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Edited by

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With a huge sense of pride and honor, I dedicate this book to the “Yasmine Revolt” by the young people of the Tunisian Republic. This book is based upon the International Finance Conference held in Tunisia in March, 2011. Papers were submitted before the “Yasmine Revolt,” and the Conference took place immediately after the revolution. This book is intended to better the understanding of the conventional finance and Islamic finance around crisis. I acknowledge the unique efforts of the Tunisian Ministry to enhance conventional and Islamic studies.

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PART 1.

ON RISK, GOVERNANCE AND RISK MANAGEMENT

THE PERFORMANCE OF HYBRID MODELS IN THE ASSESSMENT OF DEFAULT RISK

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AND JEAN JACQUES LEVY[3]

1. Introduction

Credit risk refers to the risk due to unpredicted changes in the credit quality of a counter party or issuer, and its quantification is one of the major frontiers in modern finance. The creditworthiness of a potential borrower affects the lending decision and the credit spread, since there is a doubt whether the firm will be able to perform its obligation. Credit risk measurement depends on the likelihood of default of a firm in meeting its required or contractual obligation, and on what will be lost if default occurs. When one considers the large number of corporations issuing fixed income securities and the relatively small number of actual defaults, one might regard defaulting as a rare event. However, all corporate issuers have positive probability of default. Models of credit risk measurement have focused on the estimation of the default probability of firms, since it is the main source of uncertainty in the lending decision. We may distinguish two large classes of credit risk models on the basis of the analysis they adopt. The first class, the set of traditional models, assume the fundamental analysis, called the non-structural model. The goal of these models, which goes back to Beaver (1966) and Altman (1968), is to distinguish which factors are more significant in assessing the credit risk of a firm. The second class, called structural models, assume the contingency claim analysis .The philosophy of these models goes back to

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Black and Scholes (1973) and Merton (1974), and assumes corporate liabilities as contingent claims on the assets of the firm[4].

In this paper, we investigate the hybrid contingent claim approach with French companies listed on the Paris Stock Exchange (Euronext Paris). Our goal is to assess how the combination of continuous assessments provided by the market and the values derived from financial statements improve our ability to forecast the probability of default.

The structural model of Merton has the advantage of being flexible, since the probability of default can continually be updated with changes in the value of corporate assets. Its main drawback is that it may over- or underestimate the probability of default, since asset values are unobservable and must be extrapolated from the share prices. On the other hand, the non-structural model of Altman is more accurate because it uses the accounting data of companies, but it is less flexible. Because the frequency of information is generally annual, the probabilities of default cannot be updated during the fiscal year. The quarterly financial statements can be found, but they are not always audited by an external accounting firm.

The Bank of England estimated the hybrid model with data from British companies and found some interesting results. During a first phase, the probability of defaults are estimated using both methods separately, and subsequently, the probability of defaults of the structural model are integrated at each point in time in the non-structural model as an additional explanatory variable. The appeal of the hybrid model allows the probability of default to be continuously updated by integrating market information via the probabilities of default extracted from the structural model. In this paper, we apply the hybrid model to French companies listed on the Paris stock exchange (Euronext Paris).

This paper is organized as follows. Section 2 reviews the main models in the literature. Section 3 presents the estimated structural model and describes the data used. And finally, section 4 presents the estimation of the hybrid model and summarizes the main results.

[4] Another widely used category of credit risk models is the reduced form approach where the dynamics of default are given exogenously by an intensity or compensator process. For a review of these models see Jarrow and Turnbull (1995), Jarrow, Lando, and Turnbull (1997), and Duffie and Singleton (1999).

2. Review of key models for risk assessment of default

2.1 Non-structural models

Traditional non-structural models adopt fundamental analysis and try to find which factors are important in explaining the credit risk of a company. They assess the significance of these factors, mapping a reduced set of financial ratios, accounting variables and other information into a quantitative score. The latter, can be interpreted as a probability of default, and can be used as a classification system[5].

In 1966, Beaver introduced the univariate approach of discriminant analysis in the explanation of default risk of a firm. Altman in 1968 extended this to a multivariate context and developed the Z-Score model. It weights the independent variables (financial ratios and accounting variables) and generates a single composite discriminant score. In 1977 Altman, Haldeman, and Narrayman developed the ZETA model, which integrated some improvements to the original Z-Score approach. Then the binary dependent variables models, known as the logit and probit model, were used in bankruptcy prediction[6]. Ohlson (1980) used logit methodology to derive a default risk model known as O-Score. Probit (Logit) methodology weights the independent variables and allocates scores in a form of failure probability using the normal (logistic) cumulative function.

