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Bankruptcy risk and productive efficiency in manufacturing firms ☆

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Abstract

The paper investigates the determinants of bankruptcy in three representative unbalanced samples of Italian firms for the periods 1989–91, 1992–94 and 1995–97. Two important results are that: (i) the degree of relative firm inefficiency measured as the distance from the efficient frontier has significant explanatory power in predicting bankruptcy (ii) qualitative regressors such as customers' concentration and strength and proximity of competitors have significant predictive power and suggest that banks should not restrict their monitoring activity to balance sheet variables. These findings remain significant after controlling for balance sheet liquidity and profitability variables usually considered in these estimates.

JEL classification: G21; D21
Keywords: Bankruptcy prediction; Stochastic frontiers; Qualitative indicators

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1. Introduction

The empirical literature of bankruptcy prediction has recently gained further momentum and attention from financial institutions. [1] Academicians and practitioners have realized that the problem of asymmetric information between banks and firms lies at the heart of important market failures such as credit rationing and that improvement in monitoring techniques represents a valuable alternative to any incomplete contractual arrangement aimed at reducing the borrowers' moral hazard (Stiglitz and Weiss, 1981, 1986, 1992; De Meza and Webb, 1987; Milde and Riley, 1988; Xu, 2000).

Among the three existing approaches to the problem (accounting analytical approach, option theoretical approach and statistical approach), [2] the statistical approach tries to assess corporate failure risk through four widely known methods which make use of balance-sheet ratios: linear or quadratic discriminant analysis, logistic regression analysis, probit regression analysis and neural network analysis.

Many empirical studies adopt the statistical approach. They aim to classify correctly a sample of firms into one of two pre-established categories (sound or unsound firms) on the basis of selected balance sheet variations in levels or trends. After the pioneering research of Beaver (1966) and Altman (1968), relevant results in this field have been obtained by Zmijewsky (1984); Frydman et al. (1985) and Gentry et al. (1987). Examples of empirical analyses on Italian data are given by Appetiti (1984); Barontini (1992); Altman et al. (1994); Laviola and Trapanese (1997) and Foglia et al. (1998).

The contribution of our paper to this literature goes in two directions: (i) a broader test on the significance of nonbalance sheet data (such as market share, customer concentration, strength of local competitors and others); [3] (ii) a test on whether remoteness from the "best practice" (distance from the effi-

[1] An example is the more risk sensitive framework for bank capital adequacy set by the New Basel Capital Accord promoted by the Basel Committee on Banking Supervision. According to the Committee "The new framework intends to provide approaches which are both more comprehensive and more sensitive to risks than the 1988 Accord, while maintaining the overall level of regulatory capital. Safety and soundness in today's dynamic and complex financial system can be attained only by the combination of effective bank-level management, market discipline, and supervision" (BIS, 2001). The New Basel Capital Accord (see first and second pillar) requires banks to have sound internal processes in place to assess the adequacy of its capital based on a thorough evaluation of its risks. This creates a great incentive for banks to implement their own risk management skills.

[2] The accounting analytical approach is largely followed by rating agencies. For recent applications of the structural or reduced form option approach see Duffie and Lando (1998) and Nickell et al. (2000).

[3] As to this point Zavgren (1985) affirms that "any econometric model containing only financial statement information will not predict accurately the failure or nonfailure of a firm", while Keasey and Watson (1987) conclude that their results "indicate that marginally better predictions, concerning small company failure may be obtained from nonfinancial data as compared to those which can be achieved from using traditional financial ratios". On the same point see Ohlson (1980). Among the few authors using qualitative variables, Fisher (1981) identifies permanent and temporary information on sample firms from qualitative and socio-political data, while Keasey and Watson (1987) evaluate the impact of qualified audit on the probability of failure.

cient productive frontier) has some predictive power on the probability of failure.

The paper is divided into five sections including introduction and conclusion. In Section 2 we describe our database and outline the methodology adopted to classify sound and unsound firms. In Section 3 we outline the stochastic frontier approach and comment on the results obtained with this method. In Section 4 we present logit estimates of the determinants of bankruptcy and test the explanatory power of the distance from the efficiency frontier and of nonbalance sheet indicators recorded by the Survey and included in the estimates.

2. Sample features and the definition of variables

The database used in our empirical analysis is extracted from three different Mediocredito Centrale Surveys covering respectively the 1989–91, the 1992–94 and the 1995–97 periods. [4] The sample is stratified by industrial activity, geographical area and size [5] for firms with from 10 to 500 employees, while it includes all firms with more than 500 employees. Collected data are of two types: quantitative (balance-sheet data) and qualitative (questionnaire). [6]

[4] Significant attrition among the three different sample periods of the survey prevented the creation of a large panel. While each three-year sample includes about 4500 firms, only 800 firms participated in the last two Surveys and only 300 firms in all of them. This number drops considerably when we rule out observations with missing values. We therefore analyse the three periods as separate samples and consider even firms participating in only one Survey. In this way we have more than 4000 firms for each sample period as indicated in Table 1.

[5] Size and composition of each stratum have been defined according to Neyman's (1934) formula in order to minimize sample variance.

[6] All balance sheet data contained in the Mediocredito database are accurately checked. Balance sheet data come from CERVED which obtains official information from the Italian Chambers of Commerce and is currently the most authoritative and reliable source of information on Italian companies.

Qualitative data from the questionnaire are based on answers from a representative appointed by the firm collecting information from the relevant division of the firm. The questionnaire has a system of controls based on "long inconsistencies", namely inconsistencies between answers to questions placed at a certain distance in the questionnaire. As an example answers on the use of government subsidies (export subsidies) are matched with answers on the exact composition of the flow of funds available for investment – internal finance, debt finance, grants, soft loans – (on the share of exported net sales).

In case of inconsistent information the firm is subject to a second phone interview. Firms which do not provide reliable information after being contacted again are excluded from the sample. A supplementary list of 8000 firms is built for each of the three year surveys in order to avoid that exclusions, generated by missing answers or inaccuracies in the questionnaire, may alter the sample design. Substitutions follow the criteria of consistency between the sample size and the population of the Universe.

