Evaluation of credit risk based on firm performance

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Abstract

In this paper we investigate whether technical efficiency is an important ex-ante predictor of business failure. We use samples of French textiles, wood, and R&D companies to obtain efficiency estimates for individual firms in each industry. These efficiency measures are derived from a directional technology distance function constructed empirically using non-parametric Data Envelopment Analysis (DEA) methods. We summarize the effect of efficiency on the likelihood of default in terms of the franchise value hypothesis which states that more efficient firms will be less likely to fail. Estimating probit and logit regression models we find that efficiency has significant explanatory power in predicting the likelihood of default over and above the effect of standard financial indicators. Our empirical analysis also shows that caution needs to exercised when using the solvency ratio as an ex ante predictor of business failure.

JEL Classification: G21

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1. Introduction

It is well established that the effective use of screening technology greatly reduces the costs of informational asymmetries between borrowers and lenders thereby enhancing the efficiency of the financial intermediation process. As emphasized in a series of papers by Stiglitz and Weiss (1981, 1986 and 1992) improvements in screening and monitoring techniques are a valuable alternative to incomplete contracts aimed at reducing moral hazard and adverse selection problems. These informational asymmetries lie at the heart of market failures such as credit rationing (see Stiglitz and Weiss 1981 and Becchetti and Sierra, 2003).[1]

The forces of globalization, financial deregulation and innovation have not diminished the importance of credit risk albeit market risk has become increasingly important in view of recent episodes of turmoil in the world's financial markets (see Paradi et al., 2004). Yet credit risk is still the most significant risk for financial institutions. The New Basel Capital Accord places explicitly the onus on banks to adopt sound internal credit risk management practices to assess their capital adequacy requirements.[2] Through effective management of credit risk exposure banks not only support the viability and profitability of their own business but also contribute to systemic stability and to an efficient allocation of capital in the economy.

The aim of this paper is to investigate the role of non-financial factors in credit risk evaluation. In particular, we examine whether an assessment of a firm's technical or managerial inefficiency conveys useful ex-ante information in predicting business

[1] Rothschild and Stiglitz (1976), Guesnerie and Laffont (1984) and Spence (2002) use self-selection models to analyze sorting effects on borrowers under imperfect information. Deshons and Freixas (1987) and Psillaki (1998) demonstrate that it is not generally possible to sort different types of borrowers in the presence of moral hazard and adverse selection, and that credit rationing may exist even by increasing the dimensionality -i.e. both price (interest rate) and non-price (collateral) terms- of contracts available to banks.

[2] The New Basel Capital Accord (Basel II) requires banks to implement a robust framework for the evaluation of credit risk exposures that they face (Basel Committee on Banking Supervision, 1999, 2001, 2006). While in the 1988 Capital Accord the Basel Committee favored the ratings provided by external credit ratings agencies, it is now encouraging an Internal Ratings-Based (IRB) approach under which banks use their own internal rating models to estimate default risk. The effect of these changes is likely to be more pronounced on small and medium enterprises (SMEs) which are more informationally opaque compared to large corporations (European Commission, 2005).

failures. While much empirical research has emphasized the importance of traditional financial performance measures in bankruptcy prediction albeit with various degrees of success, the role of non-financial information remains largely unexplored. We postulate that a combination of financial and non-financial factors should enhance a bank's ability to predict business failures more accurately than a model that relies solely on the use of financial indicators.

This study contributes to the credit risk literature by outlining a flexible procedure to be used by banks to assess firm performance and the likelihood for borrower default. Rather than focusing on financial measures which are typically backward looking we use technical efficiency as a measure of firm performance and as part of a mechanism for selecting potentially distressed firms.[3] We expand on techniques used in previous studies to assess firm performance. More specifically, we employ the directional technology distance function, a generalization of the more widely used Shephard (1970) input and output distance functions, to measure technical efficiency. These performance measures are constructed by allowing firms to simultaneously adjust in the direction of fewer input and greater output production as much as it is technologically feasible. This entails an extremely flexible description of technology without restricting firms to optimize by either increasing outputs proportionately without changing inputs or by decreasing inputs proportionally for given outputs. In this sense the directional distance function has a dual association with the profit function and thus it provides a useful performance companion when profitability is the overall firm goal.