Mester (1997) recognized the prevalent use of the binary credit risk models: 70% of banks have used them in their non-listed firm lending procedure.

Several banks use this method for privately and publicly traded companies, either by buying a model, such as RiskCalc Moody's, or by programming their own estimate. One problem they often face is to build an appropriate and proper database. Very often, credit files are not computerized or do not contain historical data.

[5] For a review of traditional models see: Jones (1987), Cauette, Altman, and Naraynan (1998), and Saunders (2002).

[6] Jones (1987), in his review of bankruptcy literature, concludes that binary dependent variable models do not lead to notable improvements in the predictive power of fundamental analysis when compared to the earlier LDA models.

The main advantage of non-structural models is their accuracy in estimating probabilities of default. In addition, they are easy to use for financial institutions equipped with solid management systems of database and may produce very accurate default probabilities. Nonetheless, these models are not flexible, because they need information from financial statements. Thus, it is very difficult to update the probabilities of default over a year. Some financial institutions may require reporting on a quarterly basis, but they are rarely audited by accounting firms.

2.2 Structural Models

The original Merton model is based on some simplifying assumptions about the structure of the typical firm's finances. The event of default is determined by the market value of the firm's assets in combination with the liability structure of the firm. When the value of the assets falls below a certain threshold, the firm is considered to be in default. The main criticism levelled at Merton's model is that it does not account for the possibility that the firm may default before the debt matures. To improve this basic model, several extensions have been suggested in the literature.

Crosbie and Bohn (2002) summarize KMV's default probability model. KMV's default probability model is based on a modified version of the Black-Scholes-Merton framework in the sense that KMV allows default to occur at any point in time and not necessarily at the maturity of the debt. In this model multiple classes of liabilities are modelled. There are essentially three steps in the determination of the default probability. The first step is to estimate the market value and volatility of the firm's assets; the second step is calculate the distance-to-default, the number of standard deviations the firm is away from default; and the third step is to transform the distance-to-default into an expected default frequency (EDF) using an empirical default distribution.

Brockman and Turtle (2003) propose using barrier options. Thus, rather than stockholders who wait for the debt to mature before exercising a standard European call option, we have a down-and-out option on the assets, in which lenders hold a portfolio of risk-free debt and a short put option combined with a long down-and-out call option on the firm's assets. The last part gives them the right to place the company into bankruptcy when they anticipate that its financial health can only deteriorate. Wong and Choi (2004) demonstrate that estimating the parameters of the Brockman and Turtle (2003) model by maximum likelihood yields results that resemble those from the iterative estimation method used in this literature when the theoretical model is Merton's. The appeal of the maximum likelihood method is that it allows for statistical inference or, more specifically, calculating descriptive statistics for the estimated parameters, such as the value of the firm.

Tudela and Young (2003) present an application of the hybrid model. This application uses barrier options with a down-and-out call option. They estimate various models on data from non-financial English firms for the period 1990–2001. They use data on firms that did, and did not, default, for their estimates of probabilities of default in the structural model. First, they verify whether the two firm types represent different predicted probabilities of default. Second, they compare their hybrid model with other non-structural models to verify whether the additional probability of default (PD) variable is significant for explaining probabilities of default. Third, they measure the performance of their model with power curve and accuracy ratio type instruments.

3. Estimation of the probabilities of default with the structural model: Application of the Tudela and Young Model (2003) (the Bank of England model)

3.1 Model description

In this model, the authors use the theory of barrier options[7] and, more precisely, the call option down-and-out, which vanishes when the underlying asset reaches the barrier. In this model we assume that the capital structure consists exclusively of debt and equity (as Merton). The level of debt is denoted B and (T-t) represents the time remaining to maturity of the debt, the value of the firm is At, and the value at time t of the debt maturing at time T is V (A, T, t). The share value at time t is f (A, t). Therefore the total value of the firm at time t is:

$$A_t = V(A, T, t) + f(A, t) \tag{1}$$

[7] Other equity-based models of credit risk that use the concept of barrier options are Black and Cox (1976), Longstaff and Schwartz (1995), and Briys and de Varenne (1997).

