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Credit risk of non-financial companies in the context of financial stability

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Abstract

The aim of this paper is: (i) to examine the determinants of default on bank loans for Romanian non-financial companies, (ii) to evaluate risks to financial stability stemming from the real sector – via the direct channel and (iii) to provide with a stress-testing framework that enables to investigate the impact of various macroeconomic variables on the probability of default. We find that trade arrears, interest burden and receivables cash conversion cycle are the most frequent determinants of default both at short term and long term horizon. We also develop two separate default models for large firms and foreign trade firms. We determine a measure of risk to financial stability – *debt at risk* – via the direct channel, by multiplying the estimated probability of default with the outstanding bank loans. Debt at risk is concentrated into above average risk firms, but risks to financial stability stemming from the real sector remain at a moderate level. Finally we propose some guidelines on how to build stress-testing scenarios that enables to analyze the impact of various macroeconomic shocks on the probabilities of default. We find that non-financial firms are resilient to potential interest rate shocks, which is consistent with the fact that firms finance their activity through bank loans only to a small extent.

Key words: Default, logit, financial stability

JEL classification: C25, G33

1. Introduction

Credit risk is inherently present in economic activity. This calls for proper risk management techniques that identify, assess and mitigate these *threats* both at micro- and macroeconomic level. The stakeholders of credit risk assessment and mitigation techniques can be broadly classified in two categories: (i) entities who buy credit risk – such as banks, investment companies, hedge funds etc. – and (ii) central authorities/governments that have to ensure a smooth functioning of the economy – i.e. price stability and financial stability. This paper aims to provide *a credit risk assessment of the real sector of the Romanian economy – non-financial companies (NFC)* - from the perspective of a central authority.

Corporate defaults[1] on bank debt can result in adverse effects on financial stability by means of (i) *a direct channel* – in which defaults on bank loans may trigger contagion in the banking system and (ii) *an indirect channel* – in which defaults on bank loans can lead to failure, with systemic implications on the real economy (output loss, unemployment). We try to estimate the risks to financial stability[2] via the direct channel by taking into consideration the probability of default (both at individual and aggregate level) and the exposures on which NFC could potentially default.

We use firm-level data for *all* NFC with bank loans between 2003 and 2006, which allows us to employ discrete time models in order (i) to *analyze the determinants of default* and (ii) to *estimate the probability of default*. The fact that we use the whole population in our model overcomes some limitations of previous papers that were biased towards large firms or small samples and enables us to draw conclusions at economy level. The explanatory variables used capture various financial features of NFC such as profitability, liquidity, solvency, indebtedness, asset utilization and group specific variables. The identified determinants of default with best discriminatory power are: (i) trade credits arrears, (ii) receivables cash conversion time and (iii) interest burden.

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[1] A company is considered to be in default if it has 90 days past due credit obligations. This definition is also consistent with Basel II definition of default.

[2] We follow the methodology proposed by Bunn and Redwood (2003)

The probability of default is estimated for two time horizons: (i) short term – 1 year and (ii) medium-long term – 3 years. The reason why we have chosen to estimate a three year probability of default is related to the timeliness of input data – usually financial statements are available with a time lag of six month, thereby reducing the effective period of forecast. We investigate the probability of default for all NFC and two additional sub-groups: large firms and firms engaged in foreign trade activities.

The risks to financial stability are assessed through a measure of aggregate debt at risk, which is essentially the estimated probability of default for an individual firm times its total bank loans, summed across the whole population. At economy level, debt is concentrated in above average risk firms but evolutions in the last years indicate an improvement in this context.

We then build stress-testing scenarios to see how resilient the real sector is to interest rate shocks. We find that an interest rate shock will have a low impact on financial stability, a fact that can be intuitively explained by the reduced share of bank loans in firms financing sources.

The paper is organized as follows. Section 2 provides a review of literature on default models. Section 3 describes the employed methodology and input data. Section 4 presents and analyses the results in the context of financial stability. Section 5 constructs stress-testing scenarios to evaluate the real sector's resilience to financial shocks. Section 6 concludes the paper.

2. Literature review

This section provides a snapshot of previous research done on bankruptcy modeling. *Beaver (1966)* is considered to be the pioneer of bankruptcy prediction models. He performed an univariate discriminant analysis on 30 financial ratios using a dataset of 158 firms (50:50 ratio of bankrupt to non-bankrupt). He concluded that *cash-flows/equity* and *debt/equity* generally increased when approaching default.

Altman (1968) integrated several variables into one model by means *of multivariate discriminant analysis* (MDA). The aim of MDA is to classify observations into two groups based on their explanatory variables. The classification is done through a linear function, whereby the optimum weights are derived by maximizing the ratio of squared difference between the two groups' average scores divided by their pooled variance. The final scoring function included the following financial ratios: (i) working capital/total assets, (ii) retained earnings/total assets, (iii) earnings before interest and taxes/ total assets, (iv) market capitalization/debt and (v) sales total assets. The model correctly identifies 90% of the cases one year prior to failure.

Merton (1974) proposes another approach to bankruptcy modeling. He considers the *equity of the firm* as being equivalent with *a call option* on the firm's assets with a strike equal to the face value of the firm's debt. Thus, when the firm's assets decline below its debt value, shareholders are more interested in walking away (i.e. liquidating the firm) than in reinvesting more funds. The output of the model is a *distance to default* and *a probability of default*. The main limitation of the model is that it requires *market values* for equity – i.e. the firm must be publicly traded – in order to deduce the parameters of the model. Thus, this approach is not applicable for modeling bankruptcy at economy level.

Ohlson (1980) is the first to use *the logistic regression* for bankruptcy prediction. It is similar to MDA in the sense that it comes up with a function of explanatory variables that can classify observations into two or more groups. However MDA has some drawbacks when compared to LOGIT models: (i) it assumes that the covariance matrices are the same for both groups (bankrupt/non-bankrupt), (ii) it requires normally distributed variables which militates against the use of dummy independent variables, (iii) it does not allow us to perform significance tests on the weights of explanatory variables, which can be done using LOGIT/PROBIT models. The use of linear models for bankruptcy prediction has two important requirements: the explanatory variables must be *linear* and *monotonous* relatively to default[3]. This explains why some variables that we reasonably expect to have an impact on default do not enter significantly or enter with the wrong sign in linear models. Ohlson's major findings can be briefly summarized as follows. A.) He identified four basic factors as being statistically significant in affecting the probability of failure: (i) *the size of the company*, (ii) *a measure of financial structure,* (iii) *a measure of performance*, (iv) *a measure of current liquidity*. B.) The inclusion in

[3] For LOGIT models explanatory variables have to be linear and monotonous relatively to the log odd of default – see Section 3

sample of firms which were already bankrupt at the time of estimation indicates that it is much easier to "predict" bankruptcy. This was the case of previous research done in this area – such as Altman (1968) – the result being an overstatement of the predictive power of models developed and tested. Ohlson included in his estimation sample only financially sound companies. The result was a larger prediction error-rate[4] in comparison to the rate reported in Altman (1968) as well as most other studies which used data drawn from periods prior to 1970.

Bardos (1998) presents the quantitative framework behind the Banque de France credit risk model. The scoring model employs the MDA technique, the reasons for these choice being: (i) robustness over time, (ii) interpretability, (iii) simple probabilistic utilization, (iv) easy maintenance. The principle of MDA consists in finding the optimum frontier between failed and non-failed companies, which in this case is a linear function of some preselected financial ratios. The scoring model is complementary to the expert based rating system in place at Banque de France. Whereas scores are produced annually, when accounting information become available, ratings are updated more frequently – as they use other information as well, especially of a qualitative nature.

Lennox (1999) finds that *profitability, leverage and cashflow* have important effects on the probability of bankruptcy. He uses *heteroskedasticity tests* in order to determine whether there are variables with non-linear effects on the probability of bankruptcy. He finds that *cashflow and leverage are non-linear* relatively to probability of bankruptcy. These effects are then incorporated into the model which significantly improves the predictive accuracy. By estimating a heteroskedastic probit model, he allows the residual's variance to be a function – he adopts an exponential functional form – of the variables which show non-linear effects. The paper also compared probit and logit models with discriminant analysis, the former models being superior to the latter. Moreover Lennox concludes that the superiority over discriminant analysis was greater for well-specified non-linear probit and logit models.

Bunn and Redwood (2003) find a *strong non-linear relationship between profitability and probability of bankruptcy*, negative profitability being associated with the highest marginal effect. They incorporate these effects by splitting the profitability variable into

[4] Average of type I and type II errors

several intervals and introducing dummy variables. The profitability boundaries are selected so as to be wide enough to allow coefficients to be significantly different from each other. The probability of bankruptcy are applied to the analysis of the risks to financial stability arising from the UK corporate sector by defining a variable called debt at risk, which is essentially an expected loss with a loss given default of one. The authors then investigate the magnitude and distribution of these risks. They find that debt at risk is concentrated among a few firms and that these firms are generally not the firms with the highest probability of failure. Furthermore firms with highest probability of default tend to be small and therefore hold relatively small amounts of debt. As a possible extension to this paper the debt at risk can be used in a contagion model for the banking system to see whether banks are able to absorb potential shocks from the real economy.

Another important element in credit risk modeling is represented by *model validation*. The importance of sound validation mechanisms stems from the fact that low quality credit risk models can lead to sub-optimal decisions (e.g.: for credit institutions this could mean sub-optimal capital allocation, while for central authorities this could adversely reflect on the policy measures because of poor aggregate risk picture at economy level).

Ooghe et al (1999) validated eight international failure prediction models[5] on one data set of Belgian firms. The models employed either a MDA or LOGIT approach. The performance indicators used to compare the models were twofold: (i) type I and type II errors based on the original and new cut-off points and (ii) Gini-coefficients which enabled to compare the models on a more global way. The authors came up with several explanations for the differences in performance across models: (i) nationality of estimation sample – models estimated on European companies are better able to discriminate between failing and non-failing Belgian firms than models on Anglo-Saxon companies – , (ii) age of the model – more recent models show a better performance – , (iii) company size – models that were initially estimated on large firms were found to be a better prediction power than those designed for both large and small firms, (iv) complexity of the model – there is no clear evidence of a strong relationship between model performance and complexity of the variables included in the model.

[5] Altman (1968), Bilderbeek (1979), Ooghe and Verbaere (1982), Zavgren (1983), Gloubos and Grammaticos (1988) – two versions – , Keasy and McGuiness (1990), Ooghe et al (1991)

Engelmann et al (2003) focus *on the discriminatory power of credit rating systems*. They review the widely used – in practice – validation techniques namely the Cumulative Accuracy Profile (CAP) and the Receiver Operator Characteristic (ROC). By demonstrating the relationship between Area Under Curve (AUC) below ROC and CAP, they show that these summary statistics of ROC and CAP are equivalent. Furthermore, they use these result in order to develop confidence intervals for these statistics. An important conclusion that can be drawn from this paper is that different rating models can be compared/ validated by means of ROC/CAP *only* on the same data set. The authors also show that replacing individual accounting ratios with their likelihood ratios improves the discriminatory power of the model.

Hammerle et al (2003) provides further guidelines on how to use performance measures to evaluate credit rating systems. The authors reach three important conclusions: A.) The results of the performance measures are dependent on the true probabilities of failure in the underlying portfolio. Thus, measures such as ROC/CAP are not able to distinguish between properties of the rating system and properties of the rated portfolio. B.) Following A.), different rating systems cannot be compared across time and across portfolios. As a positive result, it follows that traditional performance measures can be used to compare rating systems at the same point in time within one portfolio. C.) The highest performance measure is to be assigned to the rating system which assesses all true probabilities correctly.

3. Methodology and input data

3.1. Methodology

We use in this paper a *logit methodology* in order to estimate the probability of default of NFC, using as explanatory variables firms' financial characteristics prior to default. Logit models assume an unobservable (latent) dependent variable y^* which is related to an observed categorical variable y – company status, which is either default (y=1) or non-default (y=0) – through the following relationships:

$$(1)\ y_i = \begin{cases} 1 \leftrightarrow y_i^* > 0 \\ 0 \leftrightarrow otherwise \end{cases}$$

(2) $y_i^* = x_i\beta + \varepsilon_i$, where x_i is a vector of predictors for the ith observation, β a vector of unknown parameters and ε a logistic distributed[6] error term. For probit models the error term is considered to be normal distributed. The main difference between the logit and probit distribution is that it accounts better for fat tails.

The probability that a firm fails (y_i=1) can therefore be deduced as:

(3) $P(y_i = 1) = P(y_i^* > 0) = P(x_i\beta + \varepsilon_i > 0) = P(-\varepsilon_i < x_i\beta) = F(x_i\beta)$, where F(·) is the logistic cumulative density function.

The vector β of unknown parameters is estimated by maximizing the logarithm of the likelihood of any specific outcomes, as reflected by the binary sample space of defaulters versus non-defaulters:

(4) $$\max_{\beta} l(\beta)$$ $$l(\beta) = \sum_{i \in S_1} \log \mathrm{F}(\mathrm{x}_i\beta) + \sum_{i \in S_2} \log[1 - \mathrm{F}(\mathrm{x}_i\beta)]$$, where S_1 is the set of defaulting firms and S_2 is the set of non-defaulting firms. Maximizing with respect to β is equivalent to solving the following system of non-linear equations:

(5) $$\frac{\partial l(\beta)}{\partial \beta} = 0$$

The system must be solved numerically by an iterative procedure. At any stage of the iteration procedure – in case of logit and probit models – the Hessian matrix ($\frac{\partial^2 l(\beta)}{\partial \beta \partial \beta^t}$) is positive definite, and the iterations will converge to a maximum of the likelihood function independently of the initial values of β.

A useful property of logit (as well as probit) models is that they have variable marginal contribution rates, in contrast to classical linear probability models where the marginal contribution rates are constant. By taking the first derivative of the probability of observing a default we get:

(6) $\frac{\partial P(y_i = 1)}{\partial x_i^j} = f(x_i\beta) \cdot \beta_j$, where f(·) is the logistic probability density function, x_i^j is the jth explanatory variable of the ith firm and β_j is the correspondent weight/coefficient.

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[6] $F(x) = \frac{1}{1 + e^{-x}}$

In order to obtain aggregate marginal contribution rates for the whole estimation sample, we can evaluate the derivative at the mean values of explanatory variables.