Sample firms are classified into three mutually exclusive categories: "Failed", "Active" and "Stressed". Failed enterprises [7] are those that have ceased to exist, while Stressed firms are those placed under different kinds of intervention procedures (procedure concorsuali) [8] as envisaged by Italian law. These include composition with creditors, receivership, extraordinary administration, voluntary liquidation, forced liquidation, and winding-up. Firms which continue to operate without problems are classified as Active. [9] The relative share of these three groups of the total sample is presented in Table 1.

Each three-year sample is numerically unbalanced in favour of active firms, [10] but it has the advantage of being generated randomly and not for the specific purpose of credit risk analysis. This is a relevant difference when compared with many previous studies, e.g., Beaver (1966), Altman (1968) and Barontini (1992), who adopt a balanced-sampling approach and select a given number of sound and unsound firms to generate two rather reduced, homogeneous (same firm size and industry) and equally-sized groups (50% sound, 50% unsound firms).

[7] "Failed" status is defined on the basis of information provided by CERVED. Data available on firm failure may be underestimated since not all such cases are dutifully reported to the competent authority in order to avoid paying the fines established by Italian laws. The problem of misreporting is common to almost all countries Gilson and Vetsuypens (1993) find that in the US "many corporate filings are missing for bankrupt firms." To evaluate effects on the sampling methodology, see Zmijewsky (1984) and Zagrev (1985). This literature shows that random sampling tends to overstate the probability of financial distress, while "complete data" studies such as ours tend to understate this probability since distressed firms are less likely to have complete data before failure. Zmijewsky (1984) finds, however, that these two biases are likely to affect (rather unsubstantially) classification and prediction rates but do not affect statistical inferences on the impact of independent variables.

[8] The present and past legal status of any natural and legal body in Italy is reported to the Federation of Chambers of Commerce by means of a special document known as *modello AN/6* (modello CF and S3 currently). The range of intervention procedures for firms failing to meet their debt payments includes: bankruptcy (fallimento), winding-up (liquidazione), compulsory administrative liquidation (liquidazione coatta amministrativa), winding-up subject to supervision of the Court (liquidazione giudiziaria), voluntary winding-up (liquidazione volontaria), dissolution (scioglimento), dissolution with liquidation (scioglimento e liquidazione), dissolution without going into liquidation (scioglimento senza messa in liquidazione), early dissolution without going into liquidation (scioglimento anticipato senza messa in liquidazione), dissolution by the Court (scioglimento per atto dell'Autorità), fraudulent bankruptcy (bancarotta fraudolenta), bankruptcy (bancarotta semplice), adjustment of creditors' claims (concordato fallimentare), composition with creditors (concordato preventivo), receivership (amministrazione giudiziaria), temporary receivership (amministrazione controllata), extraordinary administration (amministrazione straordinaria), judicial attachment (sequestro giudiziario), writ of attachment of company shares (sequestro conservativo di quote).

[9] All procedures considered for the definition of stressed firms imply the impossibility of meeting meet obligations with banks. Our definition of stressed firms therefore coincides with the definitions produced in the most relevant Italian studies (Appetiti, 1984; Laviola and Trapanese, 1997) and it is not more restrictive than those usually found in the international literature (Beaver, 1966; Gilson, 1988, 1989; Everett and Watson, 1998).

[10] For previous empirical papers on bankruptcy using unbalanced samples see Ohlson (1980) and Zmijewsky (1984). A problem with unbalanced sampling is that the intercept (but not the regressors' coefficients) needs to be decreased by $(\log p_1 - \log p_2)$ where p_1 and p_2 are respectively the proportion of unsound and sound firms (Maddala, 1992).

Table 1
Sound and unsound firms in the Mediocredito Centrale sample

	Number of observations	% To total sample
1989–91		
Total number of firms	4194	100.0
Active	4112	98.0
Stressed[a]	11	0.3
Failed	35	0.8
Failed + stressed[a]	46	1.1
1992–94		
Total number of firms	4714	100.0
Active	4676	99.2
Stressed[a]	8	0.2
Failed	10	0.2
Failed + stressed[a]	18	0.4
1995–97		
Total number of firms	4106	100.0
Active	4081	99.4
Stressed[a]	7	0.2
Failed	18	0.4
Failed + Stressed[a]	25	0.6

[a] Firms which are under "*procedure concorsuali*". These include: Composition with creditors, receivership, extraordinary administration, voluntary liquidation, forced liquidation, and dissolution.

On the basis of the financial ratios successfully identified by past studies, 20 balance-sheet indices [11] have been considered as potential bankruptcy determinants (Table 2). [12] These indices reflect six different aspects of firm structure and performance: liquidity, turnover, leverage, operating structure and efficiency, size and capitalization, and, finally, profitability. [13] The indices have been calculated as three-year, two-year and one-year averages. [14]

[11] By analysing the existing empirical literature it is clear that there is not a definite index group presenting a high discriminant ability and forecasting power common to all previous studies. For this reason we agree with Edmister's (1972) assertion that "... Although some ratios were found to be good predictors in more than one study, no one group of ratios is common to the [four] studies. This implies that the discriminant functions can be applied reliably only to situations very similar to those from which the function was generated".

[12] In most of the empirical literature the selection criteria for regressors are based upon the choices of previous empirical studies (Zavgren, 1985; Skogsvik, 1990) or on a combination of these choices with theoretical a priori (Edmister, 1972; Lo, 1986; Keasey and Watson, 1987; Keasey and Mc Guinnes, 1990).

[13] These index categories are taken from Appetiti (1984) and are close to those of Keasey and Watson (1987) and Laviola and Trapanese (1997).

[14] A three-year time interval is not too long or uncommon in the literature. Skogsvik (1990) and Gilson and Vetsuypens (1993) start analysing the behaviour of firms in their sample six years before, Keasey and Mc Guinnes (1990) and Laviola and Trapanese (1997) five years before, while Edmister (1972); Appetiti (1984) and Lo (1986) three years before default.

