Are failure prediction models transferable from one country to another? An empirical study using Belgian financial statements

ARE FAILURE PREDICTION MODELS TRANSFERABLE FROM ONE COUNTRY TO ANOTHER ?
AN EMPIRICAL STUDY USING BELGIAN FINANCIAL STATEMENTS

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ABSTRACT

Faced with the question as to whether failure prediction models (multiple discriminant and logit analysis) from different countries can easily be transferred to other countries, this study examines the validity of a range of models on a dataset of Belgian company accounts, both when using the original and re-estimated coefficients.

Firstly, contrary to expectations, models that show bad performance results with the original coefficients reveal an improvement after re-estimation of the coefficients, while models that perform well reveal a decrease in performance. On average, the failure prediction power of the models deteriorates after re-estimation of the coefficients.

The Belgian Ooghe–Joos–De Vos and Ooghe–Verbaere models seem to be generally the best- performing models one and three year prior to failure. Furthermore, if the term of failure prediction is longer: (1) it seems more difficult to distinguish between models performing well and badly and (2) the average failure prediction abilities of the models decrease.

Finally – rather than the estimation technique, the complexity and the number of variables – the type of variables included in the models appears to be an important explanatory factor for model performance. This study makes a strong case for including all different aspects of the financial situation in a failure prediction model.

Over the years, failure prediction or financial distress models have been much discussed in accounting and credit management literature. From the late 1960s, when Altman (1968) and Beaver (1967) published their first failure prediction model, many studies have been devoted to the search for the most effective empirical method for failure prediction. In many countries, not only in developed but also in developing countries, researchers have attempted to construct a good failure prediction model. There are numerous examples: Ko (Japan, 1982), Fischer (Germany, 1981), Taffler and Tisshaw (UK, 1977), Altman et al. (France, 1974), Knight (Canada, 1979), Fernandez (Spain, 1988), Swanson and Tybout (Argentina, 1988). For a more complete list, see Altman and Narayanan (1997). In Belgium, the first financial distress models were estimated in 1982 by Ooghe and Verbaere (1982). In 1991, Ooghe, Joos and De Vos (1991) estimated a second generation of models (Ooghe, Joos and De Bourdeaudhuij, 1995).

Recently, many papers comparing different scoring techniques (for example logit analysis, neural networks and decision trees) on the same dataset have been published, for example Bell et al. (1990), Altman et al. (1993), Curram and Mingers (1994), Joos, Ooghe and Sierens (1998), Kankaanpää and Laitinen (1999). In addition, some attention has been paid to the comparison of the performance of different types of failure prediction models (Mossman et al., 1998).

Although (international) financial information agencies do apply failure prediction models in other countries than the country of origin (for example, US models are used on firms in several European countries), one may well ask whether a given failure prediction model can be easily transferred across countries. Consequently, the main objective of this study is to compare the validity of a range of failure prediction models from different countries, which have been published over the years, on a dataset of Belgian company accounts over the sample period 1995–1999, to identify the models that have the best predictive abilities in Belgium. In this respect, this study can be considered as a case study concerning the ‘transferability’ of models developed in a specific country and period to other countries and/or periods.

It should be noted here that if we were to validate the models in their current form (i.e., with their original variables and original coefficients) on the Belgian data, we would not be able to determine whether the performance results of the models are a mere consequence of the choice of variables. Bad performance results could also be caused by coefficients that fail to capture the true relationships between the variables of the model and the failures of Belgian companies. In view of this, we will re-estimate the coefficients of all models over the Belgian data, using the original variables.

As far as we know, there has been as yet no systematic comparative examination of the predictive performances of models from different countries with the original and re-estimated coefficients on the same dataset.

This paper is divided into six parts. By way of introduction, Section 2 gives a short explanation of the two modelling techniques that we focus on in this study: linear discriminant analysis and the logistic regression technique. In addition, the different performance measures that are used to examine the predictive abilities of the models are explained. Section 3 discusses the failure prediction models that are analysed in this paper, with Section 4 focusing on the population and the sampling methodology. Section 5 reports the results of our empirical research and attempts to explain the findings. The final section will highlight the most important conclusions of the study.

1. MODELLING TECHNIQUES AND PERFORMANCE MEASURES

1.1. Modelling Techniques

Modelling techniques for two-group classification in general, and failure prediction in particular, can generally be classified in four different groups (Ooghe, Joos and Sierens, 1998): classical statistical techniques, recursive partitioning analysis (or tree classification), neural networks, and genetic algorithms. The latter three classification methods may also be classified under the general heading of ‘inductive learning’ (i.e., a learning process based on examples). It is more difficult to validate these kinds of models. As a result, this study only considers failure prediction models estimated with classical statistical techniques, such as *linear discriminant analysis* and *logistic regression*.

A second reason why we focus on linear discriminant analysis and the logistic regression technique is because they are used in most failure prediction research, both in the earlier versions and in the most recent ones. In 1968, Altman started with his ‘Z-score’ discriminant model (Altman, 1968), and the same risk analysis tool is still applied in the scoring models, developed by the Central Banks of Austria, France, Germany, Italy, The United Kingdom a.o. (Anonymous, 1997) ‘International Conference of the European Committee of Central Balance Sheet Data Offices’, October 1997, Paris). The logistic regression technique was introduced at a later stage and is currently applied in both academic papers and in research from Central Banks.

Multiple discriminant analysis compares the distribution of one or more variables − which have a multivariate normal distribution − for different groups or populations (i.e., a failing and a non-failing group), which are known, identified and mutually exclusive (Altman et al., 1981). Firms are classified into the failing or non-failing groups by comparing their discriminant score D_i, which has a value between $-\infty$ and $+\infty$, with a certain cut-off score (Joos, Ooghe and Sierens, 1998; Lachenbruch, 1975).

In **logit analysis**, conditional probabilities or logit scores, lying between zero and one on a sigmoidal curve, are calculated (Hosmer and Lemeshow, 1989). On the basis of a logit score and a certain (optimal) cut-off point, a firm can be classified into the failing or the non-failing groups. Logit analysis is frequently used in classification studies because this method has some favourable qualities. For example, it is not necessary to adapt the method for disproportional samples, as only the constant term b_0 is distorted (Maddala, 1983; Maddala, 1992).

1.2. Performance Measures

The performance of a classification model indicates how well the model performs, and is called *'goodness-of-fit'* in the econometric literature. Two different kinds of performance measures will be discussed: measures based on a ‘classification rule’, and measures based on the ‘inequality principle’. Measures based on entropy and R^2-type measures are not used in this study (Joos, Ooghe and Sierens, 1998).

1.2.1. Measures based on a classification rule. Because classification into a group of failing and non-failing companies is the main objective of a failure prediction model, it is obvious that performance measures based on a classification rule are frequently applied.

In this study, a high (logit or discriminant) score indicates a healthy financial situation, while a low score indicates a bad financial situation and hence a high failure probability. In this respect, a firm will be classified into the failing group if its score is lower than a certain cut-off point, while it will be classified into the non-failing group if its score is higher than the cur-off point. For a continuous score model, the classification rule can be formulated as follows:

$$y_i^* = \begin{cases} 1 \text{ if the logit or discriminant score } \hat{y}_i \text{ of firm } i > y^* \\ 0 \text{ if the logit or discriminant score } \hat{y}_i \text{ of firm } i \leq y^* \end{cases} \tag{1}$$

with y_i^* = estimated class of firm i

y^* = threshold or ‘cut-off point’.

Here, two types of misclassifications can be made:

1. A ***Type I error*** represents a ‘credit risk’: a failing firm is classified as a non-failing one;
2. A ***Type II error*** represents a ‘commercial risk’: a non-failing firm is classified as a failing one.

In this respect, the optimal threshold or ***‘optimal cut-off point’*** of a failure prediction model can be calculated as the point at which the unweighted average of both types of errors – the unweighted error rate (UER) – is minimized. This optimal cut-off point corresponds to the score for which the greatest difference ($D_{\text{non-failing, failing}}$) between the cumulative distributions of the scores of non-failing firms ($F_{\text{non-failing}}$) and those of the failing firms (F_{failing}) exists. (Koh, 1992; Joos, Ooghe and Sierens, 1998).

In this study, we use the ***unweighted error rate (UER)*** because this is the most objective performance measure. The allocation of weights to the different types of errors is subjective and depends on the degree of risk aversion of the risk analyst. Furthermore, we do not want to take into account the population proportions because of the unbalanced proportion of failing and non-failing companies. The over-representation of non-failing companies would lead to a focus on the minimization of type II error rates, and hence, to cut-off points that are too low and a decision process that is too tolerant.

It should be mentioned here that the unweighted error rate of a model does not indicate the real percentage of the firms in the total population of failing and non-failing companies that is classified falsely by the model. The unweighted error rates reported in the tables, are only intended as a measure of accuracy – based on the unweighted type I and type II error rates – which are used to compare the accuracies of the different models.