We follow a two step methodology to evaluate credit risk. First we use non-parametric linear programming methods to obtain a measure of firm's performance (technical efficiency) relative to its peers computed as the distance from the industry's empirically constructed best practice frontier. Second, we use probit and logistic regression analysis to assess the importance of efficiency in predicting business failures over and above of that explained by financial factors. For empirical analysis purposes we choose two traditional French manufacturing industries (textiles and wood and paper products) and a growth industry (computer activities and R&D).

[3] Previous studies that have examined the use of non-financial data as predictors of company failures include Zavgren (1985), Keasey and Watson (1987), and Becchetti and Sierra (2003).

The reminder of this paper is organized as follows. The next section provides a brief overview of approaches used in the literature for predicting business failures. Section 3 explains how we propose to construct the firm efficiency measures and outlines the specification of the bankruptcy model. Section 4 describes the data and discusses the relative importance of financial and non-financial factors as default predictors.

2. Literature review

A variety of analytical techniques have been used for credit-risk assessment. They include statistical methods, such as linear, multivariate or quadratic discriminant analysis, logistic and probit regression analysis; models based on contingent claims and asset value coverage of debt obligations; neural networks; and operational research (OR) methods such as linear or quadratic programming and data envelopment analysis (DEA). The bulk of this literature has concentrated on the use of financial factors such as liquidity, profitability and capital structure in risk evaluation.[4]

Since the pioneering work of Altman (1968) a host of statistical bankruptcy prediction studies appeared using discriminant analysis (e.g. Altman et al.1983), logistic regression (e.g. Martin 1977; Ohlson 1980; Zavgren 1985; Keasey et al. 1990), and probit analysis (e.g. Zmijewski 1984; Skogsvik 1990). More recent work in this area includes Kolari et al. (2002) who developed an early warning system for bank failure based on logit analysis and Trait recognition, Jones and Hensher (2004) who used a mixed logit model to predict firm financial distress, and Canbas et al. (2005) who combined discriminant analysis, probit, logit and principal component analysis to form an integrated early warning system for bank failure.

Decision support systems in conjunction with multi-criteria decision-making techniques were introduced to financial classification problems aimed at evaluating the risk of business failures in a number of studies (e.g. Zopounidis 1987; Mareschal and Brans 1991; Zopounidis et al. 1992; Diakoulaki et al. 1992; Siskos et al. 1994;

[4] See Altman and Saunders (1997) and Ravi Kumar and Ravi (2007) for a comprehensive review of this literature.

Zopounidis and Doumpos 1998; Emel et al. 2003). In the late 1990s, Data Envelopment Analysis (DEA) was introduced in credit risk evaluation as in Troutt et al. (1996); Simak (1999), Cielen and Vanhoof (1999) and more recently by Emel et al. (2003), Paradi et al. (2004) and Cielen et al. (2004).

DEA is a non-parametric approach developed by Charnes et al. (1978) as a technique to assess the relative efficiency of 'decision making units' (DMUs). DEA derives a unit-free single performance index formed as a ratio of aggregated outputs to aggregated inputs. Conceptually, DEA compares each one of the DMUs' observed outputs and inputs in order to identify the relative 'best practices' and establish an efficient frontier. Based on the efficient frontier the degree of efficiency of individual DMUs is then measured. Thus DEA provides a flexible and powerful alternative to traditional credit scoring techniques by producing relative performance measures as input-output ratios in which credit assessors might value inputs and outputs differently and therefore adopt different weights.[5] This situation is particularly useful when there is disagreement over the value of some input or outputs entering the credit scoring algorithm.