To derive the probability of default using a barrier option, we suppose that the value of the firm's underlying assets follows the following stochastic process:

$$uA = A\, d_A\, dt + \sigma_A\, A\, dz \qquad (2)$$

Where $dz = \varepsilon \sqrt{dt}$ and $\varepsilon \sim N\,[0, 1]$.

As to the liabilities, assume, on one hand, that the firm's liabilities L are the sum of short-term liabilities plus one-half of long-term liabilities. On the other hand, we assume that L follows a deterministic process:

$$dL = \mu_L\, L\, dt \qquad (3)$$

We note the asset-liability ratio by k:

$$k = \frac{A}{L} \qquad (4)$$

A default occurs when k falls below the default point called $\widetilde{k}$ at any time. To estimate the probability of default we need to model how k changes over time.

If we differentiate (4) and use (2) and (3) we get:

$$dk = (\mu_A - \mu_L)\, k\, dt + \sigma_A\, k\, dz \qquad (5)$$

We define: $\mu_A - \mu_L = \mu_k$
And $\sigma_A = \sigma_k$

The values of μ_k and σ_k are needed to calculate the probabilities of default. Maximum likelihood techniques are used to obtain estimates of those two parameters, but to build the maximum likelihood function, we need first to derive an expression for the density function of k.

Given equation (5) we can derive the density function of $\ln\left(\frac{k_T}{k_t}\right)$. It can be shown that the defective density function is given by $\{\ln\left(\frac{k_T}{k_t}\right)\}$ by the following expression:

$$h\left(\ln\left(\frac{k_T}{k_t}\right)\right) = \frac{1}{\sqrt{2\pi\,\sigma_K^2 (T-t)}}\left\{\exp\left[-\frac{\left(\ln\left(\frac{\mathrm{k_T}}{\mathrm{k_t}}\right) - \left(\mu_\mathrm{k} - \frac{\sigma_\mathrm{k}^2}{2}\right)(\mathrm{T} - \mathrm{t})\right)^2}{2\,\sigma_\mathrm{k}^2\,(\mathrm{T} - \mathrm{t})}\right]\right.$$

$$\left. - \exp\left[\frac{2\ln\left(\frac{\tilde{\mathrm{k}}}{\mathrm{k_t}}\right)\left(\mu_\mathrm{k} - \frac{\sigma_\mathrm{k}^2}{2}\right)}{\sigma_k^2} - \frac{\left(\ln\left(\frac{\mathrm{k_T}}{\mathrm{k_t}}\right) - 2\ln\left(\frac{\tilde{k}}{k_t}\right) - \left(\mu_\mathrm{k} - \frac{\sigma_\mathrm{k}^z}{2}\right)(\mathrm{T} - \mathrm{t})\right)^2}{2\,\sigma_\mathrm{k}^2\,(\mathrm{T} - \mathrm{t})}\right]\right\} \tag{6}$$

Equation (6) represents the probability density of not crossing the barrier and being at the point $\ln\left(\frac{k_T}{k_t}\right)$ at time T. This expression is used to construct the likelihood function that we must maximize in order to obtain estimates of μ_k and σ_k. These estimates will be used to calculate the probability of default as shown below. The probability of the firm not defaulting until date T is given by the probability of $k_T > \tilde{k}$ conditionally $k_\tau > \tilde{k} \quad \forall \tau \; t \leq \tau \langle \mathrm{T}$ =>

$$\mathrm{PD} = 1 - \{[1 - \mathrm{N}(\mathrm{u}_1)] - \overline{\mathrm{w}}\,[1 - \mathrm{N}(\mathrm{u}_2)]\}$$

Where:

$$u_1 = \frac{\tilde{\mathrm{K}} - \left(\mu_\mathrm{k} - \frac{\sigma_\mathrm{k}^2}{2}\right)(\mathrm{T} - \mathrm{t})}{\sigma_\mathrm{k}\,\sqrt{\mathrm{T} - \mathrm{t}}}$$

$$u_2 = \frac{-\tilde{K} - \left(\mu_k - \frac{\sigma_k^2}{2}\right)(T - t)}{\sigma_k \sqrt{T - t}}$$

$$\overline{w} = \exp\left[\frac{2\tilde{K}\left(\mu_k - \frac{\sigma_k^2}{2}\right)}{\sigma_k^2}\right]$$

$\ln \frac{\tilde{k}}{k_t} = \tilde{K}$ and N is the cumulative density function of the normal distribution. In the case of a European call option, the probability of default equals N (u_1). However, for the barrier option we see that the term $\overline{w}$ [1- N (u_2)] adjusts the probability of default to take into account that the firm can default before the horizon date T.