1.2.2. Measures based on the inequality principle. The performance of a model can also be demonstrated graphically with the construction of a ***trade-off function*** (Figure 1). Here, the cumulative frequency distributions of the scores for 'non-failing' and 'failing' firms are located in a co-ordinate system, with the type II error (=$F_{non\text{-}failing}\ (y)$) on the X-axis and the type I error (= $1 - F_{failing}(y)$) on the Y-axis (Steele, 1995),

with $F_{failing}(y)$ = cumulative distribution function of the scores of the failing firms;

$F_{non\text{-}failing}\ (y)$ = cumulative distribution function of the scores of the non-failing firms.

Each element of this trade-off function represents an optimal cut-off point for a given classification cost ($C_{Type\ I}$ and $C_{Type\ II}$) and population proportions ($p_{failing}$ and $p_{non-failing}$).

Insert Figure 1 about here

It is clear that the best-performing (i.e., most discriminating) model has a trade-off function that coincides with the axes. By contrast, the non-discriminating model, which cannot distinguish between non-failing and failing firms, has a linear descending trade-off function from 100% type I error to 100% type II error. Comparing the location of the trade-off function of a failure prediction model with the location of the most discriminating and the non-discriminating models gives a clear indication of the performance of the model: a model has higher performance is its curve is located closer to the axes.

The ***Gini-coefficient*** of a model is an aggregated performance measure that reflects the difference between the trade-off function of the model and the trade-off function of the non-discriminating model. In a normal situation, this coefficient lies between zero and or and is equal to the proportion of the area between the model and the non-discriminating model (i.e., the grey area in Figure 1) and the area between the non-discriminating and the best model (i.e., the triangle with the axes as sides). As a result, a higher Gini-coefficient corresponds to a curve that is situated closer to the axes, and hence, to a better performing model. A negative Gini-coefficient implies that a model classifies most companies falsely. An empirical approximation of the Gini-coefficient is shown in the formula below (Joos, Ooghe and Sierens, 1998):

$$\begin{aligned}\hat{GINI} &= \frac{\frac{x_{\max} y_{\max}}{2} - \sum_{i=1}^{n} (x_i - x_{i-1}) \frac{y_{i-1} + y_i}{2}}{\frac{x_{\max} y_{\max}}{2}} \\ &= 1 - \sum_{i=1}^{n} (x_i - x_{i-1})(y_{i-1} + y_i)\end{aligned} \qquad (2)$$

with x_i = type II error rate with threshold I;

y_i = type I error rate with threshold I;

x_{max} = maximum type II error rate, i.e., 100%;

y_{max} = maximum type I error rate, i.e., 100%.

2. FAILURE PREDICTION MODELS

Because the aim of the study is to compare the validity of a range of failure prediction models from different countries, that have been published over the years, we have to select a number of models. In the selection process, several criteria are taken into account.

Firstly, as already mentioned, this study only focuses on models estimated with *linear discriminant analysis* and *logistic regression*.

Secondly, we restrict ourselves to the analysis of models that are *'frequently referred to'* in research papers. For example, on the basis of this criterion, the Altman (1968) model and the Zavgren (1983) model are included in this study.

Thirdly, the *availability of variable and coefficient* information is an important criterion. As many recent models are licensed to commercial companies, they are not fully described in academic publications and therefore could not be included in this study. One example of a model that is excluded because of the unavailability of coefficients is the Taffler (1984) model.

Furthermore, the *ease of use* of the models with respect to the calculation of the variables is taken into consideration. Models that include non-financial data, such as gross national product, are left out of this study. For example, the Ohlson model (1980), which includes the GNP price index, is excluded from the analysis.

In addition, this study only incorporates *'developed country models'* (Altman and Narayanan, 1997). 'Developing country models' fall outside the study, as we expect these models to show extremely large error rates when validated on Belgian annual accounts. In developing countries, free market economies do not occur and it is difficult to detect company failure because of the degree of government protection.

Finally, we opt for *general models* and hence exclude models investigating the probability of failure of, for example, new, high-tech or small firms. One example concerns the exclusion of the Laitinen model (1992), which was designed to predict failures of newly founded firms.

At the end of the selection procedure, eight models remain: Altman (1968), USA; Bilderbeek (1979), The Netherlands; Ooghe–Verbaere (1982), Belgium; Zavgren, (1985) USA; Gloubos–Grammatikos (discriminant analysis and logistic regression) (1988), Greece; Keasey–McGuinness (1990), United Kingdom; and Ooghe–Joos–De Vos (1991), Belgium. In Appendix 1, Table 1 summarizes the characteristics of each of these eight models, and in Tables 2 to 8 the variables of the models are shown. In these tables, each different variable is attributed a unique name (X1, X2,…, X40). Detailed analysis of the variables reveals that the same variables are frequently used in several models.

The signs of the original coefficients must be defined according to the general settings of this study. As already mentioned, in this paper a high (logit or discriminant) score indicates a healthy financial situation. The signs of the original coefficients of all models in Tables 2 to 8 in Appendix 1 are defined accordingly. Therefore, for some models, the signs of the original coefficients are opposite to those reported in the original papers of the authors.

However, comparing the performances of the different models in their current form (i.e., with their original variables and original coefficients) will cause some difficulties. We should bear in mind that models perform badly out-of-sample when there is a large difference between the estimation sample and the validation sample, especially if the differences are the result of differences in the definitions of the dependent variables, exogenous factors (such as macroeconomic conditions and institutional and legal factors unique to the country of origin) and the sample period. It is clear that the calculation of the original coefficients of the various models was influenced by the correlations between the variables that are included in the original estimation samples and the variables that are not included in these samples, such as macroeconomic conditions, institutional factors and sample period. Consequently, if we validate the models with their original coefficients on the Belgian data, we will be unable to determine whether bad performance of the models is the consequence of an inappropriate choice of the variables or of the use of coefficients that fail to capture the true relationship between the variables and failures of Belgian companies.

The re-estimation of the coefficients of all models over the Belgian data using the original variables, will allow the models to take into account some factors specific to the Belgian validation dataset. As a result, we will be able to compare model performances more precisely, and to indicate whether the performance results can be explained solely by the choice of variables. In this view, it is clear that, besides the validation of the models with their original coefficients, we must also validate the models with their re-estimated coefficients.

3. POPULATION AND SAMPLES

Before describing the population and the sampling method for re-estimation and validation, it seems appropriate to give some important definitions that are frequently used in this study.

3.1. Definitions of Failing and Non-Failing Firms

A ***'failing'*** firm is a firm in the situation of bankruptcy, or with a request for a judicial composition, or with an official approval of a judicial composition.

On the other hand, firms that are characterized by the following juridical situations are included in the group of ***'non-failing'*** firms:

- Termination of activity;
- Early dissolution–liquidation;
- Liquidation followed by a merger with another company;

- Liquidation followed by absorption by another company;
- Closing of a liquidation;
- Without any particular legal status.

In other words, not only ‘normal’ firms without any particular legal status, but also firms with associated doubts about the economic reasons for their juridical situation are included in the non-failing population. As it is our aim to validate failure prediction models, it is necessary to measure the performance of the models in a realistic situation, and hence consider these doubt-causing firms as non-failing ones. However, when re-estimating the coefficients of the failure prediction models, we want to reduce the influence of these doubt-causing firms. Therefore, in the ‘re-estimation sample’, which is discussed in Section 4.3, only firms without any particular legal status are included in and all other firms are ruled out of the group of non-failing firms.

3.2. Population and Samples of Failing and Non-Failing Companies

This study is based on Belgian accounting data from the period 1994–1999. It concerns published annual accounts of non-financial companies subject to the legislation on the annual accounts of companies. The data were obtained from the CD-ROMs of Bureau Van Dijk and information supplier Graydon NV.

The ***total population*** of companies consists of all firms having published at least one annual account in the period 1994–1999. Companies that are classified into the following activity classes, are excluded because of their special situations:

- Financial intermediation, insurance and pension funding;
- Management activities of holding companies and co-ordination centres;

- Public administration, defence, services to the community as a whole, and compulsory social security;
- Education;
- Health and social work;
- Activities of membership organizations;
- Private households with employed persons;
- Extra-territorial organizations and bodies.

The total population comprises 268.465 companies, identified by their V.A.T. numbers. From this total population, two samples are taken: a sample of failing companies and a sample of non-failing firms.

It should be noted that, in Belgium, companies are required to deposit their annual accounts in a prescribed form, dependent on their size. A distinction is to be made between 'large' companies that must prepare their annual accounts in a complete form, and 'small' companies that are allowed to prepare their annual accounts in an abbreviated form. The group of larger companies consists of companies with more than 100 employees, plus companies that meet at least two of the following three criteria:

- Number of employees (yearly average): more than 50;
- Turnover (V.A.T. excluded) (yearly average): more than 200 million Belgian francs;
- Total assets: more than 100 million Belgian francs.

In Belgium, a major percentage of the companies have annual accounts in an abbreviated form: in 1999, only 6,2% of the total population of companies deposited a complete-form annual account.

The ***sample of failing companies*** consists of all firms that failed in 1997 or 1998. Only firms that failed in 1997 having annual accounts in 1994 or later, and firms that failed in 1998 having annual accounts in 1995 or later, are included. The failing sample comprises 6500 companies.

On the other hand, the ***sample of non-failing companies*** includes all firms that are non-failing on January 1, 1999, and that have annual accounts in 1994 or later. The non-failing sample involves 249.334 companies.