Table 2
Definition of financial indices and trends

No.	Ratio definition	Type
1	Net working capital[a]/current liabilities	Liquidity
2	Net working capital/medium and long term debt	Liquidity
3	Net working capital/total assets	Liquidity
4	Sales/total assets	turnover
5	Total assets/net worth	Turnover
6	Total debt/total assets	Leverage
7	Current liabilities/net worth	Leverage
8	Interest charges/sales	Operating structure
9	Interest charges/value added	Operating structure
10	Depreciation charges/gross fixed assets	Operating structure
11	Reserves/total assets	size and capitalization
12	Profit (loss) for the period/net worth	Profitability
13	Sales/gross fixed assets	Profitability
14	Operating profit/total assets	Profitability
15	Earnings before interest and taxes/total assets	Profitability
16	Profit (loss) for the period/sales	Profitability
17	Profit (loss) for the period/share capital	Profitability
18	Profit (loss) for the period/total assets	Profitability
19	Earnings before taxes/total debt	Profitability
20	Earnings before interest and taxes/sales	Profitability
21	(Gross operating profit + net financial provision − depreciation) of	Profitability
22	Provision for risk and charges/total assets	Risk
23	Firm sales/industry sales	Nonbalance sheet information
24	Macroarea location	Nonbalance sheet information
25	Size	Nonbalance sheet information
26	Export status	Nonbalance sheet information
27	Subcontracting status	Nonbalance sheet information
28	Strength and proximity of competitors	Nonbalance sheet information
29	Sales to three largest customers/total sales *(for 95–97 only)*	Nonbalance sheet information

[a] Net working capital is calculated as the sum of immediate liquidity, deferred liquidity, and total inventories (raw materials and items available for sale or in the process of being made ready for sale) net of current liabilities.

Other indices (totally or partially based on nonbalance-sheet data) have been calculated to control additional firm characteristics such as: market share (firm sales/industry sales), strength and proximity of competitors, [15] export status, subcontracting status, group membership, size, location in a macro area (South and Islands, Centre, North-West, North-East) and share of sales to the most important three customers (only for the 1995–97 database).

As an alternative to static ratios, a three-year trend has been calculated for each of the selected indicators following Edmister's methodology. [16] We define

[15] This qualitative information was collected from managers' answers to the Mediocredito questionnaire.

[16] Appetiti (1984) instead, runs a regression on the indices' values for the three periods prior to the crisis and uses the coefficients (Betas) in order to substitute for the static ratios in the discriminant function.

a trend as "three consecutive years during which the ratio moves along the same direction" and we generate up-trend (down-trend) dummy variables with a value of one if the trend is positive (negative) and zero otherwise. The up-trend and down-trend dummy variables are used as an alternative to static indices as regressors in a dynamic specification of the logit estimation (Table 2). [17]

2.1. Descriptive features of sound and unsound firms

We provide descriptive statistics for stressed and failed firms (as defined in Section 2) jointly as well as separately. Average values for static (ratios) and dynamic (trends) indices are presented in an Appendix available from the authors upon request.

Our findings show that: (i) Liquidity ratios are generally higher for active than for failed firms when we consider stressed and failed firms together; (ii) the pattern of liquidity variation is alternatively favourable to active (second period) and failed companies (first and third period); (iii) turnover indices (and, specifically, sales to assets ratios) are higher for active firms. Assets to net worth ratios are higher for failed firms presumably because of their reduced capital resources (as will be confirmed by other ratios in which the same item is implied), but variations of this index are generally more positive for active companies; (iv) the leverage indices, in turn, display greater solvency for active firms, even though their debts are slightly higher which presumably reflects higher creditworthiness, over the three-year periods examined; (v) the operating structure ratios indicate that active companies have lower ratios of interest charges to sales and interest charges to value added, and higher depreciation charges over gross fixed assets, than do failed companies.

The analysis of trend indicators generally confirms the following findings: (i) Both size and capitalization indices and their three-year trends clearly reflect the superior growth of active versus failed firms; (ii) the various profitability indices and trends emphasize the overall higher profitability of active enterprises and, finally, (iii) additional indices such as market share, competitors' locations, share of sales to the three largest customers, return and operating risk, significantly discriminate sound companies from stressed and failed ones, the latter having higher operating risk, higher customer concentration and higher local competitive pressure.

[17] Estimates presented in the paper include outliers. Estimates with 95% cut-off for regressors have been alternatively generated without showing results that are significantly different from those shown in the paper. These latter are available from the authors upon request.

3. The stochastic frontier approach and the probability of bankruptcy: The specification of the model

The adoption of a stochastic frontier approach [18] to predict bankruptcy risk is, as far as we know, a new initiative in this field. [19] We here test the hypothesis that financial unsoundness, in general, and the failure condition, in our particular case, are directly related to productive efficiency. [20] At least three definitions of efficiency may be recalled when referring to the analysis of the productivity of single firms or industries: (i) technical efficiency which implies maximizing output from a given combination of factors; (ii) allocative efficiency which refers to minimizing costs of the input mix, at given relative prices, for any output level (that is equivalent to equating the marginal product of every variable input to its corresponding opportunity cost or maximizing the profit); (iii) revenue efficiency which is related to the maximization of value added, gross earnings or any other financial parameters. [21]

We focus on technical efficiency using a parametric approach. According to the Battese and Coelli (1995) approach, we define the following generic production function:

$$Y_{it} = X_{it}\beta + (V_{it} - U_{it}) \quad i = 1, \ldots, N, \;\; t = 1, \ldots, T, \tag{1}$$

[18] The literature frequently adopts the Total Factor Productivity indicator for productivity comparisons. TFP is an accounting method which measures growth in output not explained by growth in inputs. It is purely descriptive even though it leaves the possibility of checking, at a second stage, whether subgroups of firms classified according to a chosen variable have different TFPs (Maksimovic and Phillips, 1998). The Stochastic Frontier Analysis presents at least two relative advantages with respect to TFP. First, the SFA – in the Battese and Coelli (1995) approach – simultaneously evaluates the degree of firm inefficiency and the relationship between inefficiency and various potential determinants. This approach has been widely recognized to be superior to the two-stage estimation which inconsistently assumes the independence of the inefficiency effects in the two estimation stages. The two-stage estimation procedure is unlikely to provide estimates which are as efficient as those that could be obtained using a single-stage estimation procedure (Battese and Coelli, 1995). Second, in the SFA, we separate an inefficiency component which is random and not affected by any variable and a component which is affected by several factors. The distinction between firm specific inefficiency and random shocks or statistical noise is a relevant advantage of the stochastic frontier approach as compared to any deterministic approach (Kaparakis et al., 1994).

