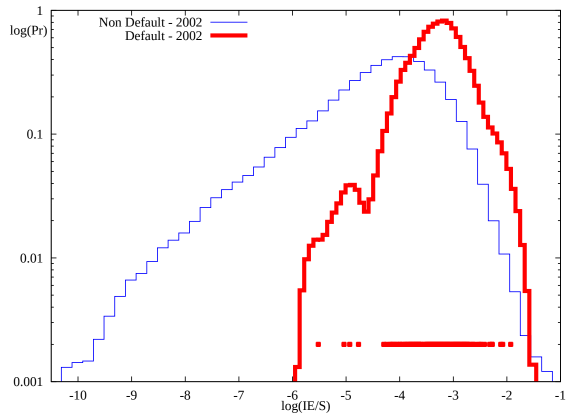


Figure 5: Empirical density of Interest Expenses scaled by size (IE/S) in 1998 (**left**) and 2002 (**right**): Defaulting *vs* Non-Defaulting firms.

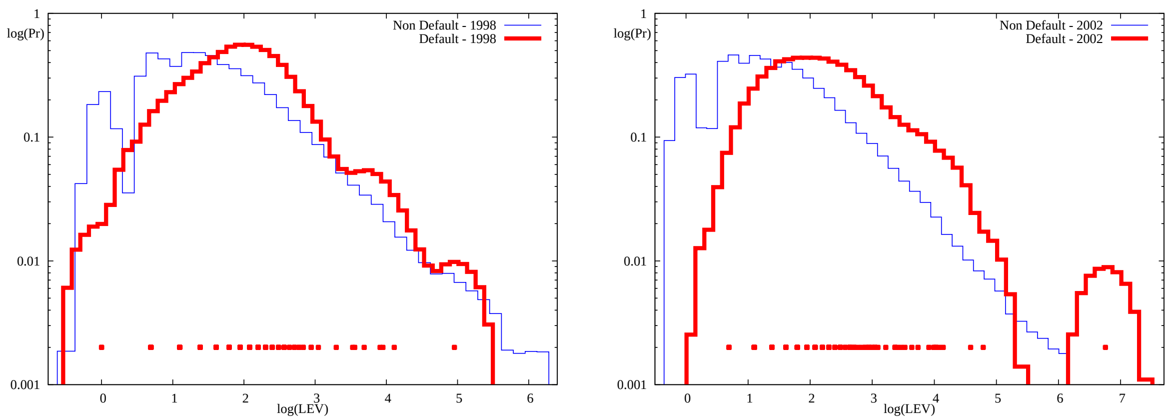


Figure 6: Empirical density of Leverage (LEV) in 1998 (**left**) and 2002 (**right**): Defaulting *vs* Non-Defaulting firms .

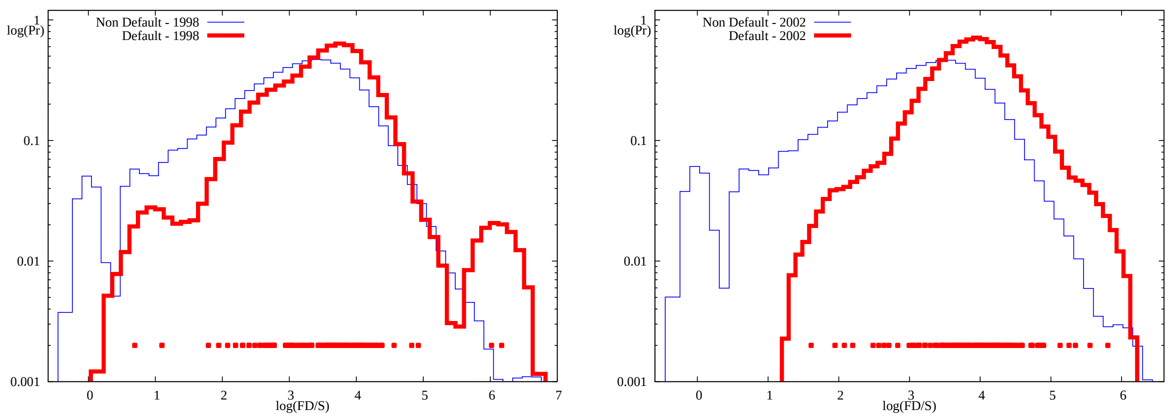


Figure 7: Empirical density of Debt-to-Sales ratio (FD/S) in 1998 (**left**) and 2002 (**right**): Defaulting *vs* Non-Defaulting firms.