Equation (6) implies constant marginal substitution rates. This means that the required variation of a variable x^j in order to compensate for a change in a variable x^h, so that the probability of default remains constant, is independent of variables x^j and x^h:

$$(7)\ \frac{\partial x^j}{\partial x^h}\Big|_{dp=0} = -\frac{\frac{\partial P}{\partial x^h}}{\frac{\partial P}{\partial x^j}} = -\frac{\beta_h}{\beta_j}$$

Such a property may be somehow unrealistic in practice. Laitinen (2000) comes up with the following example to underline the necessity of variable marginal substitution rates: he considers first a firm for which both liquidity (cash/total assets) and profitability (cash-flow/total assets) stand at the same level (say 5%). He further assumes that the level of liquidity is considered more critical in such way that a firm would be considered equally risky at level of liquidity of say 3% if profitability doubled to 10%. This implies a marginal substitution rate between the two variables of -2/5. Next he considers a firm with 5% profitability and 50% liquidity. If the same rate of compensation is maintained, a fall in liquidity, to say 48%, would still require a doubling of profitability in order for the predicted risk to remain unchanged. Laitinen argues that this is unrealistically as one would not be greatly concerned whether liquidity is measured at 50% or 48% and thus constant marginal substitution rates appear unreasonable.

Laitinen proposes[7] to solve this problem by introducing cross products and squares of variables in the logit model. However by introducing higher order terms in the model the economic intuition behind the explanatory variables may be lost and the model may suffer from *data mining bias*. Thus, for the purpose of this paper – *to find determinants of default* and *to quantify risks to financial stability* – we have chosen to use only economically meaningful variables in order to model default at the cost of having constant substitution rates.

[7] He uses a Taylor expansion of the underlying functional relationship at the mean values of the variables in order to justify the inclusion of higher order terms in the model

We will now focus on the steps that we follow in order to derive a model of default. First of all, we employ *several filters* on candidate explanatory variables in order to select only the relevant variables.

In a first step we use a Kolmogorov-Smirnov (KS) test in order to identify and exclude *problematic* ratios that do not relate to default as expected based on theoretical reasons. We perform a one tail hypothesis test to compare the distribution of values of defaulters and non-defaulters for each candidate variable. The null hypothesis for this test is that the two groups are drawn from the same continuous distribution. The alternative hypothesis is that the distribution of the variable for defaulters is smaller/larger than the distribution of the variable for non-defaulters. For each potential value *x* of the candidate variable, the KS test compares the proportion of *x1* of values – from the first group – less than *x* with proportion *x2* of values – from the second group – less than *x*. The test statistic[8] is the maximum difference over all *x* values:

(8) $KS = \max[F1(x) - F2(x)]$, where F1(x) is the proportion x1 of values less than x and F2(x) is the proportion x2 of values less than x.

In a second filter we check whether the underlying assumptions of the LOGIT model apply to the explanatory which passed the first filter. Equation (3) implies a linear, monotone relationship between the logarithm of the odds of default and the input variables:

$$(9)\ \log\frac{P(y_i=1)}{1-P(y_i=1)} = \alpha_0 + \beta_1 x_i^1 + \ldots + \beta_k x_i^k$$

To test for this assumption we divide the sample in several subsamples that contain all the same number of observation and within each group a historical default rate (the empirical logarithm of the odds of default) is computed. Finally we run a linear regression of the historical default rate on the mean values of the variable. Then we exclude the variables for which the assumptions of the linear regression do not hold.

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[8] The p-value of the test statistic is computed as $p = e^{-2\lambda^2}$, where $\lambda = \max((\sqrt{\frac{n1 * n2}{n1+n2}} + 0.12 + \frac{0.11}{\sqrt{\frac{n1 * n2}{n1+n2}}}) \cdot KS, 0)$, with n1 being the size of the first group and n2 the size of the second group.

In the next step we run univariate logit models with the remaining candidate ratios to find the most powerful variables. We check the discriminatory power both in the sample and out of the sample for each variable. The univariate discriminatory power is based on accuracy ratios (CAP/ROC) – for a detailed discussion on discriminatory power measures see below. Variables with a univariate ROC of less than 53% are dropped. It is worth mentioning that variables with high discriminatory power are not necessary significant when introduced in a multivariate model.

The last step of candidate variables selection consists of multicolinearity tests. We compute the correlation matrix for all selected variables and we choose only those ratios with the highest accuracy ratio for each correlation subgroup. Ratios are sorted in the correlation matrix by their accuracy ratio and they are dropped if the correlation coefficient is higher than 0.7[9].

Having filtered the candidate variables we proceed to derive a multivariate model of default. We employ a backward selection method where we initially estimate the *full* model – including all the variables which passed the selection filters – and then eliminating the worst covariates based on their significance (calculated with likelihood ratio test). For the significance test we use the G-test which compares the model with the variable (tested) with the model without that variable:

(10) $G = -2\log\frac{l(M_{-1})}{l(M)}$, where $l(M_{-1})$ is the likelihood of the model without the variable and $l(M)$ is the likelihood of the model with all the variables. G follows a Chi-squared distribution with two degrees of freedom. If the result of (10) gives a result inferior to some predefined confidence level (99% in this case), we can reasonably suppose that the tested variable does not add performance to the model. The variable should then be excluded.

The process of estimation of the multivariate model of default is split in two steps. *First*, we apply a bootstrapping methodology and conduct 100 simulations. In each simulation we derive a multivariate model using the backward selection method and a proportion of 50:50 of defaulted to non-defaulted companies. For this purpose we use all the defaulted

[9] The idea is to set the threshold high enough in order not to loose variables. The threshold of 0.7 is also used by Central Bank of Austria in their credit risk model.

firms and draw a random sample out of the non-defaulted firms of same size as the defaulted ones. In this way we ensure that the model is able to capture better the characteristics of defaulting entities. Finally we count how often a certain model specification is obtained as well as how often each explanatory variable is observed during the simulations. We then choose the model with the highest economic performance (ROC/CAP) and/or statistical performance. In the *second step*, in order to derive the final model we have to adjust the estimated logarithm of the odds of default with the difference between the historical observed default rate of the underlying portfolio and the proportions used in the bootstrapping exercise:

(11) $\log(\frac{PD}{1-PD}) = \alpha + X\beta + \log(\frac{\pi_d}{1-\pi_d} / \frac{p}{1-p})$, where PD is the estimated probability of default, π_d is the observed default rate in the real portfolio and p is the proportion of defaulted firms used during bootstrapping.

In the final stage we run two types of validation techniques on our final model: (i) economic performance measures and (ii) statistical performance measures.

The cost function is the first economic performance measure used. The derived model classifies firms from the riskiest (highest probability of default) to the safest (lowest probability of default). We aim to find a probability threshold in order to isolate good firms from bad ones. By doing this we are faced with two types of errors (Table 1). Type I error consists of classifying a firm as being non-defaulting and the firm subsequently defaults. Type II error is made when a non-defaulting firm is classified as being in default.

Table 1: Cost function errors

Signal\Effective	Y=1	Y=0
Y=1	Correctly classified	Type II error
Y=0	Type I error	Correctly classified

For each possible threshold we compute type I (t1) and type II (t2) errors. The associated cost function can then be defined if we additionally consider the importance (weights) associated with each type of error – respectively w1 and w2:

(12) $C = t1 \cdot w1 + t2 \cdot w2$

The choice of the weights is dependent on the objective of the decision maker. For example if a central bank uses credit risk models for monetary policy purposes, in order to determine eligible collateral for its refinancing operations, then they would be most concerned with a Type I error. Thus the central bank will set w1 equal to 1. For the purpose of this paper, we are equally concerned with making a type I or type II error. Therefore we will use a w1 of 50% and w2 of 50%. After choosing the weights the cost function has to be minimized relatively to the threshold.

The second performance measure used during model validation is the *receiver operator characteristic (ROC)*. ROC is an older test, used originally in psychology and medicine. The principle behind it is as follows: any model value output – in our case the probability of default – can be considered as a cutoff point between good and bad debtors. We can then define a performance measure as follows:

(12) $HR(C) = \dfrac{H(C)}{N_D}$, where HR(C) is the hit rate[10] for cutoff C[11], H(C) is the number of defaulters correctly predicted for the cutoff value C and N_D is the total number of defaulters in the portfolio. The second measure needed to obtain the ROC measure is the false alarm rate, defined as:

(13) $FAR(C) = \dfrac{F(C)}{N_{ND}}$, where F(C) is the type II error for cutoff C and N_{ND} is the total number of non-defaulters in the portfolio. With this two measures computed, we can proceed to construct a *ROC curve* and to calculate the *ROC measure.* The ROC curve is constructed by plotting the HR(C) versus FAR(C) for all possible values of C (Figure 1). The default model's performance is better the steeper the ROC curve is at the left end and the closer the ROC curve's position is to the point (0,1). This is similar to having a larger area under the ROC curve, which can be computed as:

(14) $A = \int_0^1 HR(FAR)d(FAR)$

A naïve model (with no discriminatory power) will always have equivalent values of HR and FAR (Figure 1) thus resulting in a area under the ROC curve (AUROC) of 0.5. At the other end lies the perfect model which will never classify a defaulted counterparty in the non-defaulted group, thus yielding an AUROC of 1. In practice AUROC for default models ranges between 0.5 and 1.

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[10] Actually this is 1-Type I error

[11] C is a probability of default ranging between 0 and 1

An equivalent performance measure for ROC is the cumulative accuracy profile (CAP). To obtain a CAP curve (Figure 2), all debtors are first ordered by their probability of default in decreasing order – or alternatively by the model output values – from the riskiest to the safest. For each quantile of the probability of default distribution, the CAP curve is constructed by calculating the percentage of defaulters out of the total number of defaulters which have a probability of default lower than the considered quantile. A perfect model will assign the highest probability of default to the defaulters. Thus, in this case, the CAP is increasing linearly and then staying at one (Figure 2 green line). For a naïve model the fraction x of all debtors with the highest probability of default will contain only $x\%$ of all defaulters.

Figure 1: Receiver operator characteristic curves

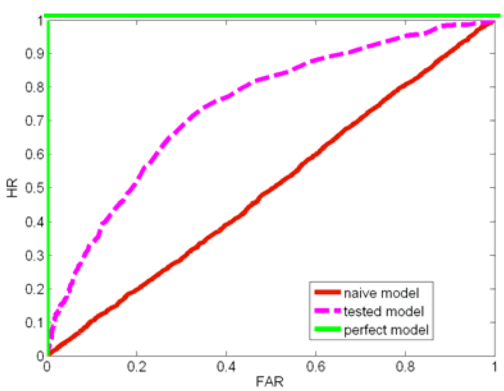
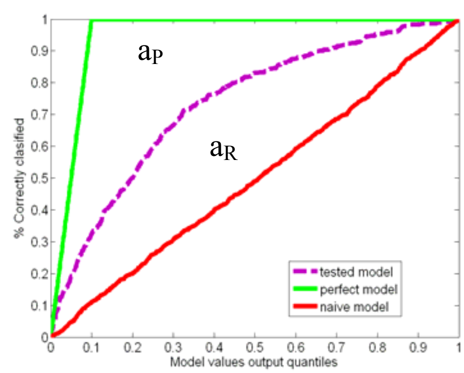


Figure 2: Cumulative accuracy profile



Note: Figures were constructed using random data

The quality of a default model as measured by CAP is the accuracy ratio. It is defined as the ratio of the area a_R between the CAP of the model being validated and the CAP of the naïve model, and the area a_P between the CAP of the perfect model and the CAP of the naïve model:

(15) $AR = \frac{a_R}{a_P}$

It can be shown[12] that the CAP measure – AR – is equivalent to the ROC measure – A – , satisfying the following relationship:

(16) $AR = 2 \cdot A - 1$

[12] Engelmann et al (2003)

As a consequence of (16) we will use throughout the model results section only the ROC measure in order to be consistent.

ROC/CAP measures can be used to validate and compare different models on the same portfolios only. This is because AUROC and AR depend on the true underlying probability of default of the borrowers in the portfolio under consideration.

Although there are no absolute values for ROC/CAP measures that enable us to label a model as *good* or *bad*, we can find the following reference values in the literature[13] (Table 2):

Table 2: Indicative values for ROC and CAP measures

AR(%)	A(%)	Description
0	50	Naïve model
40-60	70-80	Acceptable discriminatory power
60-80	80-90	Excellent discriminatory power
+80	+90	Exceptional discriminatory power

The second type of validation techniques that we employ are *the statistical tests*. We aim to verify with these tests whether the probabilities of default predicted by the model are consistent with the real observed values.

The test that is most frequently used when explanatory variables are continuous is the Hosmer-Lemeshow goodness of fit test. It consists of dividing the predicted probabilities of default in deciles and to compare the number of *effective* defaults (y=1) in each interval to what is expected by the model:

(17) $\hat{C} = \sum_{k=1}^{10} \frac{(\hat{Y}_k - n_k \ddot{\pi}_k)^2}{n_k \ddot{\pi}_k (1 - \ddot{\pi}_k)}$, where $\hat{Y}_k = \sum_{j=1}^{k} y_j$ with y_j recording the status of the company – i.e. default/non-default –, n_k is the number of observation in group k and $\ddot{\pi}_k$ is the average probability of default in group k as predicted by the model. Hosmer and Lemeshow have showed that under the conditions of correct model specifications, $\hat{C}$ follows a Chi-square distribution with 8 degrees of freedom.

A second test which checks the calibration quality of the model is the *Spiegelhalter test*. It consists of computing the mean square error of predicted probabilities of default in a first step, as:

[13] Hosmer and Lemeshow (2000)

(18) $MSE = \frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2$, where $\hat{y}_i$ is the predicted probability of default for the ith obligor and N is the total number of firms. Using (18), a hypothesis test is conducted with the null that all predicted probabilities of default match exactly the true, but unknown, probability of default. Under the assumptions of independence of default events, MSE has an expected value and a variance of:

(19) $E[MSE] = \frac{1}{N}\sum_{i=1}^{N}\hat{y}_i(1-\hat{y}_i)$, (20) $\operatorname{var}[MSE] = \frac{1}{N^2}\sum_{i=1}^{N}\hat{y}_i(1-\hat{y}_i)(1-2\hat{y}_i)^2$

Under the null hypothesis the test statistic follows a standard normal distribution:

(21) $z = \frac{MSE - E[MSE]}{\sqrt{\operatorname{var}[MSE]}}$

After constructing and validating the default model we use the predicted probabilities of default in order to assess risks to financial stability arising from the real sector. Our approach is similar to Bunn and Redwood (2003). To assess risks to financial stability we analyze debt at risk (DAR), which is a rough measure of the expected loss on bank loans for each firm, reflecting both the probability of default and the bank exposure – it is assumed that the loss given default is 100%. DAR constitutes an upper bound for expected loss, because in practice banks recover a proportion of the defaulted loans. DAR is defined as the predicted probability of default of a firm multiplied with its total bank loans:

(22) $DAR_i = \hat{y}_i \cdot D_i$, where D_i is the total amount of bank loans for firm i.