Table 1 illustrates the number of failing and non-failing companies that are used in this study. It also reports the percentage of the non-failing sample that is made up of companies characterized by the judicial situations mentioned in the list in Section 4.1.

Insert Table 1 about here

3.3. Samples of Failing and Non-Failing Annual Accounts

The sampling procedure for the ***samples of failing annual accounts*** is rather simple. Because the aim of the study is to re-estimate and to validate the models one, two and three years prior to failure (i.e., 1 ypf, 2 ypf and 3 ypf), we select the annual accounts one, two and three years prior to failure (if available and if not concerning an extended fiscal year) for each company in the failing sample. However, not all companies deposit their annual accounts on December 31. Consequently, the annual accounts 1, 2 and 3 ypf are defined as follows:

Account one year prior to failure: account with the closing date falling within the period [date of failure, date of failure – 365 days]

Account two years prior to failure: account with the closing date falling within the period [date of failure – 365 days, date of failure – (2 * 365 days)]

Account three years prior to failure: accounts with the closing date falling within the period [date of failure – (2 * 365 days), date of failure – (3 * 365 days)]

To select the ***samples of non-failing annual accounts***, the group of non-failing companies is randomly divided into four equal groups: groups A, B, C and D. For each group of companies, the annual accounts of one specific year in the period 1994–1997, if available and if not concerning an extended fiscal year, are taken. The following non-failing annual accounts are selected:

Non-failing firms in group A: annual accounts of 1994

Non-failing firms in group B: annual accounts of 1995

Non-failing firms in group C: annual accounts of 1996

Non-failing firms in group D: annual accounts of 1997

In this study, we link the failing annual accounts one, two and three years prior to failure to the non-failing annual accounts, bearing in mind that the annual accounts of the two different samples should refer to the same time frame. Accordingly, for each year prior to failure, the annual accounts of the two relevant years are taken together. This procedure is explained in Table 2. The resulting numbers of annual accounts in the samples of failing and non-failing annual accounts are reported in Table 3.

Insert Table 2 about here

Insert Table 3 about here

Because we want to re-estimate the coefficients of the eight models on the Belgian data before validation, we require validation and re-estimation samples of failing and non-failing annual accounts. Consequently, the samples of failing and non-failing annual accounts are randomly divided into separate re-estimation samples and validation samples. Within each sample of failing and non-failing annual accounts, 50% of the accounts are classified as a re-estimation sample, and 50% are included in a validation sample.

As already mentioned, in the ***re-estimation samples,*** the annual accounts of 'doubt-causing' firms, must be excluded from the group of non-failing annual accounts. Only companies without any particular legal status should be considered as non-failing. Furthermore, we are forced to reduce the large number of non-failing annual accounts in the re-estimation samples because of the practical limitations of the statistical programme used. In this respect, about 20% of the non-failing annual accounts are selected randomly. In contrast, the number of failing annual accounts is not reduced. Finally, we eliminate all annual accounts that have not been deposited at the National Bank of Belgium and therefore are not available on the CD-ROMs of Bureau Van Dijk. This significantly reduces the original number of failing annual accounts in the sample, at 1 ypf in particular, as many failing companies cease to pay attention to financial reporting when they are close to failure. Also, the annual accounts of non-failing companies founded after 1 January, 1998 are excluded, because these companies do not have annual accounts in the period 1994-1997. Table 4 presents the number of failing and non-failing annual accounts in the 1 ypf, 2 ypf and 3 ypf estimation samples after the elimination of non-available annual accounts.

Insert Table 4 about here

It is clear that some models have different variables and coefficients depending on the period within which they aim to predict failure. Ooghe–Verbaere, Keasey–McGuinness and Ooghe–Joos–De Vos do not use the same variables for failure predictions one, two and three years prior to failure. These models are re-estimated on the basis of the corresponding re-estimation samples, being the samples 1, 2 and 3 ypf. In addition, the Zavgren model, which uses the same variables but different coefficients for failure prediction one, two and three years prior to failure, is re-estimated on the basis of these three samples.

On the other hand, the models that make no distinction between failure prediction one, two and three years prior to failure – being Altman, Bilderbeek, and Gloubos–Grammatikos discriminant and logit – use the same variables and coefficients independent of the year prior to failure. They only have 'general' coefficients and hence are re-estimated on a 'general' sample (i.e., 'total sample' in Table 4), which is composed of all annual accounts in the 1 ypf, 2 ypf and 3 ypf samples.

The ***validation samples*** of failing and non-failing annual accounts are taken in much the same way as the re-estimation samples. As with the re-estimation samples, the number of non-failing annual accounts is much too large to be able to use the statistical programme. Again, this large number of non-failing annual accounts must be reduced: about 20% of the non-failing annual accounts were selected randomly. In addition, all annual accounts that have not been deposited are excluded from the validation samples. Again, this reduces the original number of failing annual accounts in the sample 1 ypf significantly. Table 5 reports the number of failing and non-failing annual accounts in the 1 ypf, 2 ypf and 3 ypf validation samples after the elimination of non-available annual accounts.

Insert Table 5 about here

On the basis of each annual account in the re-estimation samples, we calculate a range of *variables* or ratios (i.e., the variables X1 to X40 referred to in Tables 2 to 8 in Appendix 1) to re-estimate the coefficients of the models. On the other hand, on the basis of each annual account in the validation samples, we compute a (logit or discriminant) *score* for each model to determine the model performance. Here, it is important to mention the ***influence of invalid observations***, both in the re-estimation and in the validation process.

Firstly, a detailed examination of the data concerning the variables reveals a frequent occurrence of ***invalid variables***, caused by zero values in the denominators of the variables. This is particularly the case if the denominator of a variable contains sales or inventories. According to Belgian accounting law, approximately half of the small companies, publishing their results in an abbreviated form, only state their 'gross margin' as they are not obliged to publish sales and operating costs. Furthermore, some types of companies (for example service firms) simply do not have inventories.

As a result, when re-estimating each of the models, a certain percentage of the annual accounts in the re-estimation samples show invalid observations for some variables, and hence cannot be used. Table 6 gives an overview of the percentage of annual accounts that could be used for the re-estimation of each of the models. For example, when re-estimating the Zavgren model, less than 30% of the annual accounts can be used, because the model uses ratios containing sales and inventories in their denominator. Furthermore, when re-estimating other models with ratios containing 'sales' in their denominator (Bilderbeek, Ooghe–Verbaere 2 ypf, and Keasey–McGuinness), less than 50% of the annual accounts in the re-estimation samples can be used.

Insert Table 6 about here

In this respect, we should bear in mind that, as the models use different variables, they are not re-estimated on the basis of the same samples of annual accounts. However, this causes no problems for the re-estimation process, because it is our aim to calculate the re-estimated coefficients for each of the models as precisely as possible. Consequently, we want to include as many annual accounts as possible for each individual model.

Secondly, detailed analysis of the data on the logit and discriminant scores also reveals the presence of ***invalid scores***, caused by invalid variables. However, when validating the models it is important that the performance results are based on the same samples of annual accounts, as it is our aim to compare the results of the different models on an equal basis. Consequently, all annual accounts that show an invalid score for at least one model are excluded from the validation samples. Only the annual accounts that have valid scores for each model are selected. Table 7 reports the number of annual accounts that are finally included in the validation sample. This is the total number of annual accounts that are used to validate the models.

Insert Table 7 about here

4. RESULTS AND INTERPRETATION

This section discusses the validation results of the different failure prediction models on the dataset of Belgian companies. Section 5.1 gives some preliminary remarks on the signs of the coefficients of the variables. As an illustration, Table 9 in Appendix 1 shows the validation results obtained by the authors of the models in their original studies. The performance results of the different models using the original coefficients are reported in Section 5.2. We discuss the type I, type II, and unweighted error rates corresponding to the optimal cut-off points of the models, and we calculate Gini-coefficients. We also give a graphical illustration of the results by means of trade-off functions. In Section 5.3, we analyse the performance results of the models with the re-estimated coefficients. Section 5.4 gives an overview of all validation results and discusses the change in performance results when using the re-estimated coefficients instead of the original ones. Finally, in Section 5.5 we put forward some possible explanations for the dispersed performances.

4.1. Preliminary Remarks on the Signs of the Variables

The failure prediction models are re-estimated using the re-estimation samples and are attributed new coefficients and new optimal cut-off points. These new coefficients and cut-off points are reported in Tables 2 to 8 in Appendix 1. A detailed analysis of the signs of the original and the new coefficients reveals that some of these signs do not correspond to expectations.

First, the signs of the coefficients of several variables in the original models do not match expectations:

- Appendix 1, Table 3: Bilderbeek (1979): variables X6 and X5;
- Appendix 1, Table 5: Zavgren (1985): variables X19, X21, X6 and X22;
- Appendix 1, Table 6: Gloubos and Grammatikos (1988): variables X23 and X11;
- Appendix 1, Table 7: Keasey and Mc Guinness (1990): variables X4 and X18.