The Bank of England set $\tilde{k} = 1$. We shall adopt this normalization. On the other hand we assume that the ratio, $y = \frac{X}{L}$, where X represents the market capitalization of the firm and L is its liabilities as a proxy for the ratio $k = \frac{A}{L}$ since the value of the firm's assets is unobservable.

We use Matlab to estimate μ_k and σ_k with the maximum likelihood method, then we calculate the probabilities of default. Parameters μ_k and σ_k are estimated on the basis of a 24-month window for all firms. (As starting value we take $\sigma_{k = 0,4}$ and $\mu_{k = 0,3}$). Finally, Tudela and Young find that if they add some account variables in their model, the model performance increases slightly. The final model of the Bank of England is as follows:

P D= f [probability of default (1 -2 years), profitability, Debt over assets, Cash over liabilities Sales Growth, log number of employees, GDP]

This model will be the subject of our research; the authors have applied this model to calculate the probability of default on data from non-financial English firms, and we will try to apply it to a sample of French listed companies but retain other explanatory variables for the hybrid model.

3.2 Data

In this section we present the used data and explain how we built it to calculate probabilities of default. This data is used also to estimate the hybrid model in section 4. Our initial database contains 20 companies that did not default and 14 companies that did. The study period for the probabilities of default is from January 2004 to December 2005. The methodology we use to compute the probabilities of default with the structural model requires that our data window extend 24 months prior to the estimation period for the predicted probabilities of default in order to ensure statistical reliability. Market capitalization has a monthly frequency while the values of debt are observed annually, thus the value of debt is considered during the year.

3.2.1 Companies that have defaulted

Data on companies that have defaulted are from DIANE. However, 6 companies that defaulted were removed from the database because of a lack of data (accounting and/or market) or because too large a shift between the date of publication of the last financial statement and effective date of default. Indeed many of these companies have significant gaps between these two dates. This is explained by the fact that most of the firms do not publish their financial statements during the last year prior to bankruptcy. Another explanation lies in the slow process of putting in default of certain companies. Thus we eliminated firms with a lag of more than 18 months.

3.2.2 Companies that did not default

Accounting data on companies that did not default for the year 2005 and the monthly market capitalizations are from Diane.

3.2.3 Various statistics

Financial firms are eliminated from the database because they do not generally have the same structure of financial statements as non-financial firms. Thus the final database contains a total of 23 non-financial companies; 8 of them have defaulted. The following table presents the descriptive statistics of firms retained for analysis:

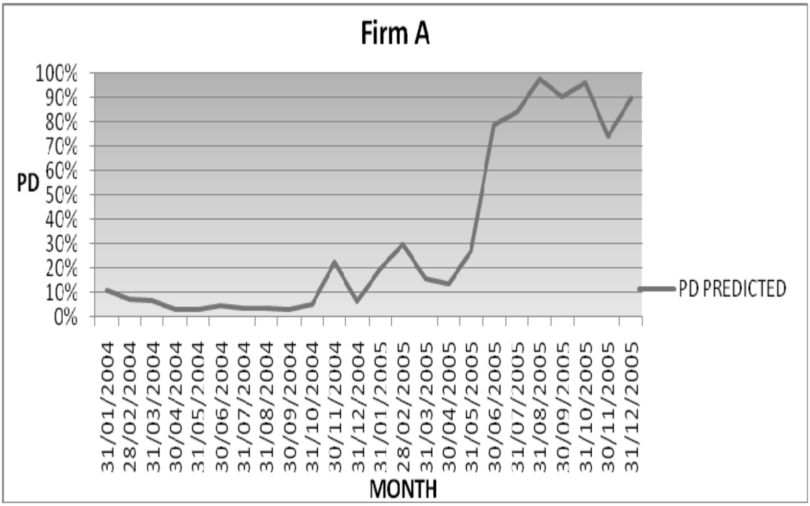
Table 1: Descriptive statistics of all firms retained for analysis (in million Euro)

	NOT-DEFAULT		DEFAULT	
Statistic	**Market value**	**Liabilities**	**Market value**	**Liabilities**
Mean	130.48	44.924	38.292	23.193
Median	101.128	38.714	17.073	9.248
Maximum	386.65	156.147	190.854	120.568
Minimum	27.65	3.955	11.473	7.492
Standard deviation	94.013	36.76	61.698	39.383
Skewness	1.464	1.829	2.259	2.2591
Kurtosis	4.7749	6.7184	6.122	6.1207
Number of observations	360	30	180	16

3.3 Estimation results

Estimating probabilities of default by the structural model allows us to obtain the following results: for companies that have defaulted, the mean of probabilities of default is 33.97%, while for companies that haven't, the mean of probabilities of default is 13.54%.