In spite of their popular appeal and wide applicability many of the aforementioned techniques share a number of disadvantages (see Basel Committee on Banking Supervision, 2000; and Grunert et al., 2005). For example, in addition to focusing on financial performance measures few of these models provide a theoretical apparatus for the use of performance factors in bankruptcy prediction. In this paper we take a different approach in assessing business default risk. We rely on recent theoretical work on production frontiers and performance measurement to establish the link between productive efficiency and bankruptcy risk.[6] More specifically, we rely on economic aggregators based directly on technology and physical input and output quantities to form performance measures which we view as potentially useful indicators of a company's future health.

[5] Cielen et al. (2004) report that the DEA model gives more accurate bankruptcy prediction results than decision trees and discriminant analysis/LP models.

[6] Fried, Lovell and Schmidt (2007) and Färe, Grosskopf and Margaritis (2007) provide an extensive review of the literature on efficiency and productivity.

Several authors including Zavgren (1985), Keasey and Watson (1987), and Becchetti and Sierra (2003) have emphasized the importance of non-financial data as predictors of company failures. Zavgren (1985) argues that econometric models that solely rely on financial statement information will not predict accurately business failures. Using a measure of efficiency obtained from a stochastic frontier model, Becchetti and Sierra (2003) find that productive inefficiency is a significant ex-ante indicator of business failure while Keasey and Watson (1987) report that better predictions for small company failures are obtained from models using non-financial data rather than conventional financial indicators.

3. Methodology

We propose a two stage procedure that can serve as an early-warning model in evaluating default risk (i.e. predicting business failure).[7] As per standard practice we refer to an early-warning model as an established procedure (usually statistical) for classifying firms into distinct groups (e.g. potentially failed versus non-failed; see Barr and Siems, 1992; and Spronk et al., 2005). The goal of such a model is to identify a firm's financial weakness at an initial stage so as to warn interested parties of potential default risk (see Meyer and Pifer, 1970; and Barr and Siems, 1992). In Stage 1 we obtain a relative measure of firm's performance (technical efficiency) using DEA methods. In Stage 2 we use probit and logistic regression analysis to assess the importance of efficiency in predicting business failures over and above that explained by financial factors.

Our approach follows the methodology of Becchetti and Sierra (2003) with some important differences. First, we use non-parametric methods (DEA) to construct the

[7] The concept of credit risk is similar to that of bankruptcy risk as in both cases the focus of the analysis is on the likelihood that a debtor (i.e. firm, organization or individual) will not be able to meet its debt obligations to its creditors (i.e. default). Bankruptcy prediction models are often used within the credit risk assessment context, but it should be noted that the two problems are slightly different: bankruptcy has mainly a legal interpretation, whereas default has a financial interpretation. The term "bankruptcy" refers to the termination of the operation of the firm, whereas financial distress associated with default risk does not necessarily lead to the termination of the operation of the firm (Spronk et al. 2005).

technological frontier and to measure firm efficiency. Becchetti and Sierra use parametric methods (a stochastic frontier model in which technology is parameterized by a Cobb-Douglas production function). DEA methods have some advantages (and disadvantages) when compared to parametric methods (see Fried et al., 2007). For our purposes, DEA is arguably a far more flexible method to construct an efficiency frontier compared to a Cobb-Douglas specification. Moreover, it readily provides the means to credit assessors to track individual firm performance. Second, by employing a directional distance function approach to the modeling of technology, we allow production decisions to be made by adjusting inputs and outputs simultaneously. This too provides more flexibility in generating performance measures compared to the more traditional (DEA) approaches in which performance is measured by optimizing either in the input or the output direction.