Using the DAR for each firm, we aggregate in order to obtain a micro-based measure of risk to financial stability:

(23) $DAR_{MICRO} = \sum_{i=1}^{N} DAR_i$

We also use a macro based measure of risk to financial stability, which involves multiplying the bank debt of each firm with the mean predicted probability of default at economy level:

(24) $DAR_{MACRO} = \tilde{y}\sum_{i=1}^{N} D_i$, where $\tilde{y}$ represents the unweighted mean of all firm-level probabilities of default. Equation (24) assumes that all probabilities of default are the

same for all firms in the micro-based measure. By comparing DAR_{MICRO} with DAR_{MACRO} we can analyze the concentration of debt – i.e. whether it is concentrated among riskier or less riskier firms. Thus, to measure DAR concentration we will use the following equation:

(25) $I = \frac{DAR_{MICRO}}{DAR_{MACRO}}$, if the index is above 1 it means that debt is concentrated into above average risk firms whereas values below one indicate the opposite.

3.2. Input data

The data used for building the explanatory variables (Annex 1) is taken from the financial statements reported to the Ministry of Public Finance (MFP) by the NFC[14] with bank loans. In order to identify companies with bank loans we mapped the database from MFP with the database from the credit register. The dataset is biased towards the manufacturing industry and retail/wholesale trade (Annex 2), as these two sectors have the largest share of total private credit.

By using financial ratios to model default we are making an implicit assumption that *accounting data provide an accurate picture of the financial position of each firm*. This is a limitation of models which use financial ratios derived from accounting data as explanatory variables. Measuring financial ratios is not equivalent to observing the *real characteristics*, but rather proxy measures for the relevant aspects. As Morris (1989) pointed out, a unique economic event can results in a variety of ratio patterns, and a single pattern of ratios can be the result of a variety of underlying economic conditions.

Figure 3: The ambiguity of financial ratios

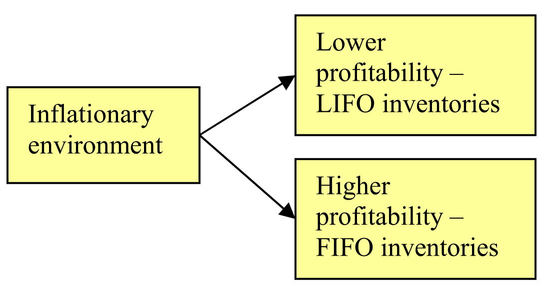


Figure 3 gives an example of the ambiguities that a financial ratio can bring about. For example, depending on the cost flow method used for inventories, in an inflationary environment a firm can have a lower profitability when using LIFO method versus a higher profitability when using the FIFO method. Another distortion

[14] In order to select the NFC from the MFP database we excluded the financial companies – NACE code: 65, 66, 67 – as well as firms with NACE code above 74.

in the financial ratios can be produced by capitalizing versus expensing specific costs decisions.

Most of the Romanian NFC report under the Romanian Accounting Standard (RAS) which implies only a simplified version of the balance-sheet, income statement and some additional qualitative information. This is why we could not take account of any potential distortions which could be present in the data as a result of different cost flow assumptions, other earnings management strategies or off balance sheet financing methods.

For the default information – i.e. a firm has 90 days or more past due payments on bank loans – there were two main sources available. Firms report their arrears in their financial statements, including the bank loans arrears. The second source is the credit register. By comparing the default information from the two sources we found data from the credit register to be more reliable. By using default information from the credit register we are constrained[15] to the timeframe between 2003 and 2006. We consider a firm to be in default if it defaults in any month of the chosen time horizon (1 year or 3 years). We define a year as a financial/calendar year extending from 1 January to 31 December.

Table 3: Data structure – number of observations and default rates

Year of financial statements	Number of observations	1 year default rate (%)	2 years default rate (%)	3 years default rate (%)
2003	30,082	3.34	5.84	7.35
2004	32,977	2.78	4.73	…
2005	42,369	2.28	…	…

Source: MFP, Credit register, own calculations

Table 3 summarizes the data structure obtained, after mapping the MFP with the credit register database and excluding firms with anomalies[16] in their financial statements (see Annex 2 for a detailed data structure). As a general remark, from Table 3 we can see that the decrease in the observed default rate can be largely attributed to the financial deepening process that our economy has undergone in the last years (i.e. the increase in the number of firms with bank loans). Large firms and firms with foreign trade activities present the same pattern for the observed default rates, with some particularities: (i) default rates for large companies were at the beginning of the observation period (2003, 2004) higher than those observed at economy level and more volatile (Annex 2) and (ii)

[15] 90 days or more past due payments are recorded in the credit register starting from 2004

[16] Firms were excluded if any of the following conditions were fulfilled: (i) Turnover<=0, (ii) Total assets<=0, (iii) Common equity<=0, (iv)Total debt<0

firms engaged in foreign trade activities recorded less defaults than the economy (NFC). A possible explanation for the high default rate in the corporate sector (large firms) could be the fact that many of the large firms were state owned, which could have enabled them to default on their debt service without any consequences.

All explanatory variables are computed at the beginning of the observation period[17] of the status of a firm. The tested explanatory variables capture various financial features of a firm's activity: (i) expense structure, (ii) profitability, (iii) leverage/ balance sheet structure, (iv) liquidity, (v) investment analysis, (vi) coverage ratios, (vii) growth rates and (viii) cash-flow analysis. We built and tested 42 financial ratios, some of which were previously used in the literature of default models other variables being new. Explanatory variables were cutoff at a threshold of 1% in order to exclude extreme values[18].

The descriptive statistics on the explanatory variables used in modeling default are broadly in line with economic intuition (Annex 3). Thus ex-ante profitability for firms who default is significantly lower and more volatile[19] than for non-defaulting firms. Firms with a higher ratio of trade arrears to total debt are more prone to default. Higher interest burden ratios are associated with higher default ratios. Cash conversion days of account receivables is another important determinant of default. Firms which convert more slowly receivables in cash are more likely to default on their debt service. The ability of a firm to generate positive cash-flows is also closely linked to the default event, higher cash-flows ratios being associated with lower default rates. Defaulting firms are ex-ante less liquid than non-defaulting firms – which may be a result of poor management, adverse economic conditions etc. Traditional leverage ratios – such as debt to equity – seem not to be able to discriminate between defaulting and non-defaulting firms. A potential explanation could be that shareholders – of small firms - usually choose to finance their business by crediting their own firm and not by increasing the equity – this is because debt is senior to equity in case of default. As the business expands,

[17] For example if we estimate a one year probability of default for year 2005 we will use financial ratios as of end of year 2004

[18] There are two ways to deal with extreme values: (i) either to exclude observations above a certain threshold, (ii) either to bring all observations at a specific threshold. The second approach has the disadvantage that it modifies characteristics of firms. Thus at the cost of loosing default observations we chose the first approach.

[19] Net profit margin and operating profit margin are more volatile for default firms than for non-defaulting firms

the total debt of the firm increases – both from external creditors and from shareholders who lend to their own firm – while equity remains relatively constant – increases only by the retained earnings – the result being an 'artificial' increase in the leverage.

4. Results[20]

Our first default model estimates the one year default probability for all NFC. We develop – using the procedures described in section 3.1 – three default models using cross-sectional data for years 2003-2004, 2004-2005 and 2005-2006[21]. After validating each model, both in-sample, out of sample and out-of time, the best model was the one built on 2004-2005 data. Thus, in presenting the results for the one year default model we will refer only to the 2004-2005 model.

In the variable selection process we used the selection filters described earlier. The linearity and monotony filter was the most subjective filter in deciding whether or not to include a variable in the final model. Annex 4 presents the results of this filter for all variables which passed the KS test (Annex 3). Clearly the results of this filter are sensitive to the choice of the number of groups[22] used when regressing the variables against the logarithm of the odds of default. After investigating all the assumptions of the regression, we select variables with an R-square greater than 50%[23]. In the last two steps we check the accuracy ratio of variables (Annex 5) and if they are correlated. Finally we run the bootstrapping exercise to derive an intermediate default model which is then adjusted to account for the real default rate of the portfolio.

The determinants of default, as resulting from the default model, are (Table 4): (i) *trade arrears to total debt*, (ii) *receivables cash conversion days*, (iii) *short term debt turnover*, (iv) *interest burden* and (v) *return on assets*. If a firm finances its activity via trade arrears it risks that at some point the suppliers will stop providing them with the necessary working capital, thus being unable to honor its contracts with the clients and

[20] Annex 6 contains additional information relevant to model results

[21] The first year relates to the financial information, while the second one relates to the default information

[22] By choosing a relatively small number of groups – 50 – we ensure that we exclude only those variables with no 'clear' linear and monotonous relationship to the default event.

[23] Although the variables which contain trade arrears do not satisfy this condition we let them pass further. There are many firms which have no trade arrears but default on their debt – for these firms the trade arrears variable has no discriminatory power. However if we look only at firms with non zero trade arrears (Annex 4), default is clearly increasing in this variable.

finally defaulting on their debt service. The time period of conversion of account receivables into cash has a direct implication on default: a delay of cash-inflows from customers will be ultimately transmitted into a delay of debt service payment, which may cause a firm to default. Short term debt turnover measures the ability of the firm to efficiently use its short term debt resources to generate income: higher values for this variable are associated with more comfortable positions as regards default (i.e. lower probabilities of default). Interest burden is a measure of the cost of indebtedness relatively to the volume of activity: thus as the variable goes up we will have progressively higher probabilities of default. The return on assets measures the ability of a firm to efficiently employ its assets to generate profit: as the profitability goes down the probability of debt service default is increasing.

Table 4: Model 1 – Logit model for 1 year default horizon using 2004-2005 data

-Number of observations in the dataset used for building the model: **17,727** out of which **456** defaults
-Number of observations in the bootstrapping exercise: **912** out of which **456** defaults
-Number of observations in the dataset used for testing the model: **8,863** out of which **224** defaults
-In sample ROC: 74.2%
-Out of sample ROC: 75%
-Out of time ROC (2005-2006): 75%
-Neutral cost policy function:
- Optimal cutoff: 2.3%, Hit rate: 71.7%, False alarm rate: 32.7%

Variables	**Occurrences***	**Coefficient**	**Standard error**	**tstat**	**Marginal effect (%)****
Intercept – from bootstrapping exercise	n.a.	-0.44	0.18	-2.4	
Adjustment coefficient	n.a.	-3.63	n.a.	n.a.	n.a.
Trade arrears to total debt	68	1.52	0.50	2.99	2.8
Short term debt turnover	48	-0.08	0.028	-2.91	-0.2
Receivables cash conversion days	94	0.0046	0.0011	4.13	0.01
Interest burden	100	14.36	2.58	5.56	26.3
Return on assets	94	-2.56	0.70	-3.67	-4.7

n.a. – not applicable
* indicates how many times a variable appeared in a final model out of 100 bootstrapping iterations. This model specification appeared in 23 iterations.
** evaluated at mean values of explanatory variables

The model presented in Table 4 produces acceptable discriminatory power both in and out of the sample used for estimation, as well as out of time. The optimal cut-off point that is can be used to make binary predictions is 2.3% for this model which implies a 71.7% hit rate and a false alarm rate of 32.7%. The adjustment made to the intercept has an important implication when using the model for forecasting purposes: we assume that the a posteriori observed default rate of the portfolio is the same with the default rate of the portfolio used in building the model.

The predicted one year probability of default at economy level recorded mixed evolutions (Figure 4). It decreased slightly in 2005 compared to 2004 and increased over the levels recorded in 2004 for the year 2006. These dynamics can be explained by the evolutions of the determinants of default: (i) trade arrears as a percentage of total debt decreased, reflecting an improved payment discipline, (ii) profitability decreased slightly, (iii) interest burden increased, mainly due to the financial deepening process, (iv) receivables cash conversion cycle deteriorated slightly and (v) short term debt turnover slowed down (Table 5).

Figure 4: One year probability of default evolution at economy level

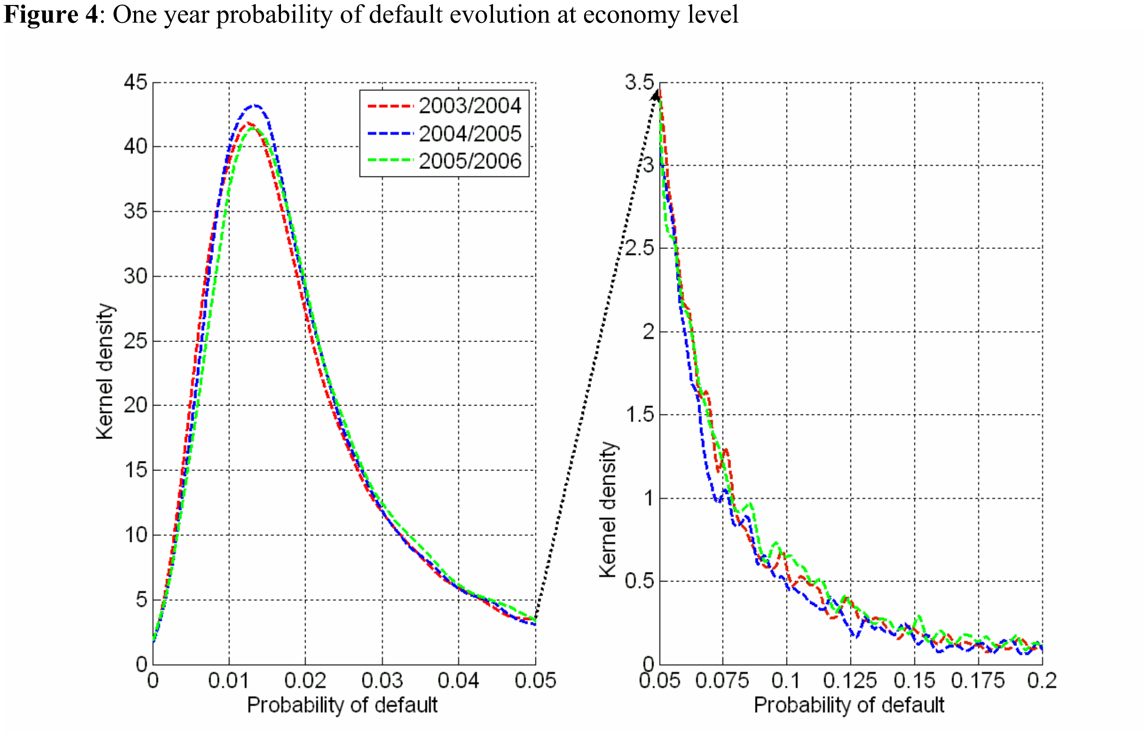


Table 5: Determinants of default dynamics – evaluated at mean level

Variables	2003	2004	2005
Trade arrears to total debt	7.8%	6.5%	5.8%
Return on assets	9.7%	9.8%	8.7%
Short term debt turnover	4.14	4.16	3.96
Interest burden	2.17%	2.38%	2.40%
Receivables cash conversion cycle	61.9	58.0	63.5

Debt at risk at firm level – computed as a percentage of total bank loans – increased slightly in the timeframe 2004-2006 (Table 6). Bank loans are concentrated into above average risk firms, as indicated by the concentration index. In 2006 the situation improved, bank loans being concentrated into less risky firms compared to year 2005. Effective defaulted debt is consistent with the evolution of the concentration index: it has increased in 2005 and it has recorded a sharp decrease in 2006. When compared to debt at risk, effective default rate is smaller and more volatile. The reason is that effective default rate is also influenced by the loss given default and the exposure at risk[24]. Thus debt at risk can be viewed as a more conservative risk measure of financial stability via the direct channel.