On the other hand, some of the new, re-estimated coefficients also have unexpected signs:

- Appendix 1, Table 2: Altman (1968): variables X1 and X5;
- Appendix 1, Table 3: Bilderbeek (1979): variables X6, X7, X8 and X2;
- Appendix 1, Table 4: Ooghe and Verbaere (1982): variables X9 and X14 (3 ypf);
- Appendix 1, Table 5: Zavgren (1985): variables X19 (2 ypf and 3 ypf), X21 (1 ypf), X 6 (1 ypf and 2 ypf) , X22 and X5;
- Appendix 1, table 7: Keasey and McGuinness (1990): variables X26 (1 ypf), X18 and X5;
- Appendix 1, table 8: Ooghe, Joos and de Vos (1991): variables X32 and X40;

The (linear) multivariate contexts of the models are the only possible explanation for these unexpected signs: the (positive or negative) influence of some variables are counterbalanced by the (negative or positive) influence of other variables.

4.2. Performance Results of the Failure Prediction Models with the Original Coefficients

The validation results of the models with their original coefficients are shown in Table 8. The best-performing models are indicated in bold letters, while the worst-performing models are printed in italic. Firstly, Table 8 reports the ***type I, type II*** and ***unweighted error rates*** corresponding to the new optimal cut-off points of the models. The ***optimal cut-off point*** is equal to the score for which the unweighted average of the type I and type II error rates reaches a minimum (see section 2.2.1). Besides the unweighted error rate, the ***Gini-coefficient*** can also be used to evaluate the 'fit' of the models. Contrary to the discussion of the type I and type II errors separately, this measure gives a global judgement of performance: the Gini-coefficient is independent of changing cut-off points. Finally, Table 8 shows the rankings of the models, both on the basis of the UER and the Gini-coefficient. These rankings clearly indicate which models perform best or worst, 1 ypf, 2 ypf and 3 ypf.

Insert Table 8 about here

Analysis of the unweighted error rates, the Gini-coefficients and the rankings of the models ***one year prior to failure*** reveals that the Belgian Ooghe–Joos–De Vos model performs best, followed closely by the models of Ooghe–Verbaere and Bilderbeek. On the contrary, Zavgren, Gloubos–Grammatikos discriminant and Keasey–McGuinness seem to be less successful in predicting failure.

The results of the models ***two years prior to failure*** are similar to the results of the short-term models: Bilderbeek and Ooghe–Verbaere are indicated as the best-performing models.

In addition, the Gloubos–Grammatikos logit model seems to have a very high Gini-coefficient. On the other hand, Zavgren clearly shows the highest UER and the lowest Gini-coefficient.

The performance results of the models ***three years prior to failure*** indicate the Ooghe–Joos–De Vos model as the model with the best failure prediction results, and, as in the short-term case, Ooghe–Verbaere and Bilderbeek follow closely. Again, the Zavgren model seems to be the worst failure predictor.

In Figures 1 to 3 in Appendix 2, we plot the ***trade-off functions*** of the models 1, 2 and 3 ypf using the original coefficients. Figure 1, which reports the results of the short-term (1 ypf) models, indicates Ooghe–Joos–De Vos, Ooghe–Verbaere and Bilderbeek as the best-performing models. Figure 2 indicates Bilderbeek, Ooghe–Verbaere and also Gloubos–Grammatikos logit as the models that have the most predictive abilities two years prior to failure. Figure 3 reveals that Ooghe–Joos–De Vos, Bilderbeek, and Ooghe–Verbaere perform best three years prior to failure.

It is noteworthy that if the term of the failure prediction is longer, the ***average*** unweighted error rate of the models increases, and the average Gini-coefficient decreases: the average UER of the short-term models is significantly lower than the average UER of the 2 ypf and 3 ypf models. This finding is not surprising as it is generally believed that it is easier to predict failure, and hence discriminate between failing and non-failing companies in the short term. One of the reasons for this finding is that specific features of failing companies are less pronounced three years before failure than they are one year before failure.

Finally, it should be noted that, when using the original coefficients, the ***performance differences*** between the models are quite small. In addition, it is clear that the performance differences depend on the term of failure prediction. A comparison of the distributions of the trade-off functions (see Figures 1 to 3 in Appendix 2) reveals that the performance differences between the best and the worst short-term (1 ypf) models are significantly larger than the differences for the 2 ypf and the 3 ypf models. Consequently, if the term of failure prediction is longer, it seems to be more difficult to make a distinction between good and bad performing models.

4.3. Performance Results of the Failure Prediction Models With the Re-estimated Coefficients

Table 9 reports the validation results (the error rates, Gini-coefficient and rankings) of the models with their new, re-estimated coefficients. As in Table 8, the best-performing models are highlighted in bold letters, while the worst-performing models are indicated in italic. Compared to the results presented above, the results in table 9 show a totally different view.

Table 9 about here

The performance results of the models ***one year prior to failure*** indicate Keasey–McGuinness as the best performing model. In addition, Ooghe–Joos–De Vos, and both Gloubos–Grammatikos models (discriminant and logit) reveal very small unweighted error rates. On the contrary, the Bilderbeek and Altman models perform worst. The Bilderbeek model even has a negative Gini-coefficient, which means that the models classifies most companies falsely.

With respect to the models ***two years prior to failure***, Gloubos–Grammatikos discriminant performs best, followed closely by Keasey–McGuinness and Gloubos–Grammatikos logit.

Furthermore, as in the short-term case, Bilderbeek and Altman reveal the highest UER and the lowest Gini-coefficient and hence are the worst performing models.

Examination of the results of the models ***three years prior to failure*** reveals that the Zavgren and the Gloubos–Grammatikos discriminant models are the ones that perform best. Again, Bilderbeek and Altman clearly are the worst failure predictors.

The trade-off functions of the models 1, 2 and 3 ypf using the ***re-estimated coefficients*** are shown in Figures 4 to 6 in Appendix 2. From Figure 4 concerning the short-term (1 ypf) models, it is apparent that four models have very high predictive abilities: Keasey–McGuinness, Ooghe–Joos–De Vos and Gloubos–Grammatikos discriminant and logit. Figure 5 indicates Gloubos–Grammatikos discriminant and logit, and Keasey–McGuinness as the best-performing 2 ypf models. Observation of Figure 6 suggests that Zavgren and Gloubos–Grammatikos discriminant show the best results with respect to long-term failure prediction. In addition, the trade-off function of the Gloubos–Grammatikos logit model seems to be very close to the axes.

When using the re-estimated coefficients, analysis of the ***average*** unweighted error rates and Gini-coefficients leads to the same conclusions as with the original coefficients (see Section 5.2). If we want to predict failure over a longer term, the average UER increases, and the average Gini-coefficient decreases. Again, the results confirm the general belief that it is easier to predict failure in the short term.

The performance results of the models with re-estimated coefficients reveal larger ***performance differences*** in comparison to the results with respect to the original coefficients. For example, the short-term (1 ypf) models with re-estimated coefficients show a variation in the UER of no less than 25,01%. Also, when analysing the general *distribution* of the trade-off functions in Figures 4 to 6 in Appendix 2, it is immediately apparent that the performance differences depend on the term of failure prediction. The difference between the trade-off functions of the best- and the worst-performing short-term (1 ypf) models is extremely large. The performance differences for the 2 ypf models are significantly smaller and, finally, the long-term (3 ypf) models reveal the smallest performance differences. Consequently, when using the re-estimated coefficients, the results again suggest that it is more difficult to indicate models with good and bad performance if the term of failure prediction is longer.

4.4. Change in Performance Results Before and After Re-estimation of the Coefficients and Overall Performance Results

If we compare the performance results of the models with their original coefficients (Table 8) to the results of the models with their re-estimated coefficients (Table 9), we find some important differences. Table 10 summarizes the results. For each model, Table 10 shows the change in the UER and Gini-coefficient when using the re-estimated coefficients instead of the original ones and it gives rankings according to these changes. Moreover, it shows the global ranking (i.e., with the original and with the re-estimated coefficients) of the models 1 ypf, 2 ypf and 3 ypf, both on the basis of the unweighted error rates (UER-ranking) and on the basis of the Gini-coefficients (Gini-ranking).

Insert Table 10 about here

Firstly, the rankings (both on the basis of the UER and the Gini-coefficients) of the models with the original coefficients (Table 8, columns 5 and 7) differ significantly from the rankings of the models with the re-estimated coefficients (Table 9, columns 5 and 7). For example, the Bilderbeek model, which is one of the best-performing models 1, 2 and 3 ypf when using the original coefficients, loses an important part of its predictive abilities when its coefficients are re-estimated. This causes the model to be indicated as the worst-performing model 1, 2 and 3 ypf in Table 9. On the contrary, one year prior to failure, the Gloubos–Grammatikos discriminant and Keasey–McGuinness models perform very badly with the original coefficients, whereas they are among the best-performing models when using the re-estimated coefficients. In addition, with their original coefficients, Zavgren and Gloubos–Grammatikos discriminant are the worst-performing 3 ypf models, whereas they seem to be the models with the best predictive abilities 3 ypf after re-estimation of their coefficients.