We apply DEA to estimate the directional distance function using a sample of French firms. Firm efficiency is measured relative to the empirically constructed frontier or 'best practice' technology for each given industry. In the second stage, we use standard probit and logistic regressions to determine the probability of firms to survive or fail as a function of non-financial and financial performance indicators. We would expect that firms which expect to sustain high efficiency rates into the future will have an incentive to guard the economic rents or franchise value generated by these efficiencies from the threat of liquidation (see Demsetz et al., 1996; Berger and Bonaccorsi di Patti, 2006). We summarise this statement in terms of a testable proposition, namely under the franchise-value hypothesis (H1) more efficient firms will be less likely to fail.

Distance functions are alternative representations of production technology which readily model multiple input and multiple output technological relationships. They measure the maximum proportional expansion in outputs and contraction in inputs that firms would be able to achieve by eliminating all technical inefficiency. They are the primal measures; their dual measures are the more familiar value functions such as profit, cost and revenue.

Following Färe and Grosskopf (2004) and Färe, Grosskopf and Margaritis (2007) we assume that firms employ N inputs denoted by $x = (x_1, \ldots, x_N) \in R_+^N$ to produce M outputs denoted by $y = (y_1, \ldots, y_M) \in R_+^M$. Technology may be characterised by a technology set T, which is the set of all feasible input/output combinations, i.e.,

$$T = \{(x, y) : x \text{ can produce } y\}. \tag{1}$$

The technology set is assumed to be a closed, convex, nonempty set with inputs and outputs which are either freely or weakly disposable.[8] To provide a measure of efficiency we use a directional technology distance function approach. This function completely characterises technology (i.e., it is equivalent to T), it is dual to the profit function and allows for adjustment of inputs and outputs simultaneously. To define it we need to specify a directional vector, denoted by $g = (g_x, g_y)$ where $g_x \in R_+^N$ and $g_y \in R_+^M$. This vector determines the direction in which technical efficiency is assessed. The directional distance function is defines as:

$$\vec{D}_T(x, y; g_x, g_y) = \sup\{\beta : (x - \beta g_x, y + \beta g_y \in T\}. \tag{2}$$

The directional distance function expands outputs in the direction g_y and contracts inputs simultaneously in the direction g_x to the frontier T. Output is expanded in the direction g_v, inputs are contracted in the direction g_v. If the observed input output bundle is technically efficient, the value of the directional distance function would be zero. If the observed input output bundle is interior to technology T, the distance function is greater than zero and the firm is technically inefficient.

The directional distance function can be estimated non-parametrically using DEA and a VRS (Variable returns to scale) technology as

$$\vec{D}_T(x, y; g_x, g_y) = \max \beta \tag{3}$$

subject to:

[8] Input weak disposability means that if all inputs increase proportionally then output will not decrease. Strong or free disposability on the other hand requires that output does not decrease if any or all feasible inputs are increased. Disposable outputs are similarly defined.

$$\Sigma_{k=1}^{K} z_z x_{kn} \leq x_{kn} - \beta g_x, n = 1,....,N$$

$$\Sigma_{k=1}^{K} z_z y_{km} \leq y_{km} + \beta g_y, m = 1,...,M$$

$$\Sigma_{k=1}^{K} z_z = 1, z_z \geq 0, k = 1,...,K$$

The solution to (3) will yield technical efficiency measures for each firm in the sample. In the second stage, we estimate probit and logistic regression models across different industries to determine the (ex post) probability of firms to survive or fail as a function of (ex ante) information on firm efficiency and financial performance ratios. The primary hypothesis of interest is summarized by our version of the franchise-value hypothesis according to which banks predict that, all else equal, less efficient firms have a significantly lower likelihood to remain solvent as they have less of incentive compared to their more efficient counterparts to protect the rents or franchise value associated with high efficiency from the threat of liquidation.

4. Empirical Analysis

The data used in this paper are extracted from the Diane database. It comprises samples of French firms from the textiles, wood and paper products, and computer activities and R&D sectors operating between 2000 and 2004. By forming unbalanced panels of data, we can determine which firms are continuing (survived) and which firms are potentially distressed (i.e. reporting consecutive negative profits) or exited their industries (failed) by the end of the sample period. For empirical analysis purposes we focus on a two year prediction model applied to each of these industries.