Table 6: Risks to financial stability via the direct channel

	2004	2005	2006
DAR_micro (% of total bank loans)	3.73	3.82	3.94
DAR_macro (% of total bank loans)	2.98	2.80	3.1
Concentration index	1.25	1.36	1.27
Effective defaulted debt (% of total debt)*	1.18	2.89	0.52

*Effective defaulted was computed by dividing the defaulted bank loans amounts to the total outstanding bank loans amounts at the beginning of the year

At sector level[25], retail and wholesale firms as well as manufacturing firms have the lowest probability of default and the lowest debt at risk (Figure 5 and Annex 5). This is benefic to financial stability as these two sectors absorb more than 70% of total bank resources that are channeled to the real sector. Agriculture, extractive industry and utilities have a more precarious profile regarding credit risk, but they do not hold significant bank resources in order to threaten financial stability.

The differences across sectors regarding credit risk can be explained by analyzing the determinants of default: (i) trade and services sectors have the *highest payment discipline*, while extractive industry and utilities sector record the lowest payment discipline – as indicated by trade arrears and receivables cash conversion cycle, (ii) *interest burden* is more prominent in the services sector and extractive industry, while posing less problems

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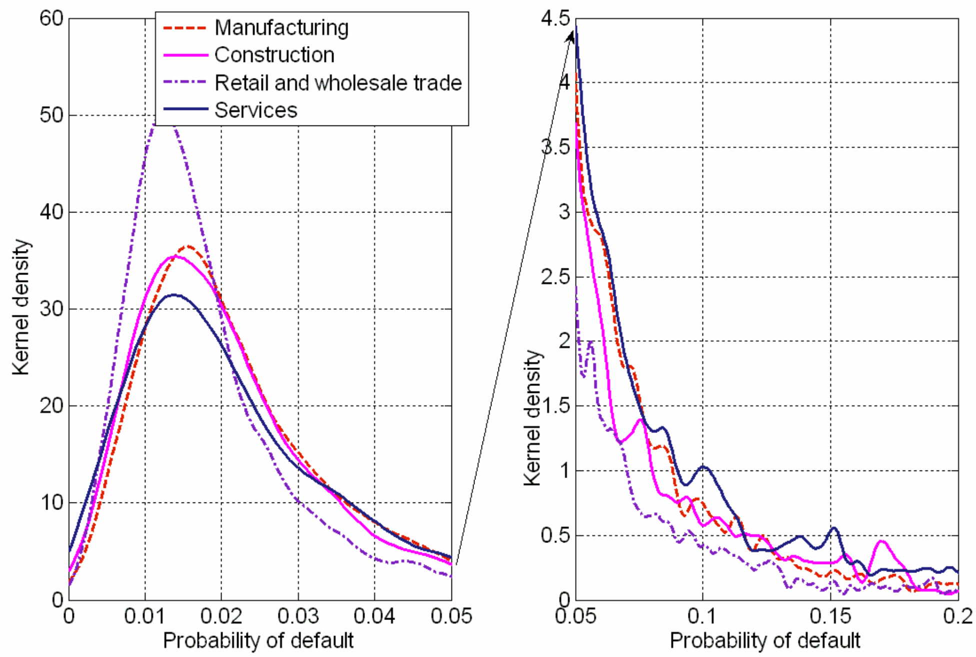
[24] Debt at risk can be considered an expected loss with 100% loss given default and an exposure at risk equal to the whole amount of bank loans outstanding at the end of the year previous to the default horizon.

[25] The results we infer at sector level should be treated with care as they are produced from a global model – i.e. we estimated the model using all sectors. To obtain a more accurate picture of risks at sector level, specific models for each sector should be developed. The main constraint here is the limited number of defaults for some sectors.

to manufacturing and trade sectors, (iii) constructions and services sector are the most *profitable* economic sectors, while extractive industry is the less efficient in resource utilization, (iv) trade and services have the *highest ability to leverage on short term debt to generate turnover*.

Figure 5: Probability of default for the main economic sectors (2006)



*The second model estimates the probability of default for a three year time horizo*n, using financial information from year 2003 and default information from years 2004-2006 Table 7). Compared to the one year default model, the three year probability of default has 4 specific determinants (apart from those that appear also in the one year model): (i) *asset turnover*, (ii) *cash ratio*, (iii) *debt to total assets* and (iv) *operating expenses efficiency*.

The model yields acceptable discriminatory power both in sample and out of the sample, but it could not be tested out of time due to limited data availability (Table 7). The optimal cutoff stands higher at 5.5% compared to 2.3% in the one year model, reflecting higher probabilities of default. Figure 6 compares the one year with the three year probability of default, the results being in line with economic theory, namely that default probability is increasing with the time horizon. Using financial information from 2005, mean one year probability of default stands at 3.1% versus 8% at a three year horizon.

Table 7: Model 2 – Logit model for 3 year default horizon using 2003-2006 data

-Number of observations in the dataset used for building the model: **16267** out of which **1080** defaults
-Number of observations in the bootstrapping exercise: **2160** out of which **1080** defaults
-Number of observations in the dataset used for testing the model: **8,133** out of which **550** defaults
-In sample ROC: 74.1%
-Out of sample ROC: 73.12%
-Neutral cost policy function:
- Optimal cutoff: 5.5%, Hit rate: 26.2%, False alarm rate: 37.62%

Variables	**Occurrences***	**Coefficient**	**Standard error**	**tstat**	**Marginal effect (%)****
Intercept – from bootstrapping exercise	n.a.	-2.20	0.40	-5.48	
Adjustment coefficient	n.a.	-2.64	n.a.	n.a.	n.a.
Trade arrears to total debt	73	1.17	0.30	3.89	5.71
Interest burden	100	19.25	2.17	8.85	93.81
Asset turnover	87	-0.19	0.04	-4.41	-0.93
Receivables cash conversion days	100	0.0037	0.00	5.26	0.02
Cash ratio	48	-1.09	0.35	-3.15	-5.32
Debt to total assets	41	0.71	0.22	3.18	3.46
Operating expenses efficiency	10	1.24	0.38	3.24	6.03

n.a. – not applicable
* indicates how many times a variable appeared in a final model out of 100 bootstrapping iterations.
** evaluated at mean values of explanatory variables

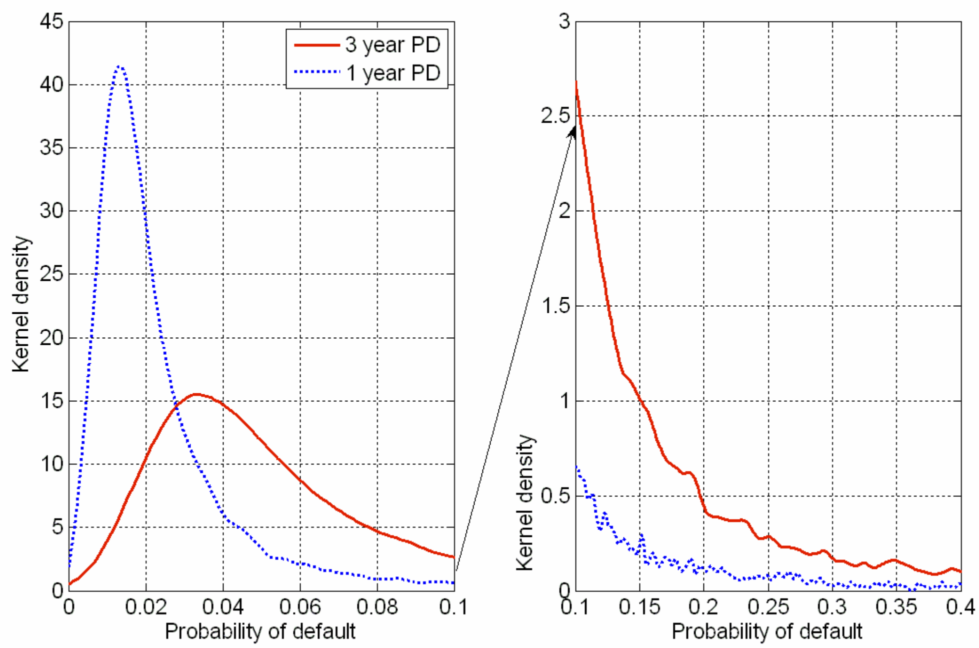
The dynamics of the three years probability of default is similar to that of the one year: it increased from a mean level of 7.5% in 2003 to 8% at the end of 2005 (see Annex 6). The distribution of probabilities of default by economic sectors is consistent with the results obtained in the first model: the less riskiest economic sectors over a three years horizon are the manufacturing and the retail and wholesale trade sectors, while agriculture, extractive industry and utilities have a higher credit risk.

The estimated debt at risk for the three years horizon overestimates the true debt at risk for this time horizon. This is because we multiplied the estimated three years probability of default with the total[26] amount of outstanding bank loans for a firm, in computing debt at risk. Thus we assume that bank loans have an average maturity of 3 years, which is not consistent with reality (most bank loans are granted on a short term). Furthermore banks usually grant medium-long term loans only to financially sound companies (i.e. low long term probability of default), which pledges again for a lower true debt at risk than the one

[26] We did not have the distribution of bank loans by maturities at firm level

we have estimated. Nevertheless we can consider the estimated debt at risk as a worst case scenario measure of risk to financial stability. Even in this case risk to financial stability is at a moderate level: retail and wholesale trade sector and manufacturing industry, which absorb together most of the bank loans, generate a debt at risk over a three years horizon (2006-2008) of 6.3% and 9.2% (Annex 6).

Figure 6: One year versus three year probability of default for all NFC (2005-2006, 2005-2008)



The third model estimates probability of default for large companies[27] on a one year time horizon, using a pooled dataset for large firms between 2003 and 2005[28]. By analyzing the empirical default data of large firms (Annex 2), it appears that they have a higher default rate when compared to all NFC (2004 and 2005 only). A possible explanation could be the fact that large firms usually have a higher negotiation power[29] in their relationship with credit institutions, which could enable them to have 90 days past due bank loans payments without any consequences. For the year 2006 the empirical default rate stands below that of the real sector, reflecting an improved payment discipline.

[27] Net sales in excess of EUR 50 million OR more than 250 average number of employees during a year
[28] We use this approach because of the limited number of defaults of large firms in each year (see Annex 2).
[29] Moreover some defaults come from large state owned companies with poor corporate governance policies.

The estimated model[30] identified five determinants of default for large firms: (i) productivity, (ii) interest burden, (iii) debt to total assets, (iv) asset turnover and (v) cash balance. The dynamics of explanatory variables indicate *a decrease of liquidity* coupled with *an increase in productivity* of large firms in the time period 2003-2005 (Table 9). Part of these dynamics could be attributed to the way we defined large firms: as the EURRON exchange rate fluctuated, the threshold for large firms changed, pushing firms in and out of the estimation sample.

The model produces *excellent* discriminatory power (in sample) with a ROC of 80.6%. The HL test indicates that the estimated probabilities of default are well calibrated to the true default probabilities. The optimal cutoff for a neutral cost policy function is 2.3% with a hit rate of 89.5% and a false alarm rate of 42% (Table 8).

Table 8: Model 3 – Logit model for 1 year default horizon for large firms using a pooled dataset between 2003 and 2005

-Number of observations in the dataset used for building the model: **3199** out of which **105** defaults
-Number of observations in the bootstrapping exercise: **210** out of which **105** defaults
-In sample ROC: 80.57%
-Calibration quality: HL-test=15.88 (Critical value at 99% confidence=21)
-Neutral cost policy function:
- Optimal cutoff: 2.3%, Hit rate: 89.5%, False alarm rate: 42%

Variables	**Occurrences***	**Coefficient**	**Standard error**	**tstat**	**Marginal effect (%)****
Intercept – from bootstrapping exercise	n.a.	0.44	0.61	0.71	
Adjustment coefficient	n.a.	-3.83	n.a.	n.a.	n.a.
Cash ratio	187	-4.15	1.75	-2.36	-3.5
Interest burden	565	34.60	11.05	3.13	29.3
Asset turnover	192	-0.78	0.31	-2.49	-0.7
Debt to total assets	5	1.59	0.66	2.40	1.3
Productivity	366	-0.25	0.075	-3.34	-0.2

n.a. – not applicable
* indicates how many times a variable appeared in a final model out of 1000 bootstrapping iterations
** evaluated at mean values of explanatory variables

Estimated probability of default for large firms increased in 2005 relative to 2004, mainly due to the drop in liquidity, while ameliorating in 2006 on the basis of productivity gains. (Figure 7). Debt at risk as a percentage of total bank loans (for large firms) decreased in 2006 at 4.74% after peaking in 2005 at 5.09%. Concentration index indicates that bank loans to large firms are absorbed by above average risk firms. Despite the relative high

[30] For this model we removed outliers above 99.5% (two tail) for each explanatory variable

level of debt at risk of large firms when compared to debt at risk of all NFC, large firms' effective defaulted debt stands much lower when compared to the effective defaulted debt at economy level.