The following figures show the evolution of the probabilities of default predicted for several firms. Figure 1 shows the evolution of the probabilities of default for the ones that have defaulted.



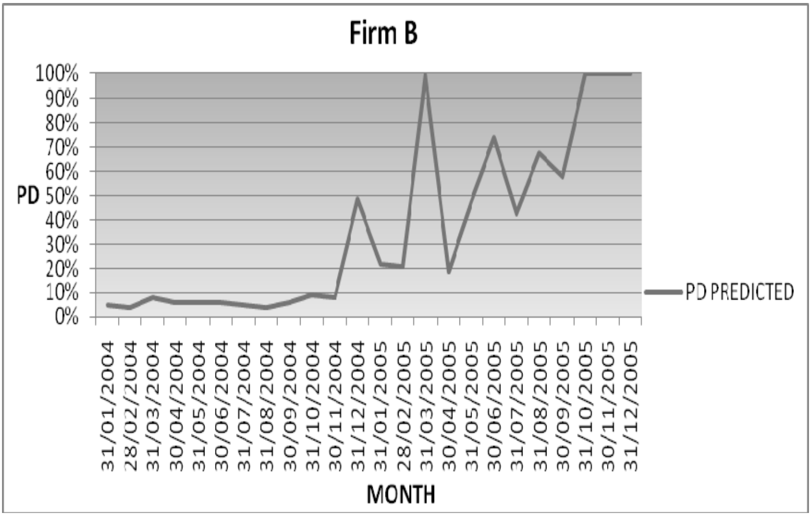


Figure 1: Monthly default probabilities (2 years) of defaulting firms

Modelling the probabilities of default of these companies seems consistent with the model, since it takes the form of probabilities of default being predicted higher when approaching the year of default. Indeed, most of the companies that did default present a similar evolution of the probabilities of default.

However, the results in Figure 2 are somewhat surprising. They represent an extreme case and show an example of the overstatement of the probabilities of default in the structural model. The model appears very sensitive to significant fluctuations in the values of this firm's stocks and provides the rationale for using the hybrid model, which contains more information for conditioning the estimates of the probabilities of default. Two smoother examples are featured in Figure 3.

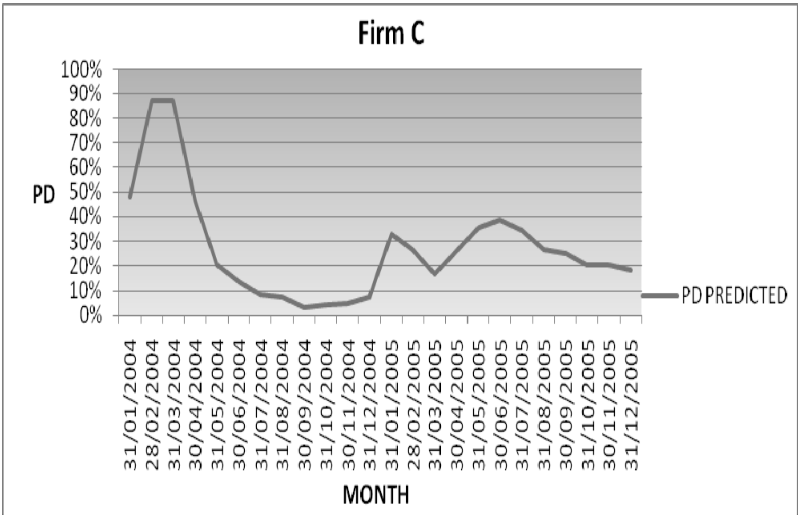
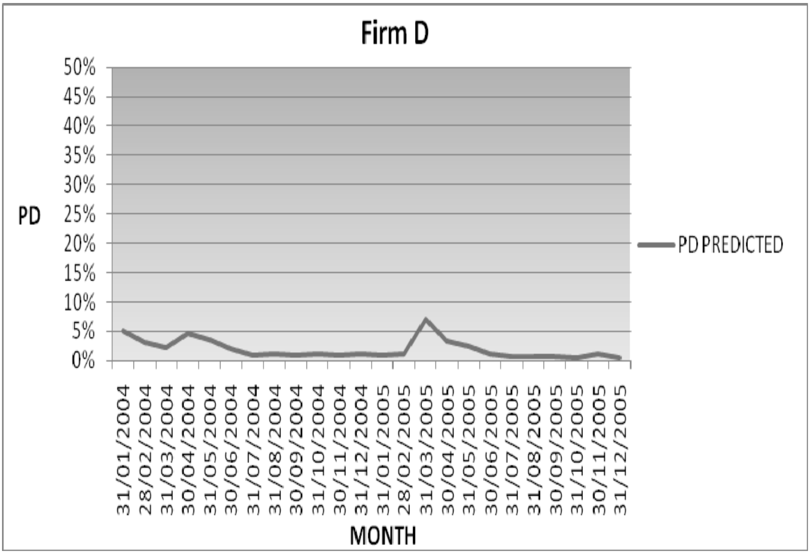