A detailed examination of the ***changes in the unweighted error rates*** and the ***changes in the Gini-coefficients*** for each model when using the re-estimated coefficients instead of the original ones (table 10 columns 2 to 5) reveals that, after re-estimation, some models improve their failure prediction abilities, while others show worse performance results. Generally, when re-estimating the coefficients, the models that perform best with the original coefficients (small UER and a high Gini-coefficient in Table 8) deteriorate (increase of the UER and decrease of the Gini-coefficient in Table 10). On the other hand, models that perform very badly with the original coefficients improve (decrease of the UER and increase of the Gini-coefficient in Table 10). This is an interesting finding, because, in contrast to expectations, re-estimation does not improve the performance results for all models.

Table 10 reveals that after re-estimation the ***average failure prediction power*** of the models (1 ypf, 2 ypf and 3 ypf) deteriorates: the average UER increases, the average Gini-coefficient decreases, and the average UER-rankings and Gini-rankings with respect to the re-estimated coefficients are less favourable in comparison with the average rankings for the original coefficients.

Its is remarkable that, on an overall comparison (with the original coefficients and with the re-estimates ones), the best-performing models are the models with the original, non re-estimated coefficients:

- 1 ypf: Ooghe–Joos–De Vos and Ooghe–Verbaere;
- 2 ypf: Bilderbeek;
- 3 ypf: Ooghe–Joos–De Vos and Ooghe–Verbaere.

Moreover, it is important to mention that the globally best-performing 1 ypf and 3 ypf models (Ooghe–Joos–De Vos and Ooghe–Verbaere) have a Belgian origin. The model that performs best 2 ypf (Bilderbeek) is a Dutch model.

4.5. Possible Explanations for the Performance Results

There is no clear general answer whether failure prediction models are transferable from one country or period to another one. Several explanatory factors for individual model performance can be proposed:

1. the age of the model, measured by the period of deposit of the annual accounts included in the estimation sample of the model;
2. the country of origin of the model, being the nationality of the companies from which the annual accounts are included in the original estimation sample of the model;
3. the definition of failure that was applied to determine the estimation sample of failing companies;
4. the types of companies that had their annual accounts included in the estimation sample of the model;
5. the technique on which the estimation of the model is based;
6. the number of variables included in the model;

7. the complexity of the variables included in the model;
8. the types of variables included in the model.

As discussed earlier, if we compare the performance results of the different models using their original coefficients, we are unable to determine whether model performance is a consequence of the variables that are included in the models (i.e., Factors 7 and 8), or of the modelling technique (Factor 5). A bad performance result can also be caused by model coefficients that fail to capture the true relationship between the independent variables and the failures of Belgian companies. If there are large differences between the original estimation sample of a model and the validation sample with respect to the time frame and the nationality of the annual accounts, the definition of failure and the types of companies (i.e., Factors 1 to 4), the performance results of the model will be low, even if the model includes 'the right' variables and is based on 'the right' modelling technique.

By applying the ***re-estimated coefficients*** when validating the models, we take into account some factors specific to the Belgian validation dataset. If we re-estimate all models on the same re-estimation sample of Belgian companies, the following possible explanatory factors can be eliminated: the age of the model, the country of origin, the definition of failure and the type of companies. The remaining explanatory factors that should be considered are: the estimation technique, the number of variables, the complexity of the variables, and the type of variables.

Taking a closer look at the characteristics of the worst performing models after re-estimation (Altman and Bilderbeek) and comparing these with the characteristics of models that show better results (for example, Ooghe−Joos−De Vos, Gloubos−Grammatikos discriminant, Zavgren and Keasey–McGuinness), it is possible to indicate which of these factors are the most important ones.

First, it is clear that the *estimation technique* does not have an influence on model performance. Altman and Bilderbeek are estimated using linear discriminant analysis, but some of the better-performing models are also based on this technique. Secondly, the *complexity of the variables* does not seem to be an explanatory factor for model performance. Altman and Bilderbeek include simple variables, but the better-performing models (for example Keasey–McGuinness) also consist of rather simple variables. Furthermore, the *number of variables* does not seem to have an important impact on the model performance. For example, not only the worst performing Altman and Bilderbeek models, but also the good-performing Gloubos–Grammatikos logit and discriminant models use the same variables 1, 2 and 3 ypf. In addition, the Gloubos−Grammatikos logit model consists of only three variables, while Altman and Bilderbeek have five variables.

On the other hand, the *types of the variables* (i.e., Factor 8) seem to be an explanatory factor. On the basis of Tables 2 to 8 in Appendix 1, it is clear that the poorly performing Altman and Bilderbeek models are primarily based on variables concerning profitability and added value, whereas the better- performing models like Ooghe–Joos–De Vos, Zavgren and Gloubos−Grammatikos also concentrate on solvency and liquidity. At least half of the variables in these models concern liquidity or solvency.

Consequently, this study makes a strong case for including all aspects of financial health in a failure prediction model. Solvency and liquidity seem to be as important as profitability and added value!

5. SUMMARY AND CONCLUSIONS

By examining the validity of a range of international failure prediction models on a dataset of Belgian companies and by identifying these models that have the best and the worst failure prediction ability, the aim of this study is to answer the question whether failure prediction models from different countries can easily be transferred to other countries.

We validated eight international failure prediction models on one dataset of Belgian company accounts. All models were based on one of the two basic modelling techniques in failure prediction research: linear discriminant analysis and logistic regression.

The predictive abilities of the models were assessed on the basis of several performance indicators. Firstly, we discussed type I, type II and unweighted error rates (UER) corresponding to the optimal cut-off points. Secondly, we compared the models in a more global way with Gini-coefficients and finally, the trade-off functions provided a graphical presentation of the research results. These performance indicators were calculated both corresponding to the original coefficients and to the re-estimated ones.

The study started by re-estimating the coefficients of all failure prediction models over the Belgian dataset. In this way, we excluded the influence of some factors specific to the original estimation sample, which allowed a more precise comparison of the performance results. In addition, by using the re-estimated coefficients, it was possible to determine whether performances were the result of the choice of variables and/or of the applied modelling technique.

When using the original coefficients, the ranking order of the models differed significantly from the ranking order when using the re-estimated coefficients. Contrary to expectations, models that showed poor performance results with their original coefficients revealed an improvement when using the re-estimated coefficients, while models with good performance revealed a decrease in performance when using the coefficients after re-estimation. On average, the failure prediction power of the models deteriorated after re-estimation of the coefficients. Overall, with and without re-estimated coefficients, the best-performing models were those with the original, non re-estimated coefficients.

It is important to mention that the globally best-performing 1 ypf and 3 ypf models are the Belgian Ooghe–Joos–De Vos and Ooghe–Verbaere models.

This study confirms the general belief that it is easier to predict failure in the short term: the average error rate of the short-term models both with the original coefficients and with the re-estimated ones seemed to be significantly lower than the average error rate of the long-term models. Also, the performance differences seem to depend on the term of failure prediction: if the term is longer, it seems to be more difficult to make a distinction between models that perform well or poorly.

In general, it is not clear whether failure prediction models can be transferred to other countries and/or periods. Several possible explanatory factors for model performance were proposed. However, by re-estimating the coefficients of all models on the same sample of Belgian annual accounts, the following factors could be eliminated: the age of the model, the country of origin, the definition of failure, and the type of companies. Taking a closer look at the other characteristics of the models, neither the estimation technique, the complexity of the variables, nor the number of variables did seem to have a major influence on the model performance. On the other hand, the types of variables used, turned out to be an important explanatory factor. Models that are primarily based on variables concerning profitability and added value, revealed higher error rates than models that also concentrate on solvency and liquidity. Consequently, this study makes a strong case for including all different aspects of the financial situation in a failure prediction model.

In this paper, we validated eight failure prediction models from five different countries on a dataset of Belgian company accounts (i.e., cells A and B in Table 11). Consequently, we invite other researchers to include more failure prediction models from other countries than Belgium in a more extensive validation study (i.e., extend cell B in Table 11) and to validate these models also on company accounts of countries other than Belgium (i.e., analyse cells C and D in Table 11) in order to find out whether the same results will be found.