Figure 7: One year probability of default for large firms

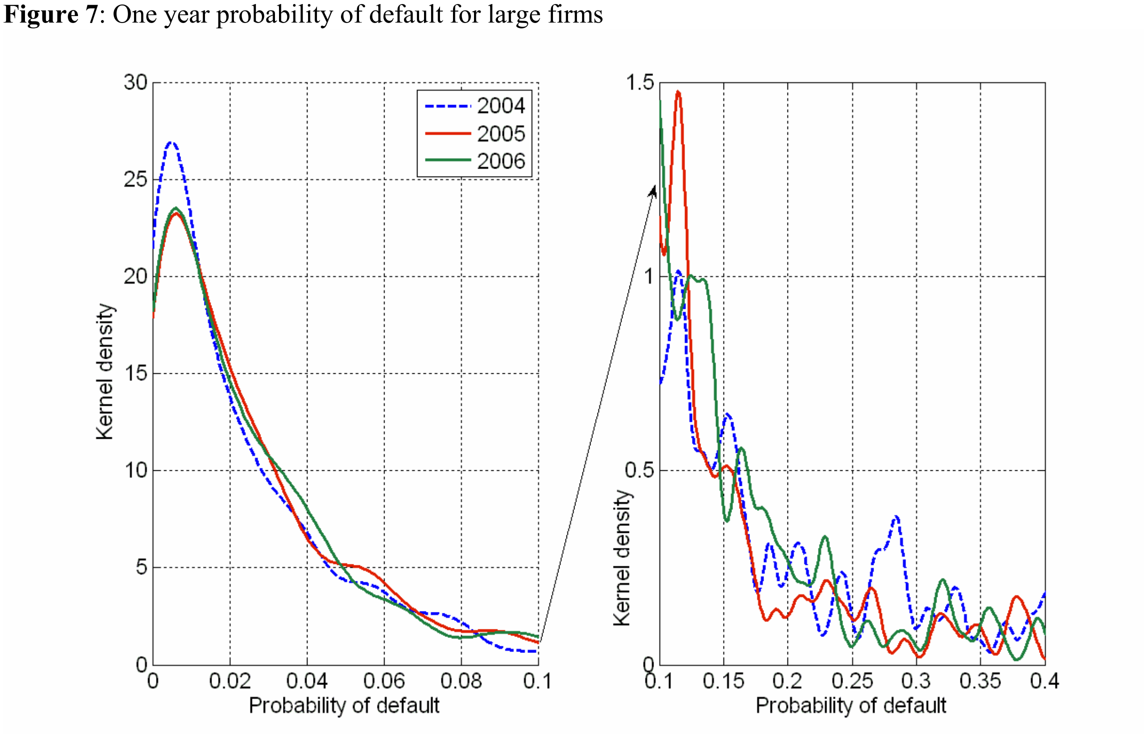


Table 9: Determinants of default dynamics for large firms – evaluated at mean level

Variables	2003	2004	2005
Cash ratio	24%	15%	16%
Interest burden	1.7%	1.9%	1.7%
Asset turnover	1.51	1.52	1.53
Debt to total assets	0.59	0.58	0.58
Productivity	4.1	4.4	4.8

The last model we developed estimates *the probability of default of firms engaged in foreign trade activities*[31]. Apart from the determinants of default identified in the model for the whole economy, a specific determinant of default for foreign trade firms is the share of labor costs to total operating costs (Table 10). Usually this ratio is higher for firms involved in active processing business, as their competitive advantage lies in the relatively cheap labor force they can employ. Wage growth and domestic currency appreciation in the last years eroded this advantage, thereby deteriorating the financial

[31] A firm was considered to do foreign trade business if it either had exported or imported goods or services in a given year

position of firms involved in this type of business. Thus higher values for labor costs to total operating costs are associated with higher probabilities of default.

Table 10: Model 4 – Logit model for 1 year default horizon for firms engaged in foreign trade activities using a pooled dataset between 2003 and 2005

-Number of observations in the dataset used for building the model: **22500** out of which **488** defaults
-Number of observations in the bootstrapping exercise: **976** out of which **488** defaults
-In sample ROC: 78.8%
-Out of sample ROC: 79.13%
-Neutral cost policy function:
- Optimal cutoff: 2.3%, Hit rate: 68.2%, False alarm rate: 76.6%

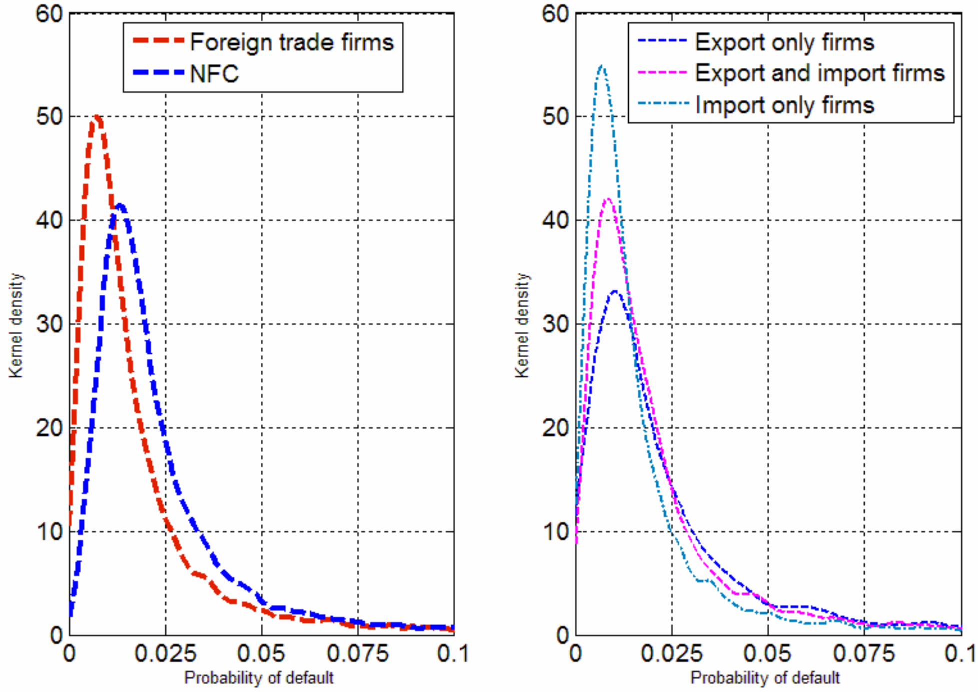
Variables	**Occurrences***	**Coefficient**	**Standard error**	**tstat**	**Marginal effect (%)****
Intercept – from bootstrapping exercise	n.a.	-0.52	0.24	-2.2	n.a.
Adjustment coefficient	n.a.	-3.8	n.a.	n.a.	n.a.
90 days past due trade arrears to total debt	42	2.33	0.78	2.97	2.9
Short term debt turnover	99	-0.21	0.047	-4.52	-0.26
Interest burden	100	21.45	3.29	6.52	27
Net profit margin	38	-4.82	0.93	-5.21	-6.08
Receivables cash conversion cycle	37	0.0032	0.0011	2.99	0.004
Personnel costs to total operating costs	41	2.37	0.78	3.03	3

n.a. – not applicable
* indicates how many times a variable appeared in a final model out of 100 bootstrapping iterations
** evaluated at mean values of explanatory variables

When compared to all NFC, foreign trade firms have a more sound financial position, which translates into lower probabilities of default (Figure 8). Firms with importing activities only, have the lowest probability of default, while firms doing only export business have the highest risk of default. This situation is benefic to financial stability as foreign trade firms absorb 73% of total bank loans while export only firms have 1.2% of total private credit.

The probability of default dynamics of foreign trade firms have slightly increased at the analyzed time horizon, mainly due to a slowdown in short term debt turnover and an increase in receivables cash conversion cycle.

Figure 8: One year probability of default of foreign trade firms (2006)



5. Stress-testing

Using the default models developed in section 4 we can build different scenarios for various macroeconomic variables and investigate their effects on the probabilities of default via the explanatory variables. There are several aspects that have to be considered when building the scenarios: (i) *consistency* – we have to take into consideration all the implications on the financial statements of a change in a macroeconomic variable, (ii) *methods of incorporating* changes in macroeconomic variables into explanatory variables – whether we have an identity or we have to estimate a relationship between input and output values of the stress-testing scenarios, (iii) *assumptions made* – for the situations when some information is not available. It is also necessary to mention that we run the scenarios on historical data, because usually annual financial statement information appears with a lag of at least 6 month. Nevertheless the stress-testing exercise remains useful, as it indicates the resilience (even though historical) of the real sector to potential changes in macroeconomic variables.

We will run scenarios in order to measure the impact of an interest rate hike on the probabilities of default. We make the assumption that all bank loans to NFC are granted at variable rate and that yield curve shifts in a parallel manner. An upward interest rate adjustment will have the following effects on explanatory variables used in the global models for default (for 1 and 3 years) (based on identity relationships):

A. **Interest burden** will increase. Here we assume that interest costs are exclusively due to bank loans.

B. Caeteris paribus, **trade arrears to total debt** will not be affected directly – if interest costs are too burdensome a firm could service its bank loans at the cost of stopping payments to its suppliers, thereby increasing its trade arrears. As we consider only first round effects in our scenarios, this variable will remain unchanged.

C. **Receivables cash conversion cycle** is not affected by the interest rate hikes directly, as this variable measures the ability of the firm to cash in its sales.

D. **Debt to total assets** will increase, as the denominator will decrease due to lower retained earnings, which are the result of higher interest costs.

E. **Short term debt turnover** remains unchanged, as net sales and short term debt are not directly affected by the interest rate changes.

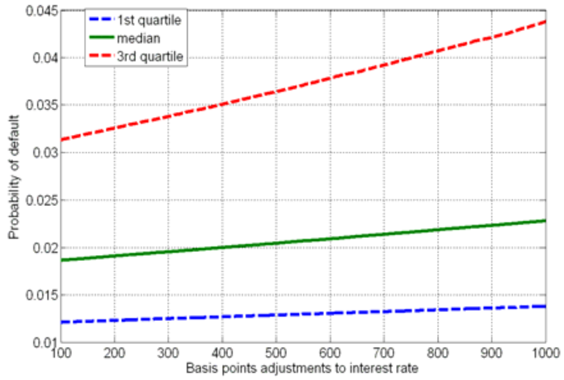
F. **Asset turnover** will be adjusted upward for the same reason as debt to total assets; we have lower assets due to lower retained earnings.

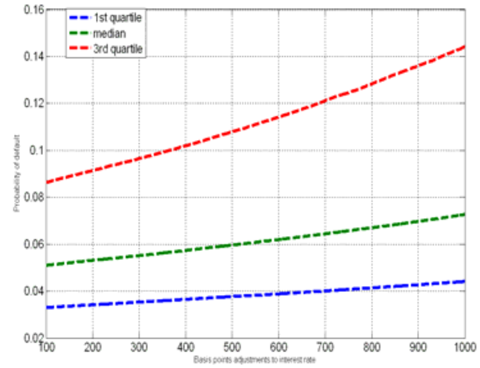
G. **Return on assets** will increase if firms are profitable (net profit>0), because of the reduction in total assets due to lower retained earnings (in the denominator) and lower taxes due to the tax deductible character of interest costs. Similarly, if net income is negative return on assets will decrease.

H. **Operating costs efficiency** will remain unchanged as interest costs will not affect operating expenses directly.

Figure 9 : Impact of interest rate adjustments to one year probability of default (2006)

Figure 10 : Impact of interest rate adjustments to three years probability of default (2006-2008)





We run simulations to see the impact of interest rate changes on one year and three years probability of default. We consider a range of interest rate changes between +100bps to +1000bps, which are applied to the average reference rate for year 2005 (9.6%). The results indicate a modest impact on probabilities of default even for large interest rate adjustments (Figure 9, 10). The economic explanation lies in the fact that NFC are financing their activity only in a small proportion through bank loans, the associated costs of bank indebtedness being relatively small.

6. Conclusions

The aim of this paper was (i) to develop a model of default using firm level data for all Romanian NFC with bank loans, (ii) to quantify risks to financial stability stemming from the real sector and (iii) to provide a stress-testing framework to test the resilience of NFC to various macroeconomic shocks.

A. Determinants of default: **At economy level**, trade arrears, interest burden and receivables cash conversion cycle are the most frequent determinants of default both on short and long term horizon. On the short term, return on assets and short term debt turnover have also an influence on default, while on the long term asset turnover, operating expenses efficiency, debt to total assets and cash balance are specific default determinants. For **large firms,** productivity, debt to total assets, asset turnover, interest burden and cash ratio are key variables for estimating probability of default on the short term. Apart from the determinants of default identified in the model for the whole economy, a specific determinant of default for **foreign trade firms** is the share of labor costs to total operating costs. Usually this ratio is higher for firms involved in active processing business, as their competitive advantage lies in the relatively cheap labor force they can employ. Wage growth and domestic currency appreciation in the last years eroded this advantage, thereby deteriorating the financial position of firms involved in this type of business (active processing)

B. Probability of default dynamics: **At economy level,** one year probability of default increased slightly in 2006 compared to 2005 mainly due to: (i) a deterioration in profitability, (ii) a slow down in short term debt turnover, (iii) an increase in interest burden, and (iv) a slightly higher receivables cash conversion cycle. At sector level, manufacturing and retail and wholesale trade firms have the lowest probability of default, while agriculture extractive industry and utilities have a more precarious credit risk profile. **Large firms** are more likely to default when compared to all NFC with bank loans. A possible explanation could be the fact that large firms usually have a higher negotiation power in their relationship with credit institutions, which could enable them to have 90 days past due bank loans payments without any consequences. Moreover some large firms are state owned, which may induce moral hazard situations: these firms may engage in less efficient activities or may have poor corporate governance policies which will adversely reflect on their debt servicing ability, because they know that the state will ultimately bail them out. Estimated probability of default for large firms increased in 2005 relative to 2004, mainly due (i) to a drop in liquidity, while ameliorating in 2006 on the basis of productivity gains. The probability of default dynamics of **foreign trade firms** have slightly increased at the analyzed time horizon, mainly due to a slowdown in short term debt turnover and an increase in receivables cash conversion cycle

C. Risks to financial stability: **At economy level**, debt at risk increased slightly in the timeframe 2004-2006, but remains at a moderate level. Bank loans are concentrated into above average risk firms, but in 2006 there was a shift in bank loans towards less risky firms. Effective defaulted debt ratio is much lower than the estimated debt at risk, pointing to the fact that the loss given default and effective exposure at default are less than the values[32] used in computing debt at risk. For **large firms**, debt at risk as a percentage of total bank loans decreased in 2006 after peaking in 2005. Concentration index indicates that bank loans to large firms are absorbed by above average risk firms.