[19] The SFA has two main applications in finance: (i) To evaluate the efficiency of industries in the financial sector (Aly et al., 1990; Kaparakis et al., 1994; Allen and Rai, 1996; Berger and Mester, 1997); (ii) as an original approach to generate inefficiency measures which are relevant in typical finance issues (Hunt et al., 1996).

We apply it to test whether productive efficiency may predict the incidence of bankruptcy in an unbalanced panel, in addition to typical balance sheet variables. Maksimovic and Phillips (1998) focus on the same issue using total factor productivity instead of the stochastic frontier approach for a panel of large US firms.

[20] An illustrative explanation on the origin and operative variations of the concept of efficiency applied to economic analysis is provided by Scazzieri (1981).

[21] The last type of efficiency depends on the first two classes and, as noted by Fanti (1997), if output, labor, and capital are empirically proxied in the production function by value added, cost of labor, and capital stock respectively, the resulting readout measuring "revenue inefficiency" caused by technical and allocative inefficiency does not distinguish one from the other.

where Y_{it} is the production of the ith firm; X_{it} is a $k * 1$ vector of input quantities of the ith firm; β is a vector of unknown parameters; the V_{it} are random variables which are assumed to be iid. $N(0, \sigma_V^2)$, and independent of the U_{it} which are nonnegative random variables that account for technical inefficiency in production and are assumed to be independently distributed as truncations at zero of the $N(m_{it}, \sigma_U^2)$ distribution. [22] $m_{it} = z_{it}\delta$, z_{it} is a $p * 1$ vector of variables that may influence the efficiency of a firm, and δ is a $1 * p$ vector of parameters to be estimated.

Parameters σ_V^2 and σ_U^2 are replaced with $\sigma^2 = \sigma_V^2 + \sigma_U^2$ and $\gamma = \sigma_U^2/(\sigma_V^2 + \sigma_U^2)$. The measure of technical efficiency is defined as

$$\mathrm{EFF}_i = E(Y_i^*|U_i, X_i)/E(Y_i^*|U_i = 0, X_i), \tag{2}$$

where Y_i^* is the production of the ith firm, which is equal to Y_i, if the dependent variable is in original units, and is equal to $\exp(Y_i)$ if the dependent variable is in logs. EFF_i takes up a value between zero and one. The efficiency measures relative to the production function may be defined as $\exp(-U_i)$ if the dependent variable is lagged, or as $(X_i\beta - U_i)/(X_i\beta)$ if it is not. These expressions for EFF_i rely upon the value of the unobservable U_i, being predicted.

Within this general framework, we choose a Cobb–Douglas production function specified as follows:

$$\ln(Y/L)_{it} = \beta_0 + \beta_1 \ln(K/L)_{it} + \sum_{j=1}^{m-1} \lambda_j \ln(K/L)_{it} * \mathrm{Industry}_j + (V_{it} - U_{it}) \tag{3}$$

in which real output is proxied by the log of real sales value per worker of the ith firm at time t $(I = 1, \ldots, N; t = 1, \ldots, T)$, production inputs are represented by the log of the capital stock per worker, the latter being evaluated at the replacement cost of capital. The prices of both inputs and outputs have been deflated using the industry inflation indexes computed by ISTAT.

The Cobb–Douglas production function includes output and capital stock per worker. The input variables have been multiplied by the corresponding industry dummies [23] in order to account for industry specificities which may influence the intercept and the slope of the production function. In fact, each industry is expected to have a different production function. This implies the existence of variations in the output-per-worker/capital-per-worker elasticities across industries.

[22] It has been shown that these strong distributional assumptions have limited effects for the purpose of our analysis (Aigner et al., 1977; Cowing et al., 1983; Greene, 1990). In particular, even though the absolute level of inefficiency differs over different distributional assumptions on the one-sided error term, the ranking of firms seems unaffected (Greene, 1990).

[23] Nineteen industries have been defined according to the four-digit ISTAT classification: (1) Food, beverages, and tobacco; (2) Textile and clothing; (3) Leather and shoes; (4) Wood, wood products, and furniture; (5) Paper, paper products, printing, and publishing; (6) Chemicals; (7) Rubber and plastic products; (8) Glass and ceramic products; (9) Building industry; (10) Metal extraction; (11) Metal products; (12) Mechanical materials; (13) Mechanical equipment; (14) Electronic equipment; (15) Electric equipment; (16) Precision instruments and apparatus; (17) Transport vehicles; (18) Transport – other; (19) Energy production.

The nonzero mean residual of the production function is regressed on the following variables that are assumed to affect efficiency:

$$U_{it} = \delta_0 + \sum_{i=1}^{m-1} \alpha_i \text{Industry}_i + \sum_{j=1}^{p-1} \eta_j \text{Area}_j + \sum_{k=1}^{q-1} \theta_k \text{Size}_k + \delta_1 \text{Marketshare} + \delta_2 \text{Subsidies} + \delta_3 \text{Innovation} + \delta_4 \text{Export} + \delta_5 \text{Age} + \delta_6 A/F \text{dummy} + w_{it} \quad (4)$$

while, for the 1995–97 model, three additional regressors (available only for this data set) are included:

$$\cdots + \delta_7 \text{Largestcl} + \delta_8 \text{Competarea} + \delta_9 \text{Caput} + \cdots$$

The variables affecting efficiency are: Number of employees (Size), market share (Market share), sales to the three biggest customers (Largestcl), capacity utilization rate (Caput), age and a series of dummy variables: Area (geographic location in the North-East, North-West, Centre, South and Islands), sector of economic activity (Industry), export status (Export), access to state subsidies (Subsidies), process and/or product innovating status (Innovation), Active/Failed status (A/F dummy) and presence of direct competitors in the same geographic area (Competarea).