Insert Table 11 about here

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APPENDIX 1 : TABLES

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APPENDIX 2: TRADE-OFF FUNCTIONS

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FIGURE 1

Trade-off function of a model

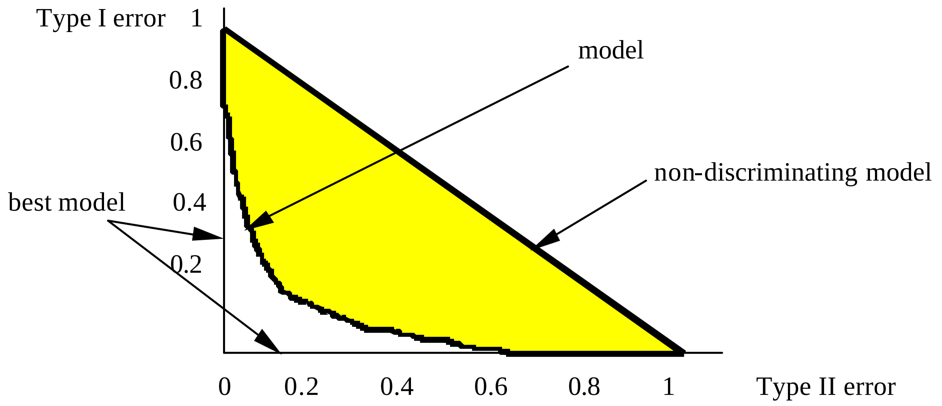

TABLE 1

Samples of failing and non-failing companies

Sample	Number of companies	Percentage of non-failing
Failing firms :		
Failing in 1997	3.313	50,97%
Failing in 1998	3.187	49,03%
Total	6.500	100%
Non-failing firms :		
Termination of activity	122	0,05%
Early dissolution- liquidation	5795	2,32%
Liquidation followed by a merger	44	0,02%
Liquidation followed by an absorption	3.148	1,26%
Closing of a liquidation	16.674	6,69%
Without any particular legal status	223.552	89,66%
Total	249.334	100%

TABLE 2

Sampling procedure

	Failing group		Non-failing group	
	Failing firms	**Year annual accounts**	**Year annual accounts**	**Non-failing firms**
1 ypf	Failing in 97	1996	1996	group C
	Failing in 98	1997	1997	group D
2 ypf	Failing in 97	1995	1995	group B
	Failing in 98	1996	1996	group C
3 ypf	Failing in 97	1994	1994	group A
	Failing in 98	1995	1995	group B

TABLE 3

Number of annual accounts in the samples of failing and non-failing annual accounts

	Failing annual accounts	**Non-failing annual accounts**
Sample 1 ypf	6500	124.671
Sample 2 ypf	6500	124.678
Sample 3 ypf	6500	124.684

TABLE 4

Number of failing and non-failing annual accounts in the re-estimation samples

(after the elimination of non-available annual accounts)

	Failing	**Non-failing**	**Total**
Sample 1 ypf	778	9.164	9.942
Sample 2 ypf	2.409	8.590	10.999
Sample 3 ypf	2.705	7.932	10.637
Total sample	5.892	25.686	31.578

TABLE 5

Number of failing and non-failing annual accounts in the validation samples

(after the elimination of non-available annual accounts)

	Failing	**Non-failing**	**Total**
Sample 1 ypf	738	9.943	10.681
Sample 2 ypf	2.445	9.391	11.836
Sample 3 ypf	2.653	8.987	11.640

TABLE 6

Number and percentage of the valid annual accounts in the re-estimation samples

Model	Year before failure	Number	Percentage (*)
Altman	-	31.235	98,9%
Bilderbeek	-	14.292	45,3%
Ooghe - Verbaere	1 ypf	9.755	98,1%
	2 ypf	4.805	43,7%
	3 ypf	10.192	95,8%
Zavgren	1 ypf	2.620	26,4%
	2 ypf	3.122	28,4%
	3 ypf	3.112	29,3%
Gloubos & Grammatikos	logit	31.504	99,8%
	discriminant	31.132	98,6%
Keasey & McGuinness	1 ypf	4.064	40,9%
	2 ypf	4.966	45,1%
	3 ypf	4.615	43,4%
Ooghe - Joos - De Vos	1 ypf	9.703	97,6%
	3 ypf	10.594	99,6%

(*) Percentage of the total number after the elimination of the non-available annual accounts (see table 4)

TABLE 7

Number and percentage of the valid annual accounts in the validation samples

	Failing		**Non-failing**		**Total**	
	Number	**Percentage (*)**	**Number**	**Percentage (*)**	**Number**	**Percentage (*)**
Sample 1 ypf	218	29,5%	2487	25,0%	2705	25,3%
Sample 2 ypf	799	32,7%	2466	26,3%	3265	27,6%
Sample 3 ypf	868	32,7%	2302	25,6%	3170	27,2%

(*) Percentage of the total number after the elimination of the non-available annual accounts (see table 5)

TABLE 8

Performance results of the models with the original coefficients

	Type I error	**Type II error**	**UER**		**Gini**	
			Percentage	**Ranking**	**Percentage**	**Ranking**
1YPF						
- Altman	22,48%	35,83%	29,15%	4	53,93%	4
- **Bilderbeek**	26,15%	27,22%	**26,68%**	**3**	**58,23%**	**3**
- **Ooghe-Verbaere**	23,85%	23,84%	**23,85%**	**2**	**65,16%**	**2**
- *Zavgren*	44,95%	17,53%	*31,24%*	6	*21,79%*	8
- Gloubos-Grammatikos logit	29,82%	30,32%	30,07%	5	53,24%	5
- *Gloubos-Grammatikos discriminant*	16,06%	49,66%	*32,86%*	8	43,17%	7
- *Keasey-McGuinness*	25,69%	38,04%	*31,86%*	7	45,60%	6
- **Ooghe-Joos-De Vos**	22,48%	23,84%	**23,16%**	**1**	**67,58%**	**1**
Average	26,43%	30,78%	28,61%		51,09%	
2YPF						
- Altman	26,41%	41,61%	34,01%	3	41,62%	4
- **Bilderbeek**	23,28%	39,09%	**31,19%**	**1**	**46,72%**	**1**
- **Ooghe-Verbaere**	19,52%	46,80%	**33,16%**	**2**	**45,30%**	**2**
- *Zavgren*	64,58%	14,27%	*39,43%*	7	*6,35%*	7
- **Gloubos-Grammatikos logit**	23,28%	45,70%	34,49%	4	**44,04%**	**3**
- Gloubos-Grammatikos discriminant	26,91%	46,80%	36,85%	6	32,96%	6
- Keasey-McGuinness	29,66%	42,01%	35,84%	5	33,84%	5
Average	30,52%	39,47%	34,99%		35,83%	
3YPF						
- Altman	32,03%	41,01%	36,52%	5	33,17%	5
- **Bilderbeek**	22,24%	45,48%	**33,86%**	**3**	**41,27%**	**3**
- **Ooghe-Verbaere**	28,46%	38,31%	**33,39%**	**2**	**41,63%**	**2**
- *Zavgren*	*75,35%*	9,69%	*42,52%*	8	*8,88%*	8
- Gloubos-Grammatikos logit	44,70%	31,02%	37,86%	6	34,05%	4
- Gloubos-Grammatikos discriminant	20,85%	57,25%	39,05%	7	27,53%	7
- Keasey-McGuinness	37,10%	35,71%	36,40%	4	32,25%	6
- **Ooghe-Joos-De Vos**	17,74%	46,61%	**32,18%**	**1**	**44,09%**	**1**
Average	34,81%	38,13%	36,47%		32,86%	

TABLE 9

Performance results of the models with the re-estimated coefficients

	Type I error	**Type II error**	**UER**		**Gini**	
			Percentage	**Ranking**	**Percentage**	**Ranking**
1YPF						
- *Altman*	60,55%	28,47%	*44,51%*	7	*9,32%*	7
- *Bilderbeek*	97,71%	0,56%	*49,13%*	8	*-5,25%*	8
- Ooghe-Verbaere	30,28%	38,20%	34,24%	6	42,70%	6
- Zavgren	10,09%	51,19%	30,64%	5	45,92%	5
- Gloubos-Grammatikos logit	36,24%	22,11%	**29,18%**	**4**	**50,44%**	**4**
- Gloubos-Grammatikos discriminant	27,98%	29,19%	**28,59%**	**3**	**52,78%**	**3**
- Keasey-McGuinness	20,18%	28,07%	**24,12**%	**1**	**64,77%**	**1**
- Ooghe-Joos-De Vos	22,94%	31,52%	**27,23%**	**2**	**56,78%**	**2**
Average	38,24%	28,66%	33,45%		39,68%	
2YPF						
- *Altman*	55,19%	38,93%	*47,06%*	6	*5,46%*	6
- *Bilderbeek*	2,00%	97,32%	*49,66%*	7	*-4,41%*	7
- Ooghe-Verbaere	30,66%	45,05%	37,86%	5	26,69%	5
- Zavgren	22,65%	50,69%	36,67%	4	34,31%	4
- Gloubos-Grammatikos logit	30,16%	38,89%	**34,53%**	**3**	**41,91%**	**3**
- Gloubos-Grammatikos discriminant	33,29%	32,32%	**32,81%**	**1**	**45,17%**	**1**
- Keasey-McGuinness	24,03%	43,80%	**33,91%**	**2**	**42,94%**	**2**
Average	28,28%	49,57%	38,93%		27,44%	
3YPF						
- *Altman*	7,14%	89,05%	*48,10%*	7	*1,22%*	7
- *Bilderbeek*	58,76%	39,01%	*48,88%*	8	*-0,81%*	8
- Ooghe-Verbaere	37,90%	43,53%	40,72%	6	24,45%	5
- Zavgren	17,63%	56,47%	**37,05%**	**1**	**31,75%**	**2**
- Gloubos-Grammatikos logit	41,24%	36,88%	39,06%	3	29,38%	3
- Gloubos-Grammatikos discriminant	50,69%	25,41%	**38,05%**	**2**	**32,51%**	**1**
- Keasey-McGuinness	16,59%	64,21%	40,40%	5	22,43%	6
- Ooghe-Joos-De Vos	32,95%	45,92%	39,43%	4	25,27%	4
Average	32,86%	50,06%	41,46%		20,78%	

TABLE 10

Change in performance results when using the re-estimated instead of the original coefficients