The DEA model uses one output (K, value–added), and two inputs, capital stock (K) and labour (L, number of full time equivalent employees), to generate a firm's efficiency measure relative to best practice in each industry. We apply the DEA model given in (3) above to each industry separately using 2002 data. The DEA efficiency scores that we obtain are used along with financial performance indicators (profitability, growth, asset structure, intangibility) and firm characteristics (size) as predictor variables in probit and logit models to determine the probability of firms to survive or fail. We define a dummy variable (D) which takes on the value of zero if a firm was active in 2004. For firms that exited the industry in 2004 or reported negative profits in consecutive years we set the D value equal to one. We restrict negative profits to 2003 and 2004 to avoid sample selection problems in assessing the effect of efficiency on the probability of default. Our main testable proposition is that firm efficiency is an important ex-ante indicator of business failure.

We include the following financial factors in the probit and logistic regression models:

Profitability (PR) – This variable is measured by pre-interest and pre-tax operating surplus divided by total assets (see Titman and Wessels, 1988; Fama and French, 2002). We would expect a negative relationship between profitability and the likelihood that a firm will default.

Asset structure (TA) - This is measured as the ratio of tangible assets divided by total assets (e.g. Titman and Wessels 1988, Rajan and Zingales 1995, Frank and Goyal 2003). The existence of asymmetric information and agency costs may induce lenders to require guarantees in the form of tangible collateral (Myers 1977, Scott 1977, Harris and Raviv, 1990). The costs of financial distress depend on the types of assets that a firm employs. We would expect that firms with large investments in land, equipment and other tangible assets will have smaller costs of financial distress than firms relying primarily on intangible assets. These firms tend to borrow more than companies with risky, intangible assets (Myers, 2001). We would normally expect a negative relationship between tangibles and the probability of default.

Intangibility (INT) - This is measured as the ratio of intangible assets divided by the total assets of the firm. Intangible assets can be considered as future growth opportunities and add value to the firm but cannot be collateralized (Titman and Wessels, 1988; Michaelas et al., 1999). We would normally expect a negative relationship between intangibles and the likelihood to default. However, as argued by Myers (1977) the underinvestment problem becomes more intense for companies with more growth opportunities and that intangible assets are more likely to sustain damage during financial distress. It is thus possible to find in some cases a positive relationship between intangibles and firm default.

Solvency ratio (SR) – This is measured by the company's net worth (total assets minus total liabilities) divided by total assets. It is customary used as an indicator of a company's ability to meet its long term debt obligations.

Firm size (SIZE) – This is measured by the logarithm of the firm's sales (see Titman and Wessels, 1988; Rajan and Zingales, 1995, Ozkan 2001). As larger firms are more diversified and tend to fail less often than smaller ones, we would expect that size will be negatively related to business failure. In addition, larger firms may be able to incur lower transaction costs associated with debt. The information costs are lower for larger firms because of better quality (accuracy and transparency) of financial information. In fact, according to the Observatory of European SMEs (2003/2) inadequate company information is often mentioned as one of the main factors hampering bank finance to SMEs.[9] However, size may also have a positive effect on default in situations where there could be a loss of control resulting from inefficient hierarchical structures in the management of the company (see Wiliamson, 1967).

Table 1 gives the descriptive statistics of the variables used in the empirical analysis. We have used data from 1445 firms operating in the textiles industry, 1577 firms from the wood and paper products industry, and 1757 firms from the computer activities and R&D industry in 2002. To obtain the efficiency measures we chose a directional vector equal to the mean input and output values in each industry. Suppose that an R&D firm has an efficiency measure of $\vec{D}_T$(x, y; g_x, g_y) = 0.12 and that $g = (\overline{K}, \overline{L}, \overline{Y})$ = (54.7, 66, 4621). If this firm were to operate efficiently it would have been able to expand output (*Y*) by 4621*0.12=554.5 thousand Euro while using 66*0.12=8 fewer full time equivalent employees (*L*) and 456*0.12=54.7 thousand Euro less in physical capital (*K*).