The model is estimated for each of the three samples as a cross-section in which all the quantitative variables are expressed as three-year averages.

3.1. The stochastic frontier approach and the probability of bankruptcy: Econometric results

A positive and statistically significant gamma coefficient indicates that the variation of the nonzero mean residual explains a significant part of overall variability (Table 3). The model specified therefore fits the data well and supports the presence of relevant technical inefficiencies.

As expected, the signs and coefficients reported show that firms which we know are going to fail in the near future are significantly more distant from "best practice" in two of the three periods, while the coefficient has the expected sign but is not significant in the first period. [24]

Among other factors affecting the distance from the efficiency frontier, we find that firms located in the south are significantly less efficient. [25] Another result, which is not sample specific, and holds for all of the three considered periods is the relatively higher efficiency of exporting firms vis-á-vis those which sell only in the

[24] This result is consistent with the hypothesis of the strong relevance of financial factors on bankruptcy for firms surveyed in the first period in which they are presumably affected by a shift in monetary policy and by the consequent increase in real interest rates. Since the distance from the frontier mainly measures firm inefficiency on the real side (and not financial difficulties), its significance in the second and third sample period parallels the higher relevance of nonfinancial efficiency in the logit estimate for the same two periods (see in this section below).

[25] To interpret this finding we may consider the influence of productive efficiency of factors such as weakness in the infrastructure, stronger crime control and lower social capital (Putnam, 1993).

Table 3
Stochastic frontier results—1989–91 (Panel A), 1992–94 (Panel B), 1995–97 (Panel C) sample[a]

Variable	First specification				Second specification			
	First equation		Second equation		First equation		Second equation	
	Coef.	*t*-Ratio	Coef.	*t*-Ratio	Coef.	*t*-Ratio	Coef.	*t*-Ratio
Panel A								
Constant	4.343	97.665	4.351	92.583	0.109	0.337	−0.050	−0.216
Ln(K/L)	0.571	16.166	0.569	16.211				
Small size					0.373	4.485	0.382	4.492
Size					−0.040	−0.445	−0.031	−0.333
Age					−0.006	−2.383	−0.005	−2.621
North-West					−8.323	−16.463	−8.242	−14.861
North-East					−0.081	−0.997	−0.088	−1.071
South					−0.191	−2.314	−0.183	−2.164
Market share					0.515	5.777	0.517	5.685
Subsidies					0.217	3.854	0.213	3.699
Innovation					−0.003	−0.026	0.003	0.025
Export					−0.686	−10.138	−0.709	−10.794
Active					−0.161	−0.807		
Failed + stressed							0.223	0.899
σ^2					0.599	20.802	0.607	19.285
γ					0.514	18.207	0.518	16.635
Log likelihood						−3288.905		−3273.320
Number of observations						3514		3493
Panel B								
Constant	4.837	101.703	4.829	98.972	2.635	6.244	2.255	5.475
Ln(K/L)	0.713	9.771	0.716	9.582				
Small size					−0.055	−0.738	−0.092	−1.212
Size					0.117	1.529	0.107	1.400
Age					−0.001	−0.376	−0.001	−0.900
North-West					−0.013	−0.168	−0.028	−0.373
North-East					−0.228	−2.730	−0.259	−3.237
South					0.472	5.291	0.484	5.535
Market share					−14.573	−2.442	−14.470	−2.265
Subsidies					−0.032	−0.546	−0.034	−0.615
Innovation					−0.014	−0.237	−0.029	−0.505
Export					−0.734	−11.599	−0.774	−12.648
Active					−0.508	−2.968		
Failed + stressed							0.677	2.715
σ^2					0.432	18.865	0.441	20.472
γ					0.371	7.934	0.386	9.121
Log likelihood						2674.306		2658.674
Number of observations						3182		3163
Panel C								
Constant	5.217	105.816	5.265	113.467	3.111	8.526	2.214	7.067
Ln(K/L)	0.563	9.334	0.516	8.675				
Small size					−0.359	−9.120	−0.346	−8.842

(*continued on next page*)

Table 3 (*continued*)

Variable	First specification				Second specification			
	First equation		Second equation		First equation		Second equation	
	Coef.	*t*-Ratio	Coef.	*t*-Ratio	Coef.	*t*-Ratio	Coef.	*t*-Ratio
Size					−0.013	−0.236	0.045	0.752
Age					0.002	1.769	0.002	2.065
North-West					0.098	1.881	0.081	1.490
North-East					0.078	1.370	0.061	1.028
South					0.504	8.358	0.468	7.627
Market share					−20.256	−4.926	−36.293	−10.586
Subsidies					−0.007	−0.202	0.003	0.076
Innovation					−0.038	−0.999	−0.028	−0.709
Export					−0.338	−8.273	−0.331	−8.023
Sales to the three largest customers					0.004	5.621	0.003	4.668
Competitors in same area					0.054	1.630	0.048	1.471
Capacity utilization					−0.009	−7.099	−0.008	−6.079
Active					−0.644	−4.008		
Failed + stressed							0.670	3.644
σ^2					0.338	27.795	0.343	29.159
γ					0.235	6.220	0.264	7.469
Log likelihood						2546.678		2541.386
Number of observations						3195		3195

[a] Coefficients and *t*-stats for the following 19 industry dummy variables are omitted for reasons of space and are available upon request: (1) Food, beverages, and tobacco; (2) Textile and clothing; (3) Leather and shoes; (4) Wood, wood products, and furniture; (5) Paper, paper products, printing, and publishing; (6) Chemicals; (7) Rubber and plastic products; (8) Glass and ceramic products; (9) Construction industry; (10) Metal extraction; (11) Metal products; (12) Mechanical materials; (13) Mechanical equipment; (14) Electronic equipment; (15) Electric equipment; (16) Precision instrument and apparatus; (17) Transport vehicles; (18) Transport – other; (19) Energy production.

domestic market. This result is consistent with most of the empirical literature (Aw and Hwang, 1995; Clerides et al., 1998; Becchetti and Santoro, 2001) and is generally explained by two nonmutually excluding rationales: (i) export is a learning process that improves firm productivity; (ii) export markets select the most efficient firms (Delgado and Farinas, 1999).