Figure 2: Monthly default probabilities (2 years) of non-defaulting firms



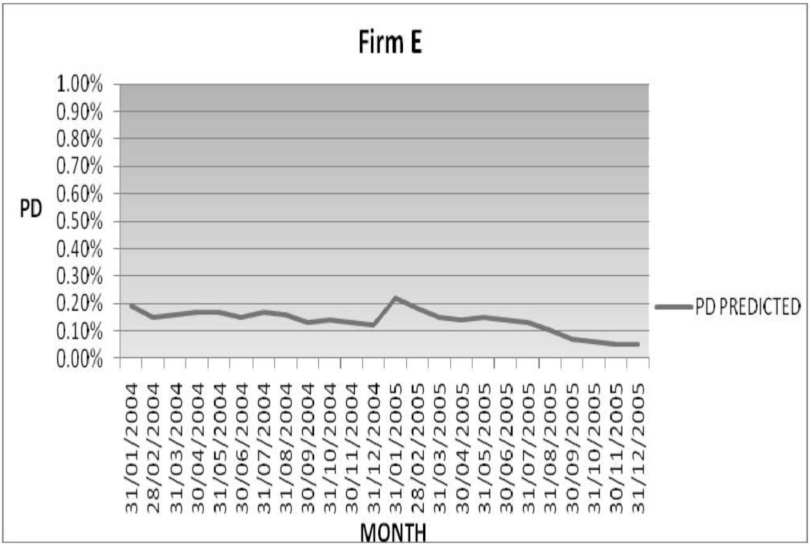


Figure 3: Other PDs (2 years) of non-defaulting firms

4. Hybrid model

4.1 Methodology

We do not estimate the model with a simple linear regression, since we know that it must reflect non-linear behaviour of the explanatory variables for defaults. In addition, it is well documented that simple linear models are inappropriate when the dependent variable is a probability. This model has the advantage of being easy to estimate but he has the disadvantage that it leads to PDs estimated to be out of the interval [0,1]. Thus, we must use other models which keep the probability of default (PD) in the considered interval; particularly the probit model. In this type of model, the dependent variable is a dichotomous variable taking the value 1 if an event occurs and 0 otherwise. In our case, the variable Y_i assumes the following values:

$Y_i = 1$ if firm I defaults, and
$Y_i = 0$ otherwise.

The vector of explanatory variables (financial ratios and accounting variables…) for firm *i* is denoted X_i, while β is the vector of weights of these variables.

The probit model assumes that there is a qualitative response variable (Y_i^*) defined by the following equation:

$$Y_i^* = \beta' X_i + \varepsilon_i. \tag{7}$$

However, in practice, Y_i^* is an unobservable latent variable. We rather observe the dichotomous variable Y_i such that:

$$\begin{aligned} &Y_i = 1 \quad \text{if } Y_i^* > 0; \\ &Y_i = 0 \text{ otherwise.} \end{aligned} \tag{8}$$

In this formulation, $\beta' X_i$ is not $E(Y_i / X_i)$, as in the simple linear model, but rather $E(Y_i^* / X_i)$. From equations (7) and (8), we get:

$$\text{Prob}(Y_i = 1) = \text{Prob}(\varepsilon_i > -\beta' X_i) = 1 - F(\beta' X_i) \tag{9}$$

where F is the cumulative distribution function of ε_i.