Table 1 shows that there are considerable differences in capital intensity among the three industries. The computer activities and R&D industry has the lowest (physical) capital to labour ratio and tangibles to total assets ratio but a higher ratio of

[9] For instance in 2002 according to the same source only about 60% of the SMEs regularly provide documents such as the balance sheet and the profit and loss statement. Around 8% of the SMEs hand over to their financier their annual budget, whilst 7% also share financial plans or cash flows forecasts with them and about 4% provide information on inventories or unpaid invoices.

intangibles to total assets compared with the other two industries. We estimate that firms in the wood and paper products industry have a better efficiency record on average relative to their peers. For all three industries we find considerable efficiency differences between firms in the top efficiency quartile compared to firms in the bottom quartile. Firms in the textiles industry are on average less leveraged compared to R&D and wood products industries and have a higher solvency ratio.

Table 2 presents the results of the logistic and probit regressions. As it is well known estimated coefficients from binary regression models do not measure the marginal effect of the regressor on the dependent variable. For example, the partial regression coefficient estimates in the logit model measure the change in the estimated logit (log of the odds-ratio) for a unit change in the value of a given predictor other things constant. The marginal effect of a variable on the probability of the response (i.e. firm default) is given by the product of the partial regression coefficient times the odds-ratio. In the probit model marginal effects are computed by multiplying the partial regression coefficients times the standard probability density function. Thus unlike partial regression coefficients the value of marginal effects depend on the values of all the regressors. The slope coefficients we report in Table 2 are marginal effects evaluated at the median data point.

Panel A of Table 2 shows that efficiency is a significant predictor of default for firms in the textiles industry. In particular, we find that more efficient firms are less likely to fail. A 0.1 unit increase in the inefficiency score increases the probability of default on average by about 2 percent. This probability decreases to about 0.35 percent for the top quartile of the most efficient firms. We also find that a one percentage point fall in profitability increases the probability of default by about 1 percent. Similarly, a one percentage point fall in intangible assets is expected to increase the probability of default by about 0.25 percent. Tangible assets had a negligible and insignificant effect on the likelihood of default in this industry so this variable was dropped from the regressions. We find that the solvency ratio (SR) is a poor predictor of a company's default. In fact our results suggest that all else equal an increase in SR is expected to increase (albeit by a small amount) rather than decrease the probability of default.[10]

[10] The usual caveat applies here; viz. the direct effect of SR on the likelihood of default should be interpreted within the partial regression context. This effect is conditioned on efficiency, profitability

This finding suggests that caution needs to be exercised when loan approvals are weighted too heavily on net worth considerations. We conclude that in spite of its simplicity and general appeal SR is a probably a backward rather than forward performance measure and thus it may not be a reliable predictor of a company's future health. Overall, we find from the estimates of the logit model that 307 out of the 1445 firms in the textiles sample have a less than five percent probability to fail. Using the forecast values from the probit model we find that 326 firms in this industry have less than five percent probability to fail.

Panel B presents the regression results for the wood and paper products industry. We find that the effect of profitability on the likelihood of default is similar in terms of both direction and magnitude to those we estimated for the textiles industry. On the other hand, inefficiency has a smaller albeit still positive and significant effect on default. Intangibles had negligible and insignificant power in predicting business failure so this variable was omitted from the regressions shown in Panel B. Again the effect of the solvency ratio on default is positive and significant. We also find that the tangibles to total assets ratio has a positive and significant effect on the default probability. This finding reinforces the caution we raised above with regards to whether some of balance sheet indicators are indeed useful ex-ante indicators of the future health of a company. Overall, the logit model predicts that of the 1577 firms in the sample 364 have less than five percent chance to default. According to the probit estimates 377 firms have less than five percent to default.