[32] As pointed out in the section 3.1. debt at risk is a measure of expected loss with a loss given default of 1 and an effective exposure at default equal to outstanding bank loans amount.

Despite the relative high level of large firms' debt at risk when compared to debt at risk of all NFC, large firms' effective defaulted debt stands much lower when compared to the effective defaulted debt at economy level. When compared to all NFC, **foreign trade firms** have a more sound financial position, which translates into lower probabilities of default. Firms with importing activities only, have the lowest probability of default, while firms doing only export business have the highest risk of default. This situation is benefic to financial stability as foreign trade firms absorb most of bank loans while export only firms have a small share of total private credit.

D. Stress-testing: We have come up with a solution to measure the impact of interest rate changes on the probability of default and ultimately on financial stability. We run simulations by considering a range of possible interest rate adjustments between +100bps and +1000bps and incorporate these changes into the explanatory variables of default. The results indicate a modest impact on probabilities of default even for large interest rate adjustments. The economic explanation lies in the fact that NFC are financing their activity only in a small proportion through bank loans, the associated costs of bank indebtedness being relatively small.

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Annex 1- Financial ratios definition evaluated during model construction and the influence on default based on theoretical reasons

Name	Definition	Expected influence on default
Expense Structure		
Operating expenses efficiency	(Operating expenses-Inventories)/Net sales	+
Share of direct operating expenses	Production expenses/Operating expenses	+/-
Interest burden	Interest expenses/Net sales	+
Productivity 1	Net sales/(Personnel costs+costs associated with third parties services)	-
Productivity 2	Net sales/(Personnel costs)	-
Share of personnel expenses	Personnel costs/Operating expenses	+/-
Share of utilities expenses	Utilities costs/Operating expenses	+/-
Profitability		
Return on equity[33]	Net profit/Equity	-
Net profit margin	Net profit/Sales	-
Equity turnover	Sales/Equity	-
Return on assets	(EBIT-Taxes)/Total Assets	-
Operating profit margin	Operating profit/Net sales	-
Asset turnover	Net sales/Total assets	-
Leverage/Balancesheet structure		
Debt to equity	Total debt/Equity	+
Short term debt to equity	Short term debt/Equity	+
Long term debt to equity	Long term debt/Equity	+
Bank loans to equity	Bank loans/Equity	+
Trade arrears to total debt	Trade arrears/Total debt	+
Trade arrears 90 days past due to total debt	Trade arrears 90 days past due/Total debt	+
Short term debt turnover	Net sales/Short term debt	-
Receivables cash conversion days	Account receivables/Sales*360	+
Inventories share	Inventories/Total assets	+/-
Liquidity		
General liquidity	Current assets/Current liabilities	-
Acid test	(Current assets-Inventories)/Current liabilities	-
Cash ratio	Cash/Current liabilities	-
Cash share	Cash/Total assets	-

[33] There were companies with negative net profit and negative equity as well. In this case using the definition from the table ROE would be positive. In order to account for these situations, we changed the sign for ROE for these companies.

Investment analysis		
Net investment growth	(Fixed Assets in t1 +Depr&Amo-Fixed Assets in t0)/Fixed Assets in to	-
Fixed assets share	Fixed assets/Total assets	+/-
Fixed Intangible assets share	Intangible assets/Total assets	+/-
Fixed tangible assets share	Tangibe assets/Total assets	+/-
Fixed financial assets share	Financial assets/Total assets	+/-
Coverage ratios		
Interest coverage ratio	EBIT/Interest expenses	-
Growth rates		
Sales growth	Net sales in t1/Net sales in t0	-
Value added growth	Value added in t1/Value added in t0	-
Net profit growth	Net profit in t1/Net profit in t0	-
Cashflow analysis		
Operational cashflow to assets	Operational cashflow/Total assets	-
Operational cashflow to turnover	Operational cashflow/Net sales	-
Financing cashflow to assets	Financing cashflow/Total assets	-
Operational cashflow to total debt	Operational cashflow/Total debt	-

Note: + means that the variable is expected to have a positive relationship to default; - means that the variable should be negatively related to default; +/- means that there is no clear relationship between the variable and default.

Annex 2 – Data structure

Number of observations and empirical default rates at sector level for all NFC

Sector	Number of observations			1 year default rate (%)			2 years default rate (%)			3 years default rate (%)		
Year of financial statements	2003	2004	2005	2003	2004	2005	2003	2004	2005	2003	2004	2005
Agriculture	1,123	1,146	1,548	8.2	4.4	3.0	11.8	7.0	…	14.3	…	…
Extractive Industry	98	87	105	5.1	2.3	1.9	8.2	4.6	…	9.2	…	…
Manufacturing	8,549	8,774	9,967	4.6	4.1	3.0	8.0	6.8	…	10.0	…	…
Utilities	109	105	102	2.8	4.8	1.0	6.4	4.8	…	6.4	…	…
Construction	2,088	2,106	2,903	3.8	4.5	2.9	7.8	6.8	…	9.3	…	…
Retail and wholsesale trade	13,668	15,062	19,550	2.4	2.0	1.8	4.3	3.5	…	5.5	…	…
Transport communication and warehousing	2,170	2,723	3,856	2.4	2.0	2.2	4.5	3.9	…	5.8	…	…
Other services	2,277	2,974	4,338	2.3	1.8	2.3	3.7	3.3	…	5.1	…	…

Number of observations and empirical default rates at sector level for large[34] NFC

Sector	Number of observations			1 year default rate (%)			2 years default rate (%)			3 years default rate (%)		
Year of financial statements	2003	2004	2005	2003	2004	2005	2003	2004	2005	2003	2004	2005
Agriculture	32	28	23	15.6	3.6	0.0	18.8	3.6	…	21.9	…	…
Extractive Industry	25	15	15	0.0	6.7	0.0	4.0	6.7	…	4.0	…	…
Manufacturing	915	733	707	4.3	5.0	2.5	8.7	7.2	…	10.8	…	…
Utilities	56	59	51	0.0	3.4	0.0	3.6	3.4	…	3.6	…	…
Construction	155	113	106	2.6	8.8	2.8	9.7	11.5	…	11.0	…	…
Retail and wholsesale trade	97	104	123	1.0	1.0	0.0	3.1	1.0	…	3.1	…	…
Transport communication and warehousing	66	53	61	0.0	1.9	0.0	1.5	1.9	…	4.5	…	…
Other services	48	38	49	2.1	0.0	0.0	2.1	0.0	…	2.1	…	…
Total	1,394	1,143	1,135	3.6	4.6	1.9	7.8	6.3	…	9.5	…	…

[34] We considered NFC large if either turnover exceeded 50 millions euros or if they used more than 250 employees in a given year

Number of observations and empirical default rates at sector level for NFC with foreign trade activities[35]

Sector	Number of observations			1 year default rate (%)			2 years default rate (%)			3 years default rate (%)		
Year of financial statements	2003	2004	2005	2003	2004	2005	2003	2004	2005	2003	2004	2005
Agriculture	345	393	548	6.4	3.3	1.5	11.6	4.6	…	13.3	…	…
Extractive Industry	47	43	60	2.1	4.7	3.3	6.4	9.3	…	8.5	…	…
Manufacturing	4,964	4,848	5,234	3.9	4.1	2.8	7.4	6.8	…	9.4	…	…
Utilities	49	41	42	0.0	0.0	0.0	2.0	0.0	…	2.0	…	…
Construction	653	665	815	3.2	3.5	2.0	6.9	5.4	…	8.1	…	…
Retail and wholesale trade	4,246	4,285	5,514	1.7	1.9	1.6	3.7	3.5	…	4.8	…	…
Transport communication and warehousing	1,014	1,211	1,580	2.1	1.2	1.5	3.9	2.5	…	4.6	…	…
Other services	559	593	808	2.0	1.2	2.0	3.2	2.4	…	4.3	…	…
Total	11,877	12,079	14,601	2.9	2.8	2.1	5.6	4.8	…	7.1	…	…

[35] We considered a firm to have foreign trade activities if it either generated *exports* or *imports* in a given year

Annex 3 – Descriptive statistics for tested variables

Variables	2003				2004				2005			
	Non-defaulters		Defaulters at 1 year horizon		Non-defaulters		Defaulters at 1 year horizon		Non-defaulters		Defaulters at 1 year horizon	
	μ	τ	μ	τ	μ	τ	μ	τ	μ	τ	μ	τ
Expense Structure												
Operating expenses efficiency (%)	97	18	109	32	96	17	104	25	98	19	107	29
Share of direct operating expenses (%)	24	25	28	25	25	25	29	26	24	25	26	25
Interest burden (%)	2	3	5	5	2	3	4	5	3	4	4	5
Productivity 1 (%)	10.4	10.4	9.2	10.7	10.0	9.3	8.3	9.1	9.3	8.6	7.7	8.0
Share of personnel expenses (%)	8	9	9	10	7	8	8	9	8	8	8	9
Share of utilities expenses (%)	1	2	2	2	1	2	1	2	1	2	2	2
Profitability												
Return on equity (%)	57	294	-13	126	40	168	1	141	25	110	-11	143
Net profit margin (%)	3	14	-7	27	4	13	-2	18	3	14	-5	22
Equity turnover	31.1	104.4	17.2	81.0	25.4	76.0	20.7	71.8	18.9	55.9	16.1	64.0
Return on assets (%)	10	14	2	14	10	12	4	13	9	12	2	14
Operating profit margin (%)	7	14	1	23	7	13	4	17	6	14	1	21
Asset turnover	2.2	1.7	1.2	1.1	2.1	1.5	1.5	1.3	1.8	1.3	1.2	1.0
Leverage/Balance-sheet structure												
Debt to equity	13.0	50.3	11.5	51.7	11.5	40.6	13.5	48.5	9.5	32.9	9.8	36.4
Short term debt to equity	10.8	42.2	10.2	48.8	8.9	31.5	11.5	41.9	7.1	24.7	8.4	30.5
Long term debt to equity	1.2	5.1	1.0	5.6	1.6	6.1	1.8	7.4	1.7	6.5	1.6	7.0
Bank loans to equity	3.4	13.3	3.4	14.3	2.7	10.3	3.6	11.8	2.5	8.9	2.9	10.8

Variables	2003				2004				2005			
	Non-defaulters		Defaulters at 1 year horizon		Non-defaulters		Non-defaulters		Defaulters at 1 year horizon		Non-defaulters	
	μ	τ	μ	μ	τ	μ	μ	τ	μ	μ	τ	μ
Trade arrears to total debt (%)	8	16	13	18	6	14	11	17	6	13	11	17
Trade arrears 90 days past due to total debt (%)	3	8	6	11	2	7	4	10	2	6	4	10
Short term debt turnover	4.3	3.9	2.1	2.6	4.4	4.4	2.5	3.0	4.2	4.6	2.2	3.0
Receivables cash conversion days	65	86	141	157	61	77	110	113	66	84	120	126
Inventories share (%)	26	22	21	20	26	22	23	21	25	22	23	22
Liquidity												
General liquidity	1.10	0.87	0.88	0.72	1.12	0.99	1.02	0.98	1.23	1.24	1.04	1.17
Acid test	0.61	0.64	0.53	0.53	0.60	0.70	0.58	0.66	0.67	0.84	0.60	0.75
Cash ratio	0.12	0.22	0.05	0.13	0.11	0.24	0.06	0.15	0.16	0.35	0.11	0.28
Cash share	0.05	0.08	0.03	0.07	0.04	0.07	0.03	0.06	0.06	0.09	0.05	0.09
Investment analysis												
Net investment growth (%)	…	…	…	…	…	…	…	…	…	…	…	…
Fixed assets share (%)	41	25	39	26	43	25	41	26	43	26	39	28
Fixed Intangible assets share (%)	0	0	0	0	0	0	0	0	0	0	0	0
Fixed tangible assets share (%)	39	25	38	26	42	25	39	26	42	26	38	27
Fixed financial assets share (%)	1	3	1	3	0	2	0	2	0	2	0	2
Coverage ratios												
Interest coverage ratio	…	…	…	…	…	…	…	…	…	…	…	…
Growth rates												
Sales growth (%)	…	…	…	…	…	…	…	…	…	…	…	…
Value added growth (%)	…	…	…	…	…	…	…	…	…	…	…	…
Net profit growth (%)	…	…	…	…	…	…	…	…	…	…	…	…
Cashflow analysis												

Variables	2003				2004				2005			
	Non-defaulters		Defaulters at 1 year horizon		Non-defaulters		Non-defaulters		Defaulters at 1 year horizon		Non-defaulters	
	μ	τ	μ	μ	τ	μ	μ	τ	μ	μ	τ	μ
Operational cashflow to assets (%)	17	24	9	25	16	24	9	23	15	24	9	25
Operational cashflow to turnover(%)	13	29	14	41	13	29	11	37	14	32	13	42
Financing cashflow to assets (%)	30	31	19	38	30	31	23	37	27	32	26	39
Operational cashflow to total debt (%)	24	36	12	32	24	35	12	31	23	36	13	33

Notes:

-Mean (μ) and standard deviation (τ) were computed after excluding extreme values (1% two tail) for each variable