The functional form of F in equation (11) depends on the retained assumptions regarding the distribution of the residual errors (ε_i) in equation (7). The probit model is based on the assumption that these errors are independently and identically distributed (i.i.d.) and follow a standard normal distribution N(0,1). The functional form can thus be written:

$$F(-\beta' X_i) = \int_{-\infty}^{-\beta' X_i} \frac{1}{(2\pi)^{\frac{1}{2}}} \exp\left[-\frac{t^2}{2}\right] dt \qquad (10)$$

In this case, the observed values Y_i are simply the realizations of a binomial process whose probabilities are given by (9) and vary from one observation to the next (with X_i). The likelihood function can be defined as follows:

$$l = \prod_{Y_i=0} F(-\beta' X_i) \prod_{Y_i=1} (1 - F(-\beta' X_i)) \qquad (11)$$

And the parameter estimates β are those that maximize l.

4.2 Variable selection

The main objective of this study is to verify whether combining the structural and the non-structural model into a hybrid model yields a better measure of the default risk than those obtained from structural and traditional non-structural models estimated separately. To accomplish this, our aim is to explain default deficiencies by estimating a probit model in which the explanatory variables are the estimated probabilities of default from the structural model, financial ratios, and other accounting data.

The dependent variable is binary, taking the value of 1 if the default occurs and 0 otherwise. Using the same methodology, we also estimate a model with just accounting data as explanatory variables (non-structural model) and a third probit model in which the only exogenous variable is the probability of default from the structural model (the model that contains only structural information). Thus, we examine the predictive power of the PD variable to explain corporate bankruptcy by integrating it in the non-structural model as an explanatory variable.

If we find that the estimated coefficient of the variable PD (resulting from the structural model) is statistically different from zero, the probabilities of default obtained by the structural model in this case will contain additional

information that complements that of accounting data, and we will be able to use its coefficient to update the probabilities of default when the PD from the structural model changes.
As to the choice of accounting variables and financial ratios used in the non-structural and hybrid models, we are faced with difficulties in the selection of variables given the scarcity of accounting and financial data on those French listed companies that did default. To make a sound choice, we estimated the probit model on each variable accounting separately. This enabled us to retain the most significant ones.

4.3 Estimation results

4.3.1 Estimation of the probit model with different specifications

In this section we analyse the characteristics and performance of three models: the hybrid model, the non-structural model, and the model containing only structural information. We summarize the results of these estimations in Table 2.

In Model 1, we use only the information from the structural model by considering the mean PD(2 years) from the structural model as an explanatory variable. The coefficient of PD is 0.15 per cent, and has the expected sign. It is a significant factor for predicting probabilities of default, with a p-value of less than 5 per cent and a high corrected pseudo-R^2 (52.56 per cent).

In Model 2, we estimate the non-structural model with 2 variables (the turnover and profitability ratio). The examination of Model 2 reveals that the non-structural specification largely outperforms the one using only information from the structural model (Model 1) in terms of its ability to explain corporate bankruptcy. The likelihood ratio is 17.63 for the non-structural model, versus 15.62 for the structural model with only PD as an exogenous variable (the corresponding values of R^2 are 59.34 per cent and 52.56 per cent).

Table 2: Analysis of the maximum-likelihood estimators

Parameters	Model 1	Model 2	Model 3	Model 4	Model 5
Constant	-4.2571 (0.0245)	0.6808 (0.2001)	-7.91 (0.3719)	0.7242 (0.4283)	-3.8512 (0.2486)
PD (2 years)	0.1506 (0.0226)		0.2934 (0.3252)		0.1571 (0.1886)
Profitability		-0.0405 (0.1079)	-0.0229 (0.4589)		
Turnover		-0.0161 (0.0518)	-0.0213 (0.1988)	-0.0069 (0.4615)	-0.0164 (0.3557)
Equity/Total assets				-0.0394 (0.0659)	- 0.00709 (0.8033)
Debt/Equity				0.0029 (0.8891)	0.0055 (0.8328)
Number of observations	23	23	23	23	23
Number of Defaults	8	8	8	8	8
McFadden's R squared	0.5256	0.5934	0.8277	0.6137	0.7143
Likelihood ratio	15.6209 <0.0001	17.6367 0.0001	24.6009 <0.0001	18.2408 0.0003	21.2300 0.0002
Log likelihood	-7.0496	-6.0416	-2.5596	-5.7396	-4.2450

*Into parenthesis are the p-value of estimated parameters