The impact of size and age on productive efficiency seems less strong and more sample specific. This means that it is probably affected by changes in fiscal, monetary and exchange rate policies which crucially altered the economic framework in the three sample periods. [26]

[26] Expansionary fiscal policy and fixed exchange rates with real exchange rate appreciation in 1989–91. Public debt and currency crisis with devaluation and shift to flexible exchange rates and restrictive fiscal and monetary policies after 1992. Fixed exchange rates again in the last sample period.

4. Distance from the efficiency frontier and the logit model

The finding that ex-post failed firms are ex-ante significantly more distant from the efficiency frontier confirms the link between productive efficiency and the probability of bankruptcy. It does not imply however that remoteness from best practice has a significant marginal impact on the probability of failure, net of the effect of other qualitative and quantitative factors. In other terms, the above mentioned result does not indicate whether the stochastic frontier approach adds valuable information to banks which already possess financial information and the relevant qualitative information considered in this paper.

At a first glance, descriptive evidence on the relationship between firm soundness and the distance from the frontier seems to support our hypothesis for the last two sample periods (Fig. 1a–c). Our results are strikingly similar for both the second and third sample as (ex-post) failed and stressed firms are gathered at the expected end of the distance from the efficiency frontier axis. [27]

To verify whether descriptive evidence is econometrically robust we test whether the distance from the efficiency frontier has additional predictive power in traditional logit estimates measuring the effects of potential determinants of bankruptcy. In these estimates the dependent dichotomic variable stands for the probability of "firm failure", delimited by the [0,1] interval, and is represented by the dual "Active/Failed" enterprise state, according to the definitions explained in Section 2. [28] We present here only one estimate for each sample period (Table 4) and we provide a synthetic description of a sensitivity analysis carried on by considering one, two or three year averages or three year trends for the regressors. (Table 5). [29]

Econometric findings support the hypothesis of a marginal significant effect of the distance-from-frontier factor net of balance sheet and qualitative regressors included in the estimates in the last two periods (Table 4). The significance is between 5% and 10% and in one case (1995–97 sample) we also find evidence of nonlinearity since the

[27] The result obviously does not consistently hold in the first period with what was found in the stochastic frontier estimate where ex-post failed firms are ex-ante not significantly more distant from the efficiency frontier.

[28] The model takes on the usual specification:

$$P(g_1|X) = \exp(-Z)/(1+\exp(-Z)) \quad P(g_2|X) = 1/(1+\exp(-Z)), \tag{5}$$

where $P(g_i|X) - i = 1, 2, \ldots, n$ – is the probability of belonging to group i given a set of observed variables X, and Z is a linear combination of the set of X-variables:

$$Z = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_n X_n. \tag{6}$$

The set of X-variables consists of 24 financial indices adopted to evaluate the strength of the firms' structure and performance (see Table 2).

[29] Detailed results of these estimates are available from the authors upon request.

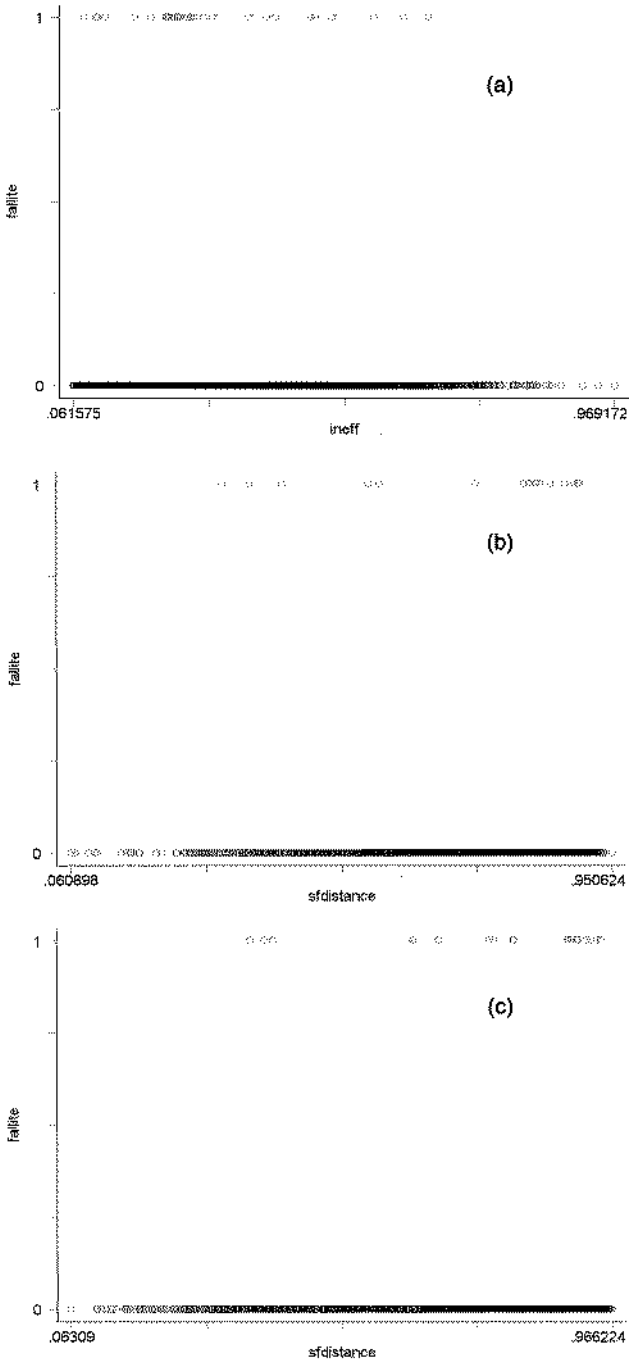

Fig. 1. The ex-ante distance from the efficiency frontier of failed and stressed firms: (a) 1989–91 sample, (b) 1992–94 sample and (c) 1995–97 sample.