	Change in UER		**Change in Gini**		**Global UER Ranking**		**Global Gini Ranking**	
	Percentage	Ranking	Percentage	Ranking	original	Re-estimated	Original	Re-estimated
1YPF								
- *Altman*	*+15,36%*	*7*	*-44,61%*	*7*	7	15	6	15
- *Bilderbeek*	*+22,45%*	*8*	*-63,48%*	*8*	4	16	3	16
- Ooghe-Verbaere	+10,39%	6	-22,46%	6	2	14	2	13
- *Zavgren*	-0,60%	4	+24,13%	1	11	10	14	10
- Gloubos-Grammatikos logit	-0,89%	3	-2,80%	4	9	8	7	9
- Gloubos-Grammatikos discriminant	-4,27%	2	+9,61%	3	13	6	12	8
- Keasey-McGuinness	-7,74%	1	+19,17%	2	12	3	11	4
- Ooghe-Joos-De Vos	+4,07%	5	-10,80%	5	1	5	1	5
Average	+4,85%		-11,41%		7,4	9,6	7,0	10,0
2YPF								
- *Altman*	*+13,05%*	*7*	*-36,16%*	*7*	5	13	7	13
- *Bilderbeek*	*+18,48%*	*6*	*-51,13%*	6	1	14	1	14
- Ooghe-Verbaere	+4,70%	5	-18,61%	5	3	11	2	11
- Zavgren	**-2,76%**	**2**	**+27,96%**	**1**	12	9	12	8
- Gloubos-Grammatikos logit	+0,04%	4	-2,13%	4	6	7	4	6
- Gloubos-Grammatikos discriminant	**-4,05%**	**1**	**+12,21%**	**2**	10	2	10	3
- Keasey-McGuinness	-1,92%	3	+9,10%	3	8	4	9	5
Average	+3,93%		-8,39%		6,4	8,6	6,4	8,6
3YPF								
- *Altman*	*+11,58%*	*7*	*-31,95%*	*7*	5	15	5	15
- *Bilderbeek*	*+15,02%*	*8*	*-42,08%*	*8*	3	16	3	16
- Ooghe-Verbaere	+7,33%	6	-17,18%	5	2	13	2	12
- Zavgren	**-5,47%**	**1**	**+22,87%**	**1**	14	6	14	8
- Gloubos-Grammatikos logit	+1,20%	3	-4,67%	3	7	10	4	9
- Gloubos-Grammatikos discriminant	**-1,00%**	**2**	+4,98%	**2**	9	8	10	6
- *Keasey-McGuinness*	+4,00%	4	-9,82%	4	4	12	7	13
- Ooghe-Joos-De Vos	+7,26%	5	-18,82%	6	1	11	1	11
Average	+4,99%		-12,08%		5,6	11,4	5,75	11,25

TABLE 11

Further research options

	Country of origin of the model	
Countries from which companies are included in the validation data set	Belgium	Other countries
Belgium	A	B
Other countries	C	D

TABLE 12

Characteristics of the models under investigation

	Altman	**Bilderbeek**	**Ooghe - Verbaere**	**Zavgren**	**Gloubos - Grammatikos**	**Keasey - Mc Guinness**	**Ooghe - Joos - De Vos**
Country	United States	The Netherlands	Belgium	United States	Greece	United Kingdom	Belgium
Population	American industrial companies	Dutch industrial and trade companies	Belgian enterprises publishing their accounts in a complete form	American companies listed on the Stock Exchange with annual accounts available on Compustat tapes	Greek enterprises	UK companies with data available on Datastream	Belgian enterprises publishing their results in a complete or abbreviated form
Period	1946-1965	1950-1975	1977-1980	1972-1978	1977-1985	1976-1984	1985-1990
Definition of failure	Declaration of bankruptcy by court	Declaration of bankruptcy by court	Declaration of bankruptcy by court, request or approval of legal composition	Request of chapter 10 or 11 from the bankruptcy law	Declaration of bankruptcy by court Failed companies sustained in operation by Greek government are excluded from the non-failed sample	Declaration of bankruptcy by court	Declaration of bankruptcy by court, request or approval of legal composition
Sample :							
Non-failing	33 annual accounts	43 (original) 220 (validation)	753 (original) 347 (validation)	45 annual accounts	30 (original) 24 (validation)	43 (original) 15 (validation)	347 (original) 170 (validation)
Failing	33 annual accounts	40 (original) 127 (validation)	395 (original) 268 (validation)	45 annual accounts	30 (original) 24 (validation)	43 (original) 15 (validation)	268 (original) 218 (validation)
Method	Matched on industry and size of total assets	Matched on industry turnover, size of total assets and number of employees	Random selection	Matched on industry and size of total assets	Matched on industry and size of total assets	Matched on industry and size of total assets	Systematic selection
Estimation technique	Linear discriminant analysis	Linear discriminant analysis	Linear discriminant analysis	Logistic regression	Multiple discriminant, logit & probit analysis and linear probability models	Logistic regression	Logistic regression
Model	1 model applicable to data 1-5 ypf	1 model (and 2 derived classification functions) applicable to data 1-5 ypf	3 models, 1-3 ypf and one general model, each with different variables & coefficients	5 models, 1-5 ypf, each with different variables & coefficients	1 model applicable to data 1-3 ypf (based on data 1 ypf)	5 models, 1-5 ypf, each with different variables & coefficients	2 models, 1-3 ypf, each with different variables & coefficients
Number of variables	5	5	5 for each model	7	5 (discriminant analysis) / 3 (logit)	3 / 4 / 4	8 / 6
Classification rule	Cut-off score	Cut-off score	Cut-off score	Cut-off score and entropy	Cut-off score	Cut-off score and entropy	Cut-off score

TABLE 13

Altman (1968), USA

	VARIABLES	Original coefficients			New coefficients		
		1 ypf	2 ypf	3 ypf	1 ypf	2 ypf	3 ypf
	Intercept	0,000	0,000	0,000	+0,133	+0,133	+0,133
X1	Net working capital / Total assets	+0,012	+0,012	+0,012	-0,016	-0,016	-0,016
X2	(Accumulated profits or losses + Retained earnings) / Total assets	+0,014	+0,014	+0,014	+0,014	+0,014	+0,014
X3	Earnings before interest and taxes (EBIT) / Total assets	+0,033	+0,033	+0,033	+0,068	+0,068	+0,068
X4	Equity / Liabilities	+0,006	+0,006	+0,006	+0,000	+0,000	+0,000
X5	Sales / Total assets	+0,0099	+0,0099	+0,0099	-0,132	-0,132	-0,132
CO	Cut-off point	**0,0190**	**0,0221**	**0,0229**	**-0,1757**	**-0,1203**	**0,0574**

TABLE 14

Bilderbeek (1979), The Netherlands

	VARIABLES	**Original coefficients**			**New coefficients**		
		1 ypf	**2 ypf**	**3 ypf**	**1 ypf**	**2 ypf**	**3 ypf**
	Intercept	-0,45	-0,45	-0,45	-0,218	-0,218	-0,218
X6	Net return on equity after taxes	-0,15	-0,15	-0,15	-0,008	-0,008	-0,008
X7	Accounts payable / Sales	-4,55	-4,55	-4,55	+0,003	+0,003	+0,003
X5	Sales / Total assets	-0,17	-0,17	-0,17	+0,107	+0,107	+0,107
X8	Gross added value / Total assets	+1,57	+1,57	+1,57	-0,029	-0,029	-0,029
X2	(Accumulated profits or losses + Retained earnings) / Total assets	+5,03	+5,03	+5,03	-0,006	-0,006	-0,006
CO	Cut-off Point	**-1,5495**	**-0,8523**	**-0,4955**	**-0,2145**	**0,4924**	**-0,0737**

TABLE 15

Ooghe-Verbaere (1982), Belgium

	VARIABLES	**Original coefficients**	**New coefficients**
	1 year prior to failure		
	Intercept	+2,6803	-0,653
X9	Overdue taxes and Social security charges / Short-term liabilities	-51,3394	+0,125
X10	Accumulated profits or losses / (Equity + Liabilities)	+10,0870	+0,003
X11	Gross return on total assets before taxes	+4,4145	+0,142
X12	Equity / (Equity + Liabilities)	+2,0318	+0,005
X13	Cash / Current assets	+2,6314	+3,078
CO	Cut-off Point	**2,0996**	**-0,4515**
	2 years prior to failure		
	Intercept	+0,1837	-0,290
X10	Accumulated profits or losses / (Equity + Liabilities)	+4,6524	+0,058
X9	Overdue taxes and Social security charges / Short-term liabilities	-16,5456	+0,760
X13	Cash / Current assets	+3,2732	+3,740
X14	(Work in progress, Finished goods and Contracts in progress) / Current working assets	-1,7381	-1,252
X15	Cash flow / Sales	+0,0738	+0,011
CO	Cut-off Point	**-0,2497**	**-0,3420**
	3 years prior to failure		
	Intercept	+0,2153	-0,735
X9	Overdue taxes and Social security charges / Short-term liabilities	-18,3474	+0,044
X16	(Accumulated profits or losses + Retained earnings) / (Equity + Liabilities)	+3,3847	+0,032
X13	Cash / Current assets	+2,3601	+4,137
X14	(Work in progress, Finished goods and Contracts in progress) / Current working assets	-1,9230	+0,010
X17	Earnings before interests and taxes (EBIT) / (Equity + Long-term liabilities)	+0,0617	+0,031
CO	Cut-off Point	**-0,2047**	**-0,4459**