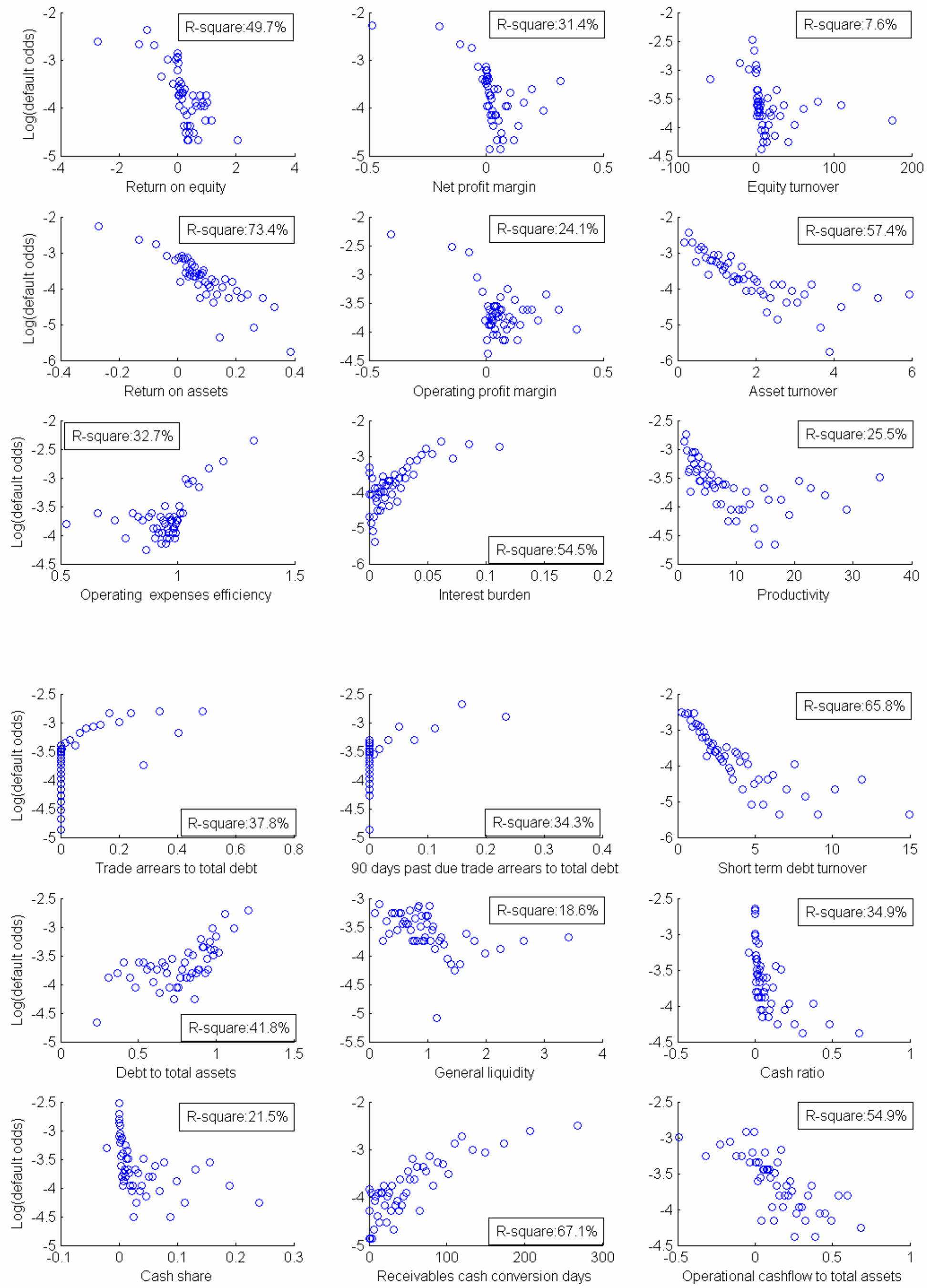
'…'- means that at the 1% threshold there were still abnormal values left over (such as infinity or 0/0) in the variable, which prohibited from computing mean and standard deviation

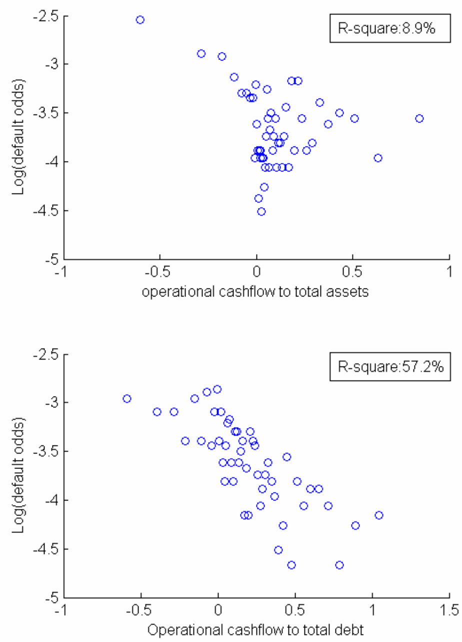
- A KS test was conducted to test for each variable whether the distribution of defaulters is different from the distribution of non-defaulters (one-tail test) – in other words we checked to see if the variable has the expected influence on default based on economic reasoning (see Annex 1). In the above table each variable has a specific color which relates to a specific test outcome:

	Variable for defaulters<Variable for non-defaulters at 99% confidence level – in 2003, 2004 and 2005 and at all default time horizons (1 year, 2 years, 3 years)
	Variable for defaulters>Variable for non-defaulters at 99% confidence level – in 2003, 2004 and 2005 and at all default time horizons (1 year, 2 years, 3 years)
	The a priori relationship between the distribution of defaulters and non-defaulters could not be validated at the 99% confidence interval
	Mixed evidence. For some years/default horizons the a priori relationship is validated while for other periods it doesn't hold
	Not applicable, as the distribution of defaulters can be greater or less than the distribution of non-defaulters, depending on the situation. Based on economic intuition we cannot deduce an a priori relationship between the two distributions in order to test it.
	KS test is not conducted for these variables. After extreme values above 1% (two tail) were removed there were still abnormal values left over (such as infinity)

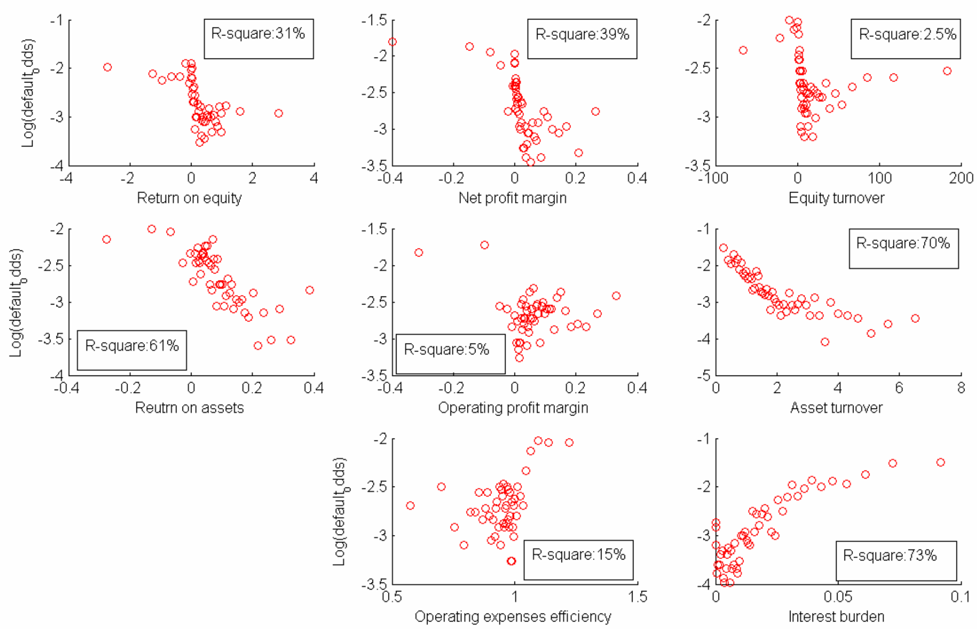
Annex 4 – Linearity and monotony tests

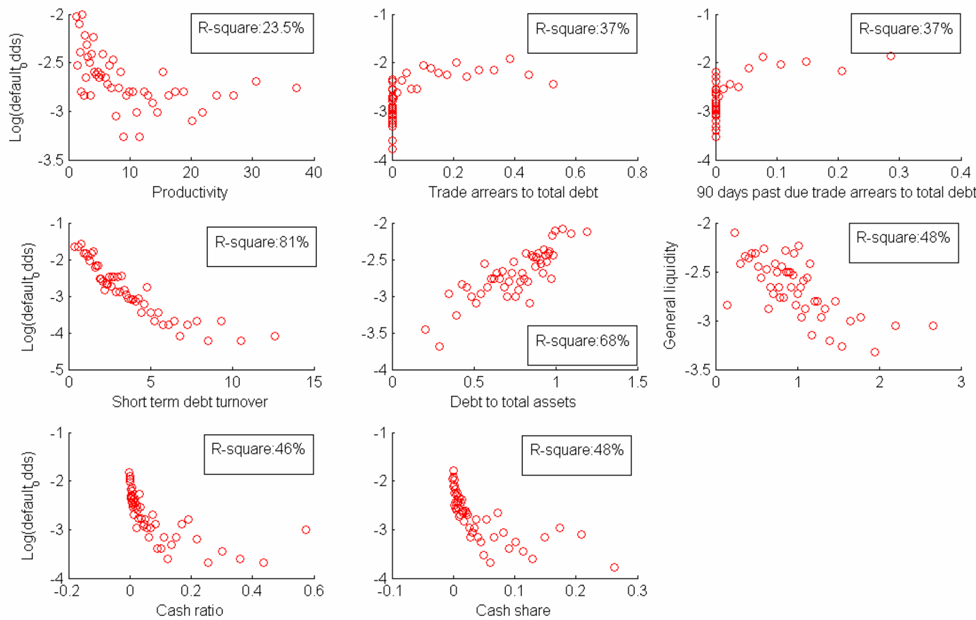
Explanatory variables vs 1 year default using financial information from year 2004 for all NFC





Explanatory variables vs 3 year default using financial information from year 2003 for all NFC




R-square:23.5%
Log(default_b dds)
Productivity
R-square:37%
Trade arrears to total debt
R-square:37%
90 days past due trade arrears to total debt
R-square:81%
Short term debt turnover
R-square:68%
Debt to total assets
R-square:48%
General liquidity
R-square:46%
Cash ratio
R-square:48%
Cash share

Annex 5– Accuracy ratio tests

Accuracy ratio tests on 2004-2005 data for the 1 year default model

Variables	Construction sample (2/3 of total observations)		Test sample (1/3 of total observations)	
	AR	ROC	AR	ROC
Trade arrears to total debt	53	77	55	77
90 days past due trade arrears to total debt	51	75	50	75
Receivables cash conversion days	31	66	36	68
Short term debt turnover	38	69	35	68
Return on equity	22	61	33	67
Interest burden	31	65	31	65
Asset turnover	32	66	30	65
Net profit margin	23	61	29	65
Return on assets	23	62	29	65
Operating cashflow to total debt	16	58	24	62
Operating expenses efficiency	11	55	23	61
Cfashflow to total assets	15	57	20	60
Cash share	23	62	19	59
Debt to total assets	15	57	18	59
Equity turnover	12	56	18	59
Productivity	12	56	17	59
Cash share	21	61	17	58
Financing cashflow to total assets	9	54	14	57
Operating profit margin	4	52	11	55
General liquidity	11	56	7	54
Operating cashflow to net sales	-1	50	-11	45

Accuracy ratio tests on 2003-2006 data for the 3 year default model

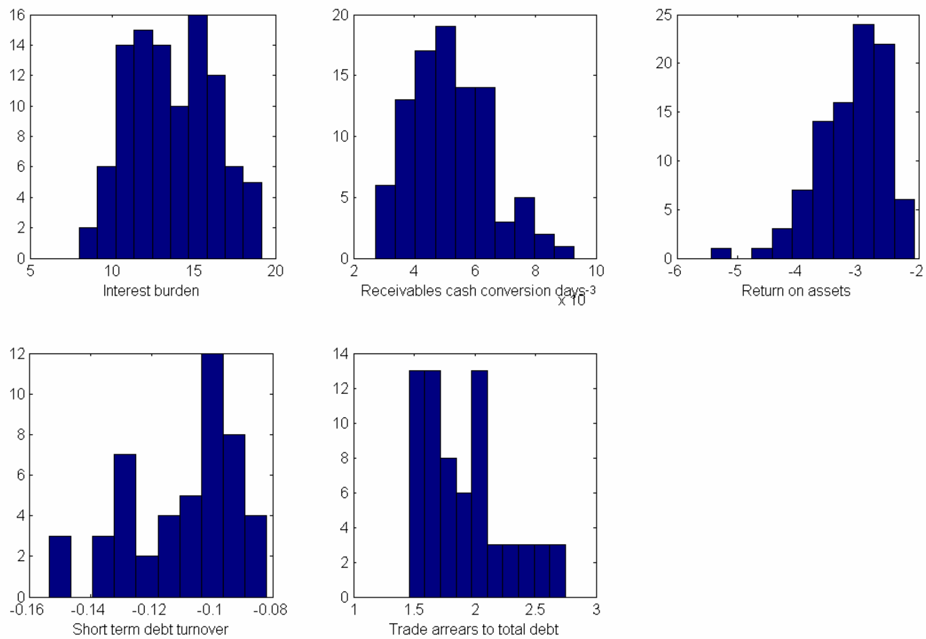
Variables	Construction sample (2/3 of total observations)		Test sample (1/3 of total observations)	
	AR	ROC	AR	ROC
90 days past due trade arrears to total debt	67	84	68	84
Trade arrears to total debt	52	76	50	75

Short term debt turnover	50	75	49	74
Interest burden	37	69	36	68
Asset turnover	36	68	37	69
Receivables cash conversion days	33	66	30	65
Cash ratio	32	66	31	66
Cash share	24	62	26	63
Return on equity	23	61	25	62
Return on assets	21	60	23	61
Net profit margin	18	59	20	60
Operating cashflow to total debt	18	59	23	62
Debt to assets	16	58	14	57
Operating cashflow to total assets	14	57	16	58
Equity turnover	13	57	11	56
General liquidity	12	56	11	56
Productivity	11	56	11	56
Operating expenses to net sales	10	55	11	55
Financing cashflow to total assets	9	54	13	56
Operating profit margin	5	53	1	51
Operating cashflow to total assets	0	50	4	52

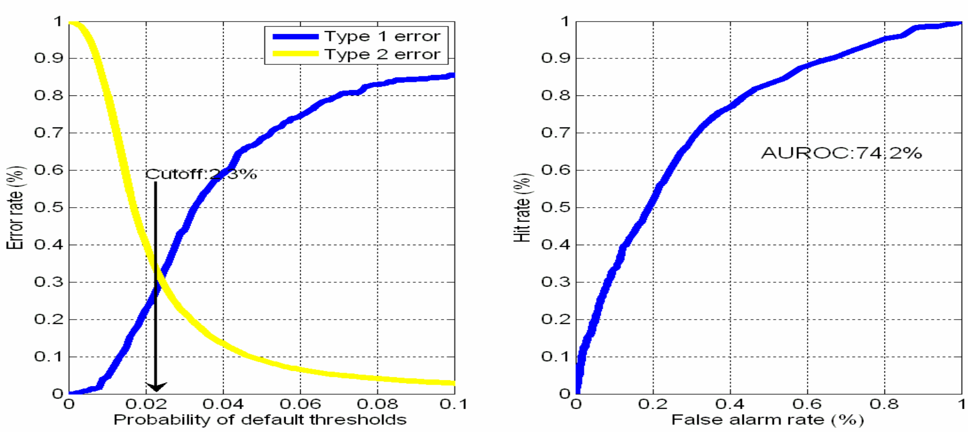
Annex 6 – Model results

Model 1 – 1 year default prediction model built using 2004-2005 dataset

Distribution of coefficients in bootstrapping exercise based on the number of occurrences in 100 simulations