Table 4
Distance from efficiency frontier and the logit model

	1989–91 Sample		1992–94 Sample		1995–97 Sample	
	Odds ratio	z-Value	Odds ratio	z-Value	Odds ratio	z-Value
Net working capital/current liabilities	0.998	−0.39	−1.733	−2.12	0.028	1.66
Net working capital/medium and long term debt	1.060	3.29	−0.015	−0.55	0.108	3.19
Net working capital/total assets	0.254	−0.84	7.327	2.25	−4.415	−1.78
Sales/Total assets	0.859	−0.23	−0.493	−0.65	0.770	1.69
Total debt/total assets	58.005	2.77	5.278	2.21	1.139	0.98
Current liabilities/net worth	1.004	1.85	0.017	1.99	0.003	0.56
Interest charges/value added	3.205	2.98	0.012	0.1	0.179	1.54
Depreciation charges/gross fixed assets	0.001	−1.46	−19.273	−2.11	−1.561	−0.33
Reserves/total assets	0.002	−2	−3.160	−1.2	−1.424	−0.54
Profit (Loss) for the period/net worth	0.944	−1.63	0.077	1.2	−0.052	−2.92
Sales/gross fixed assets	1.000	−0.25	−0.180	−0.83	−0.080	−1.23
Operating profit/total assets	3.653	0.38	−8.413	−3.84	−11.185	−2.88
Profit (Loss) for the period/sales	1.308	1.16	−1.112	−2.93	0.092	0.08
Earnings before taxes/total debt	9.707	2.2	−0.566	−1.07	−0.334	−3.54
Group membership	0.885	−0.3	−1.456	−1.72	−1.554	−1.67
Age	1.002	0.65	−0.016	−1.14	−0.019	−1.02
Subcontracting status	1.616	1.24	−0.427	−0.61	−0.121	−0.19
Small size	0.888	−0.21	0.618	0.69	−1.297	−1.73
Large size	1.902	1.07	0.571	0.72	−1.544	−0.63
Export status	1.199	0.41	0.729	0.84	−0.211	−0.36
Operating risk	2.03	1.87	−15.670	−0.87	6.066	1.12
Inefficiency	26.620	0.84	6.369	1.84	8.089	1.83
Inter25	0.089	−0.54	0.056	0.01	23.819	2.7
Inter75	0.154	−0.93	−2.761	−1.02	−5.056	−1.22
Market share	0.03	−1.39	42.423	2.11		
Sales to the three largest customers (%)					0.023	1.66
Competitors in the same area					1.802	2.79
Capacity utilization					0.03587	1.14
Number of observations				2911		3147
Wald test	$\chi^2(35,3405)$	147.78	$\chi^2(30,2911)$	240.77	$\chi^2(33,3147)$	406.66
Log likelihood		−168.307		64.3948		69.37983
Pseudo R^2		0.193		0.3148		0.402

Inefficiency: Distance from the efficiency frontier; *Inter25:* Inefficiency * D25 where D25 is a dummy taking up the value of one for the quartile of firms with the highest distance from the efficiency frontier; *Inter75*. Inefficiency * D75 where D75 is a dummy taking up the value of one for the quartile of firms with the lowest distance from the efficiency frontier.

Table 5
Variables significantly affecting the probability of bankruptcy in the logit analysis

Model	1989–91	1992–94	1995–97
Three-year indices	Net working capital/medium and long term debt (+) total debt/total assets (+) current liabilities/net worth (+) (+) interest charges/value added (+)reserves/total assets (−) earnings before taxes/total debt (+)	Total debt/total assets (+)operating profit/total assets (−) group members. (−) current profit (losses)/ sales (−) market share (+) earnings before taxes/total debt (−)	Net working capital/medium and long term debt (+) current profits (losses)/net worth (−) operating profit/ total assets (−) earnings before taxes/total debt (−) customers' concentration (+) strength of local competitors (+)
Two-year indices	Net working capital/medium and long term debt (+) total debt/total assets (+) interest charges/value added (+) reserves/total assets (−)	reserves/total assets (−) operating profit/total assets (−) group members. (−) Market share (+)	Net working capital/medium and long term debt (+) interest charges/value added (+) earnings before taxes/ total debt (−) group members. (−) Small size (−) strength of local competitors (+)
One-year indices	Current liabilities/net worth (+) total debt/total assets (+) industry 8(+) interest charges/value added (+) reserves/total assets (−)	Interest charges/value added (+) operating profit/total assets (−) market share (+) reserves/total assets (−)	Net working capital/current liabilities (+) group members. (−) Interest charges/ value added(+) current profits (losses)/net worth (−) customers' concentration (+)
Three-year trends[a]	Interest charges/sales (up) (+) net working capital/total assets (down) (−) industry 1 1 (+) total assets/net worth (down)(+) depreciation charges/gross fixed assets (down)(−) reserves/total assets (down)(+)	Interest charges/sales (up) (+) sales/gross fixed assets (up) (−) group members (−)	Interest charges/value added (up) (+) group members. (−) sales/gross fixed assets (up) (+) size (+) sales/gross fixed assets (down) (+) operating profit/ total assets (down)(−) current profits (losses)/total assets (down) (−)

The dependent dichotomic variable stands for the probability of "firm failure", delimited by the [0,1] interval, and is represented by the dual "active/failed" enterprise state, according to the definitions explained in Section 2. Three year model means three year averages of data (from year −3 to year −1) plus the year of the distress (year 0). Two year model means two year averages of data (from year −2 to year −1) plus the year of the distress (year 0).

(+): the variable has positive and significant effect on the dependent variable at 95% significance level.

(−): the variable has negative and significant effect on the dependent variable at 95% significance level.

(Up) (down): For increasing (decreasing) trends the dummy variable is called up (down) and it is given the value of one or zero otherwise.

[a] A trend is represented by a three-year period in which the indicator moves in the same direction.

interaction term of the continuous variable with a dummy for the highest distance quartile is positive and strongly significant. [30]

A first comparison of the other regressors that are statistically significant in different specifications (Table 5) shows that only four ratios (earnings before tax to total debt, net working capital to medium and long term debt, total debts to total assets, and operating profits to total assets) are significant in the expected direction in at least two periods in the case of the three-year model. This suggests that indices of liquidity, leverage, and profitability have a predominant role in the assessment of the probability of failure in our samples. Five more indices of leverage (current liabilities to net worth), operating structure (interest charges to value added), size and capitalization (reserve to total assets) and profitability (current profit/loss to net worth, current profit/loss to sales) are significant in only one period and their signs fit expectations. This is consistent with the heterogeneity of results across studies conducted in different periods and in different countries, as already noted by Edmister (1972); Begley et al. (1996) [31] and Barontini (1992), [32] among others.