Panel C presents logit and probit estimates for the computer activities and R&D industry. We have included a squared term to capture possible non-linearities in the effect of efficiency on default. The overall effect of efficiency on default is significant at the 10% level. This effect is increasing with inefficiency and remains positive within the range of sample values. The effect of profitability on default is negative although lower in magnitude compared to the estimates for the textiles and wood industries. We surmise that the positive effect of intangibles on the likelihood of default or financial distress may be a reflection of the Myers (1977) underinvestment

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and the other regressors. For example, it may be the case that firms with higher solvency ratios are actually less likely to fail than they appear to be simply because they are more efficient or more problem. The logit model predicts that 199 out of the 1757 firms in this industry have less than five percent likelihood to default. The probit model predicts that 227 have less than five percent likelihood to default.

5. Conclusion

Using samples of firms from three different French industries and a novel methodological approach we have been able to corroborate previous results showing that non-financial performance indicators are useful ex-ante determinants of business failure. We have obtained the firm performance indicator employing a directional distance function which may be viewed as a generalization of previous approaches used to model technology and measure efficiency. Our results show that profitability is also an important ex-ante predictor of firm default. We also find that caution needs to be exercised when using standard balance sheet indicators such as the solvency ratio and the tangibles to assets ratio as predictors of business failure. The effect of intangibles on default appears to be sample specific so again caution is required when using this information for credit evaluation. An important caveat about our analysis is that it does not purport to produce a comprehensive model for bankruptcy prediction. Rather our intent has been to illustrate the potential use of non-financial indicators (viz. productive efficiency) as part of the bank's overall credit evaluation technological apparatus.

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profitable. Along similar lines one can also explain the negative effect of size on the probability of default shown in Panel A.

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Table 1

2002 Descriptive Statistics

	Computer Activities and R&D			Textiles and Textile Products			Wood & Paper Products		
	Mean	Median	StDev	Mean	Median	StDev	Mean	Median	StDev
Output	4620.9	1122.9	23675.3	2456.6	951.9	6185.1	3017.2	797.1	11447.4
Labour	65.9	20.0	289.2	58.6	25.0	129.1	53.9	20.0	138.2
Capital	455.6	54.2	2286.2	671.2	135.8	2031.7	2171.3	249.9	14086.0
DDF	0.336	0.117	0.649	0.385	0.153	0.633	0.273	0.097	0.573
DDF25	0.004	0.000	0.010	0.005	0.000	0.012	0.004	0.000	0.009
DDF75	1.042	0.636	1.004	1.157	0.856	0.879	0.860	0.468	0.919
Profit	0.047	0.056	0.236	0.070	0.056	0.131	0.058	0.048	0.109
TA	0.074	0.041	0.094	0.128	0.081	0.135	0.201	0.171	0.135
Size	7.887	7.670	1.280	8.125	7.970	1.271	7.978	7.750	1.299
SR	0.321	0.350	0.324	0.422	0.441	0.619	0.368	0.358	0.216
INT	0.060	0.006	0.117	0.041	0.005	0.085	0.025	0.002	0.063
DA	0.660	0.633	0.315	0.567	0.544	0.612	0.622	0.634	0.217
# Firms	1757			1445			1577		

Table 1 Notes:

Output is valued-added and is measured in thousands of euros; labour is the number of employees; capital is measured by fixed tangible assets in thousands of euros; DDF is the firm efficiency measure; DDF25 is the top efficiency quartile; DDF75 is the bottom efficiency quartile; PR is profits divided by total assets; TA is the ratio of tangible assets over total assets; Size is (log) of total operating revenue; SR is the solvency ratio; INT is the ratio of intangibles to total assets; DA is the debt to assets ratio.