Performance measures (In sample)



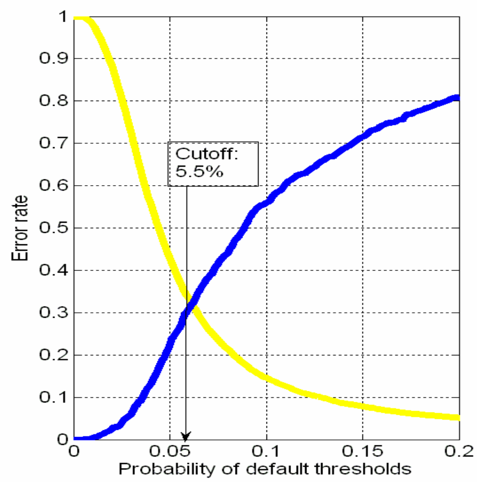
Risks to financial stability at sector level

	Mean probabilities of default (%)			Debt at risk_micro (% of total debt)		
Sectors	2004	2005	2006	2004	2005	2006
Agriculture	4.6	3.5	4.1	4.7	3.4	4.3
Extractive Industry	4.4	5.5	5.1	3.6	6.1	3.5
Manufacturing	3.2	3.0	3.3	3.2	3.4	3.7
Utilities	6.9	4.3	5.0	5.5	4.0	3.4
Construction	3.1	3.0	3.5	4.0	4.1	4.6
Retail and wholesale trade	2.5	2.4	2.6	3.0	2.9	2.4
Transport	3.3	3.1	3.4	4.2	3.5	3.4

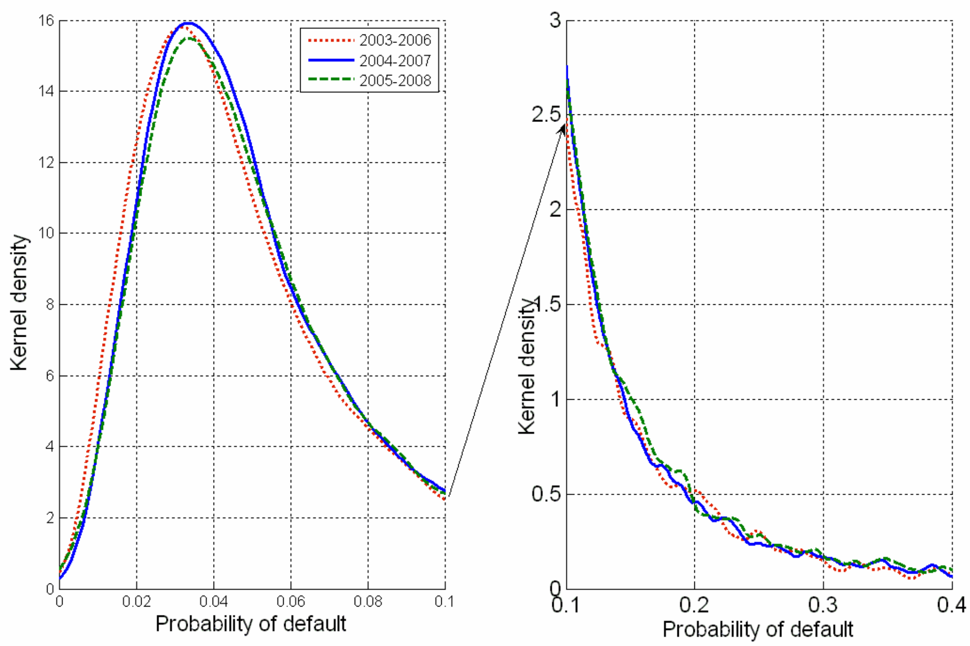
communication and warehousing						
Other services	4.1	3.9	4.3	9.4	11.6	10.5

Model 2 – 3 year default prediction model built using 2003-2006 dataset

Performance measures (in sample)



Dynamics of 3 year probability of default at economy level



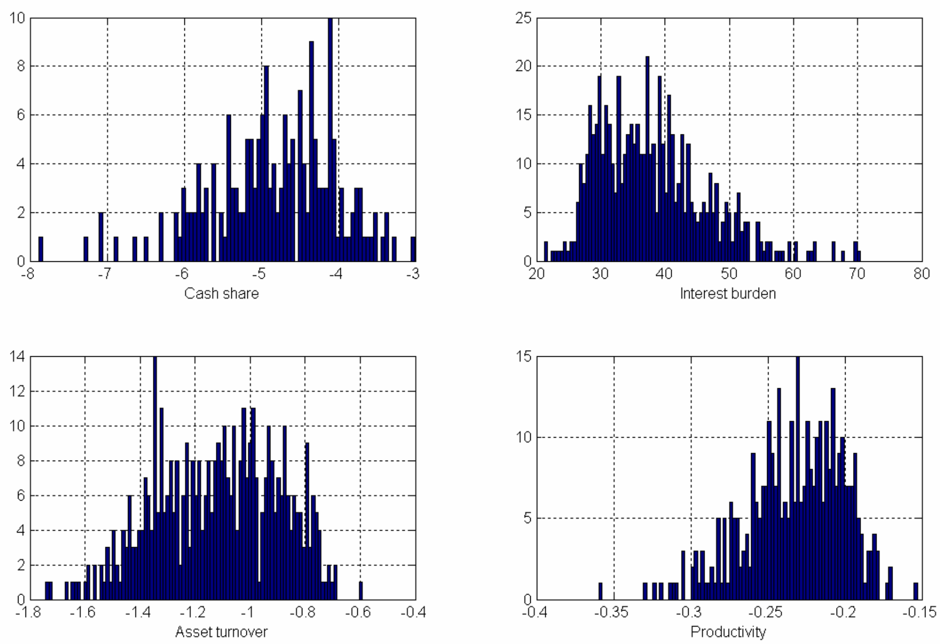
Risks to financial stability at sector level

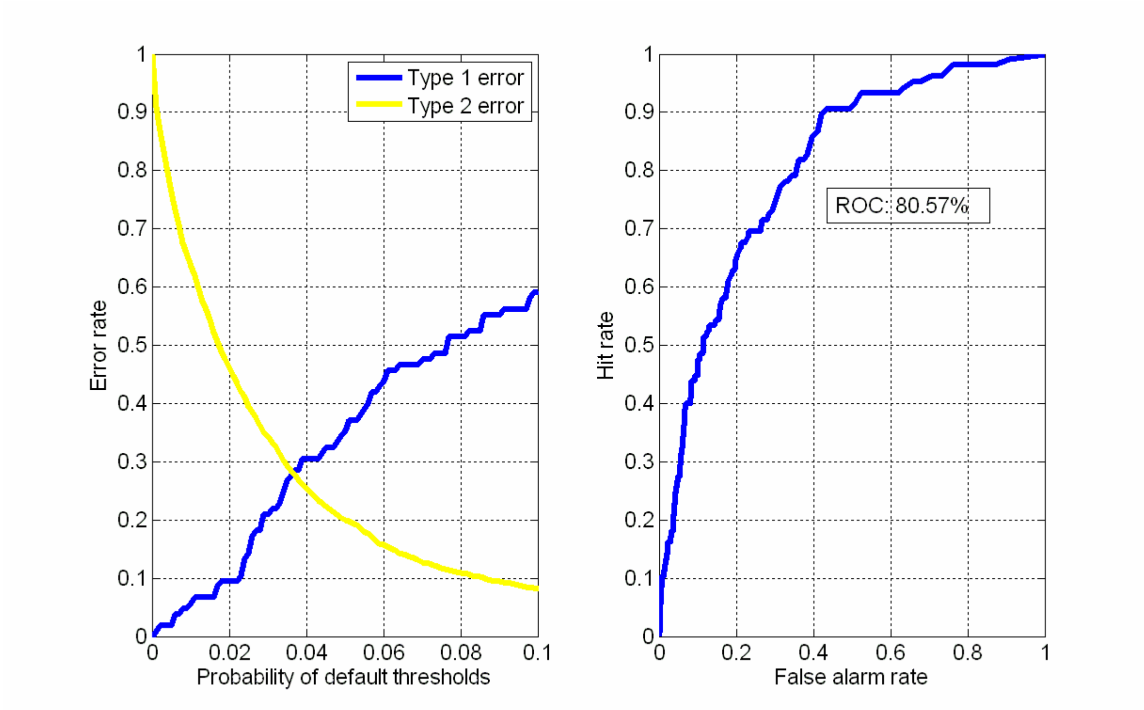
Sectors	Mean probability of default 2004-2006	2005-2007	2006-2008	Debt at risk (% of total debt) 2004-2006	2005-2007	2006-2008
Agriculture	11.6	10.1	11.2	11.8	10.3	12.8
Extractive	10.1	13.0	12.9	6.7	14.4	10.2

Industry						
Manufacturing	8.2	8.0	8.6	8.0	9.2	9.3
Utilities	13.3	9.6	10.2	9.7	8.1	5.7
Construction	7.1	7.3	8.1	8.6	9.5	11.4
Retail and wholesale trade	6.2	6.4	6.7	6.8	7.7	6.4
Transport communication and warehousing	9.8	9.5	9.9	9.8	9.2	9.4
Other services	10.6	10.8	11.3	22.8	25.0	25.6

Model 3 –1 year default prediction model for large firms built using 2003-2006 dataset

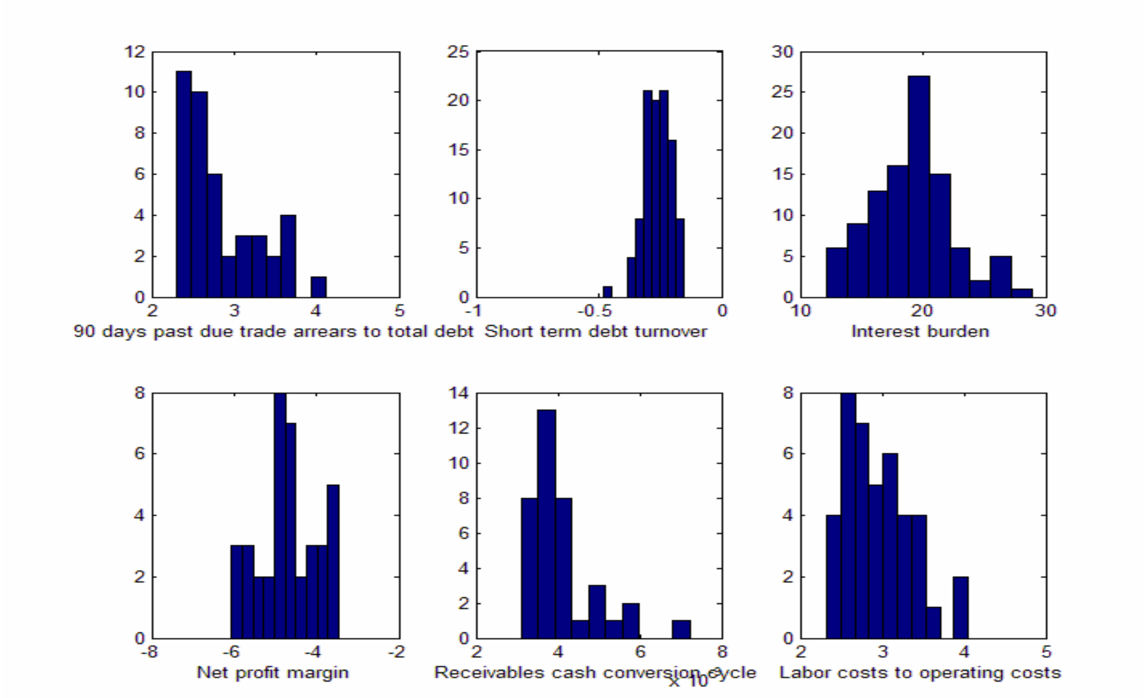
Distribution of coefficients in bootstrapping exercise based on the number of occurrences in 1000 simulations

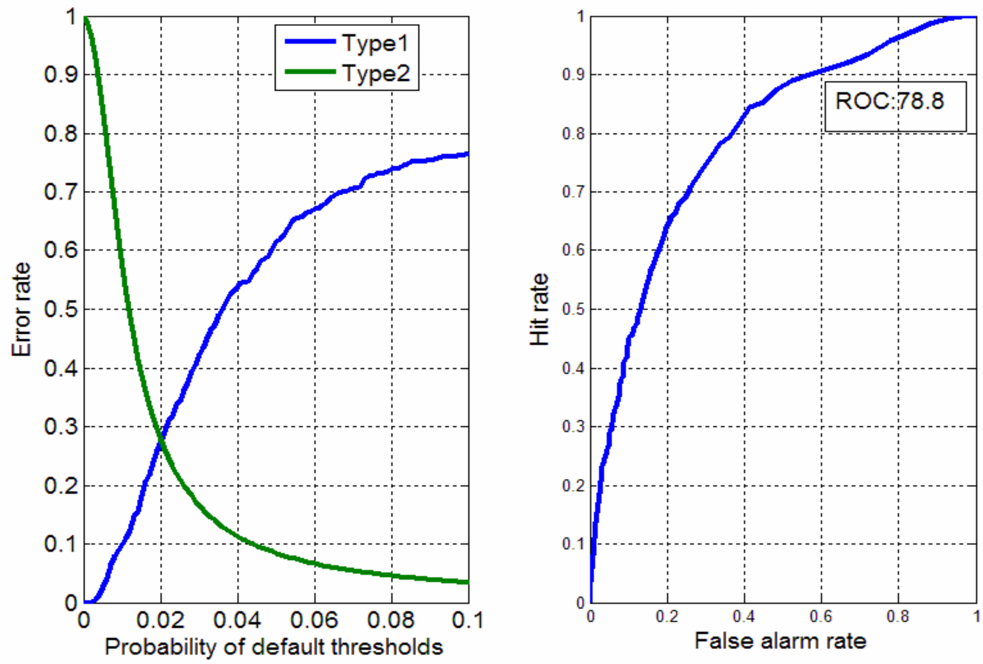




Model 4 –1 year default prediction model for foreign trade firms built using 2003-2006 dataset

Distribution of coefficients in bootstrapping exercise based on the number of occurrences in 100 simulations





Type1
Type2
Error rate
Probability of default thresholds
ROC:78.8
Hit rate
False alarm rate