By comparing the effects of regressors across different periods we find no common factors affecting the dependent variable in the two-year model and only one common factor (interest charges/value added) in the one-year model. [33] Several indices, however, have common effects with the expected sign in at least two periods. [34]

[30] The distance from the efficiency frontier has low correlation coefficients with other regressors confirming its significant marginal contribution in predicting bankruptcy. The average correlation coefficient is around 0.05 in absolute value and the strongest correlation concerns the export status (−0.45 in the 1992–94 sample and −0.19 in the 1995–97 sample). The higher negative correlation in the 1992–94 sample should reflect the impact of the exchange rate devaluation in 1992 which greatly increased the share of exporting firms in Italy.

[31] In this paper the performance of Altman (1968) and Ohlson (1980) models is tested and found less satisfactory in periods different from those originally considered by the authors, with Ohlson (1980) yielding a better performance than Altman (1968). A nice result is that the reduced model performance in different sample periods is found consistent with the authors' predictions on the effects on borrowers of changes in bankruptcy laws and increased use of debt in the 80s.

[32] Barontini (1992) tests on a balanced sample of 70 manufacturing firms the classification efficiency of more than 10 models, their transferability across time, and their sensitivity to changes in the cut-off point. He concludes that the performance of the models does not guarantee transferability given the high percentage of cut-off sensitive type I and type II errors.

[33] If we consider differences in macroeconomic scenarios across the three sample periods and evaluate them in the light of theory and empirical findings of the credit view (Gertler et al., 1990; Kashyap et al., 1993), we may consider part of sample specificity as depending on changes in monetary policy. In fact, the public debt and currency crisis occurred in Italy in 1992 generated a shift toward restrictive fiscal and monetary policies which may have significantly increased the relative relevance of financial over real bankruptcy risk factors. This would be consistent with the significance, only in the first sample period, of liquidity and leverage indicators which include firm debt. This evidence parallels the large relevance of leverage indicators in Lo (1986) who examines a sample of US firms until 1982 during the shift toward a severe antinflationary monetary policy which generated a significant rise in real interest rates.

[34] A result which needs to be interpreted is the positive and significant sign of the net working capital/medium and long term debt ratio, which might reasonably mean that inventories build up more rapidly than usual – i.e., for diving sales – in unsound firms during the considered period(s).

Table 6
Test for the joint significance of qualitative variables 1989–91 (Panel A), 1992–94 (Panel B), 1995–97 (Panel C)

Variables	Model specification	$\chi^2(7, 3413)$	Prob > χ^2
Panel A			
Group membership	Three year indices	6.53	0.471
Market share			
Age			
Subcontracting status			
Small size			
Large size			
Export status			
	Two year indices	8.04	0.3212
	One year (91) indices	9.26	0.2321
	Trend indices	13.07	0.0723
Panel B			
		$\chi^2(7, 3090)$	
Group membership	Three year indices	9.75	0.200
Market share			
Age			
Subcontracting status			
Small size			
Large size			
Export status			
	Two year indices	8.37	0.30
	One year (94) indices	22.70	0.001
	Trend indices	3.49	0.831
Panel C			
		$\chi^2(10, 3144)$	
Group membership	Three year indices	41.79	0.0000
Age			
Subcontracting status			
Small size			
Large size			
Export status			
Market share			
Sales to three largest customers (%)			
Large competitors in the same region			
Use of production capacity (%)			
	Two year indices	35.69	0.0000
	One year (97) indices	64.94	0.0000
	Trend indices	21.70	0.0041

Results from trend specification confirm that many of the variables affecting the probability of bankruptcy are sample specific. Table 5 shows no common factors across the three sample periods, though the interest charges/sales and the sales/gross fixed assets ratios have expected effects in common in two of the three samples. Once again, group membership is inversely related to the probability of failure. Results from balance sheet factors are broadly consistent with findings from previous empirical literature. Evidence on the significance of the sales/total assets ratio is wide-

spread (Bilderbeek, 1977; Altman et al., 1979; Altman and Lavallee, 1981; Altman, 1984). The total debt/total asset indicator which is significant in two out of three periods in the three-year-model is also a crucial determinant of bankruptcy in many empirical papers (Altman and Lavallee, 1981; Zavgren, 1985; Keasey and Watson, 1987).

Finally, Tables 5 and 6 (Panel A–C) show that qualitative variables (Group membership, strength of local competitors, customer concentration) become jointly significant in the logit estimate as long as there is more input of information and the addition of new variables (second and third sample periods).

5. Conclusions

A problem of the empirical literature on bankruptcy risk is the fact that results cannot be easily generalized since the significance of the relevant variables tends to be sample specific. In addition, limits to the information available and the traditional approach adopted by banks generally leads researchers to restrict the scope of the analysis to balance sheet variables. Furthermore, the potentially unlimited number of firms that can be included in the control sample leads them to build ad hoc balanced samples with obvious limits arising when the dependent variable is observed before sampling.

Our paper sheds light on how to solve some of the above mentioned problems in at least four ways.

First, results from this paper suggest that one of the indicators traditionally considered in empirical analysis – interest charges over value added – is not sample specific since it is significant in each of the three considered sample periods.

Second, our results show that nonbalance sheet items (such as customer concentration, subcontracting status, export status, presence of large competitors in the same region) significantly improve the explanatory power of models predicting bankruptcy.

Third, our findings indicate that a firm's productive inefficiency (measured as the distance from the "best practice" with the stochastic frontier approach) is a significant ex-ante indicator of business failure.

Fourth, our results show that, in the second and third sample periods, a firm's productive efficiency adds additional explanatory power to models that include balance sheet and qualitative variables to predict business failure.

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