Table 2: Logit & Probit Regression Analysis

Panel A: Textiles & Textile Products

	Logit				Probit			
Variable	Coefficient	z-Stat	Prob.	slope	Coefficient	z-Stat	Prob.	slope
DDF	1.952	2.398	0.017	0.196	1.105	2.437	0.015	0.216
PR	-9.928	-8.543	0.000	-0.995	-5.284	-7.909	0.000	-1.032
SR	1.011	3.168	0.002	0.101	0.515	2.940	0.003	0.101
Size	-0.142	-1.727	0.084	-0.014	-0.082	-1.816	0.069	-0.016
INT	-2.541	-2.082	0.037	-0.255	-1.344	-2.218	0.027	-0.262
DDF25	-1.611	-2.115	0.034	-0.162	-0.910	-2.154	0.031	-0.178
Const.	-0.896	-1.411	0.158		-0.525	-1.508	0.132	
LR (6 df)	207.901	R-sq	0.169		LR (6 df)	209.795	R-sq	0.171
P-value	0.000				P-value	0.000		
D=0	1226	Total	1445					
D=1	219							

Panel B: Wood & Paper Products

Variable	Coefficient	z-Stat	Prob.	Slope	Coefficient	z-Stat	Prob.	slope
DDF	0.314	1.933	0.053	0.029	0.183	1.983	0.047	0.033
PR	-11.600	-8.426	0.000	-1.063	-6.079	-7.225	0.000	-1.100
SR	1.109	2.697	0.007	0.102	0.578	2.609	0.009	0.105
Size	-0.107	-1.270	0.204	-0.010	-0.063	-1.376	0.169	-0.011
TA	2.273	4.126	0.000	0.208	1.214	3.967	0.000	0.220
Const.	-1.643	-2.463	0.014		-0.933	-2.567	0.010	
LR stati (5 df)	229.775	R-sq	0.177		LR (5 df)	230.283	R-sq	0.178
P-value	0.000				P-value	0.000		
D=0	1351	Total	1577					
D=1	226							

Panel C: Computers and R&D

Variable	Coefficient	z-Stat	Prob.	Slope	Coefficient	z-Stat	Prob.	Slope
DDF	0.479	1.486	0.137	0.041	0.285	1.603	0.109	0.048
DDF-Sq	-0.103	-1.711	0.087	-0.009	-0.061	-1.816	0.069	-0.010
PR	-2.979	-5.793	0.000	-0.253	-1.545	-5.875	0.000	-0.261
Size	0.139	1.449	0.147	0.012	0.069	1.382	0.167	0.012
INT	1.467	2.782	0.005	0.125	0.800	2.648	0.008	0.135
TA	-1.459	-1.258	0.208	-0.124	-0.784	-1.435	0.151	-0.132
DDF75	13.117	1.483	0.138	1.116	7.399	1.650	0.099	1.247
Const.	-3.274	-4.319	0.000		-1.818	-4.693	0.000	
LR (7 df)	139.979	R-sq	0.107		LR (7 df)	141.843	R-sq	0.108
P-value	0.000				P-value	0.000		
D=0	1541	Total	1757					
D=1	216							

Table 2 Notes:

DDF is the firm efficiency measure; size is (log) of total operating revenue; SR is the solvency ratio; PR is profits divided by total assets; tangibles (TA) and intangibles (INT) are measured as ratios over total assets; GR is the growth in earnings. All explanatory variables are measured in 2002. The dependent variable is a dummy variable (D) indicating if a firm was active (D=0) or is potentially distressed/had left the industry (D=1) by 2004.

Z-statistics are calculated using Huber-White robust standard errors. Prob are p-values of estimated coefficients. R-sq is the McFadden R-squared computed as one minus the ratio of the unrestricted over the restricted log likelihood values. The LR statistic tests the null that all slope coefficients except the constant are equal to zero.