TABLE 16

Zavgren (1985), USA

	VARIABLES	Original coefficients			New coefficients		
		1 ypf	**2 ypf**	**3 ypf**	**1 ypf**	**2 ypf**	**3 ypf**
	Intercept	-0,23883	-2,61060	-1,51150	+1,596	+0,656	+0,462
X18	Inventories / Sales	+0,00108	+0,04185	+0,06257	+0,001	+0,020	+0,009
X19	Amounts receivable / Inventories	+0,01583	+0,02215	+0,00829	-0,001	+0,001	+0,001
X20	(Cash + Short-term investments) / Total assets	+0,10780	+0,11231	+0,4248	+1,528	+4,974	+3,065
X21	Quick ratio	-0,03074	-0,02690	-0,01549	-0,962	+0,252	+0,314
X6	Net return on equity after taxes	-0,00486	-0,01440	+0,00519	-0,010	-0,001	+0,029
X22	(Liabilities less Accrued charges and deferred income) / Equity	+0,04350	+0,04464	+0,01822	+0,001	+0,000	+0,001
X5	Sales / Total assets	-0,00110	+0,00063	+0,00002	-0,053	-0,079	-0,038
CO	Cut-off Point	**0,4340**	**0,0672**	**0,1829**	**0,9150**	**0,7371**	**0,7233**

TABLE 17

Gloubos and Grammatikos (1988), Greece

	VARIABLES	Original coefficients			New coefficients		
	Discriminant analysis	**1 ypf**	**2 ypf**	**3 ypf**	**1 ypf**	**2 ypf**	**3 ypf**
	Intercept	+4,423	+4,423	+4,423	-0,017	-0,017	-0,017
X23	Current ratio	-2,044	-2,044	-2,044	+0,002	+0,002	+0,002
X1	Net working capital / Total assets	+4,421	+4,421	+4,421	+0,001	+0,001	+0,001
X24	Long-term liabilities / Total assets	-4,404	-4,404	-4,404	-0,014	-0,014	-0,014
X11	Gross return on total assets before taxes	-2,778	-2,778	-2,778	+0,203	+0,203	+0,203
X25	Earnings before interest, taxes, depreciation and amortization (EBITDA) / Short-term liabilities	+4,423	+4,423	+4,423	+0,000	+0,000	+0,000
CO	Cut-off point	**2,2441**	**2,2070**	**2,5515**	**-0,0033**	**-0,0006**	**-0,0043**

	Logistic regression	**1 ypf**	**2 ypf**	**3 ypf**	**1 ypf**	**2 ypf**	**3 ypf**
	Intercept	+3,548	+3,548	+3,548	+1,473	+1,473	+1,473
X1	Net working capital / Total assets	+5,585	+5,585	+5,585	+0,000	+0,000	+0,000
X24	Long-term liabilities / Total assets	-8,504	-8,504	-8,504	-0,001	-0,001	-0,001
X11	Gross return on total assets before taxes	+13,070	+13,070	+13,070	+0,051	+0,051	+0,051
CO	Cut-off point	**0,9444**	**0,9848**	**0,9573**	**0,8138**	**0,8142**	**0,8142**

TABLE 18

Keasey and McGuinness (1990), U.K.

	VARIABLES	Original coefficients	New coefficients
	1 year prior to failure		
	Intercept	-0,0881	+2,017
X4	Equity / Liabilities	-0,0316	+1,318
X26	Purchases / Accounts payable	+0,2710	-0,000
X27	Profit or losses before taxes / Sales	+0,3227	+0,035
CO	Cut-off point	**0,7939**	**0,8980**

	2 years prior to failure		
	Intercept	-3,3612	+1,280
X18	Inventories / Sales	-8,4286	+0,007
X1	Net working capital / Total assets	+2,7244	+0,151
X28	Net return on operating assets before taxes	+0,1081	+0,064
X6	Net return on equity after taxes	+0,01947	+0,001
CO	Cut-off point	**0,0131**	**0,7853**

	3 years prior to failure		
	Intercept	-6,4202	+1,059
X21	Quick ratio	+1,5599	+0,074
X26	Purchases / Accounts payable	+0,3010	+0,001
X5	Sales / Total assets	+0,8799	-0,067
X27	Profit or loss before taxes / Sales	+0,4216	+0,024
CO	Cut-off point	**0,1387**	**0,7400**

TABLE 19

Ooghe, Joos and De Vos (1991), Belgium

	VARIABLES	**Original coefficients (*)**	**New coefficients (*)**
	1 year prior to failure		
	Intercept	+	+
X29	Direction of the financial leverage = net return on total assets before taxes – average interest rate of debt (1 if > 0, 0 if <0)	+	+
X30	(Accumulated profits or losses + Retained earnings) / (Equity + Liabilities less Accrued charges and deferred income)	+	+
X31	Cash & Short term investments / Total assets	+	+
X32	Overdue taxes and Social security charges (1 if >0, 0 else)	-	+
X33	(Inventories + Accounts receivable – Accounts payable – Taxes, remuneration and social security debts – Advances received on contracts in progress) / Total assets	+	+
X34	Net return on operating assets before taxes	+	+
X35	Short-term financial debt / Short-term debt	-	-
X36	Debts guaranteed / Total debt	+	+
CO	Cut-off Point	**0,6588**	**0,9011**

	3 years prior to failure		
	Intercept	+	+
X30	(Accumulated profits or losses + Retained earnings) / (Equity + Liabilities less Accrued charges and deferred income)	+	+
X37	Publication lag of the annual accounts	-	-
X32	Overdue taxes and Social security charges (1 if >0, 0 else)	-	+
X38	(Earnings before interest, taxes, depreciation and amortization (EBITDA) – Capital investments) / Total assets	+	+
X39	Relationships with affiliated enterprises = (Amounts receivable from them + Commitments guaranteed on their behalf + Other financial commitments in their favour) / Total assets	+	+
X40	Total debt / (Equity + Liabilities less Accrued charges and deferred income)	-	+
CO	Cut-off Point	**0,8023**	**0,7631**

(*) Only the sign and not coefficients can be given because of a licence agreement with Graydon NV

TABLE 20

Classification results in the original publications

	Cut-off	Type I error		Type II Error		Unweighted error rate	
		Original sample	Validation sample	Original sample	Validation sample	Original sample	Validation sample
1YPF							
- Altman	2,6750	6%	n.a.	3%	n.a.	5%	n.a.
- Bilderbeek	0,0250	n.a.	n.a.	n.a.	n.a.	32%	n.a.
- Ooghe-Verbaere	3,1492	n.a.	13,6%	n.a.	21,7%	n.a.	17,6%
- Zavgren	n.a.	11%	n.a.	24%	n.a.	18%	n.a.
- Gloubos-Grammatikos logit	0,5000	16,6%	33,3%	10%	12,5%	13,3%	22,9%
- Gloubos-Grammatikos discriminant	0,0000	3,3%	33,3%	13,3%	33,3%	8,3%	33,3%
- Keasey-McGuinness	n.a.	14%	44%	14%	30%	14%	37%
- Ooghe-Joos-De Vos	0,3117	n.a.	14,7%	n.a.	22,4%	n.a.	18,5%
2YPF							
- Altman	2,6750	28%	n.a.	6%	n.a.	17%	n.a.
- Bilderbeek	0,0250	n.a.	n.a.	n.a.	n.a.	27%	n.a.
- Ooghe-Verbaere	0,1663	n.a.	27,9%	n.a.	22,8%	n.a.	29,6%
- Zavgren	n.a.	11%		22%	n.a.	17%	n.a.
- Gloubos-Grammatikos logit	0,5000	n.a.	39,1%	n.a.	17,4%	n.a.	28,3%
- Gloubos-Grammatikos discriminant	0,0000	n.a.	39,1%	n.a.	17,4%	n.a.	28,3%
- Keasey-McGuinness	n.a.	16%	22%	21%	29%	18,5%	25,5%
3YPF							
- Altman	2,6750	52%	n.a.	n.a.	n.a.	n.a.	n.a.
- Bilderbeek	0,0250	n.a.	n.a.	n.a.	n.a.	29%	n.a.
- Ooghe-Verbaere	0,3355	n.a.	26,2%	n.a.	32,9%	n.a.	29,6%
- Zavgren	n.a.	31%	n.a.	24%	n.a.	28%	n.a.
- Gloubos-Grammatikos logit	0,5000	n.a.	50%	n.a.	21,4%	n.a.	35,7%
- Gloubos-Grammatikos discriminant	0,0000	n.a.	35,7%	n.a.	14,3%	n.a.	25%
- Keasey-McGuinness	n.a.	28%	27%	19%	44%	23,5%	35,5%
- Ooghe-Joos-De Vos	0,2137	n.a.	18,3%	n.a.	34,1%	n.a.	27,7%

Figure 2 : Trade-off functions of the models 1 year prior to failure with their original coefficients

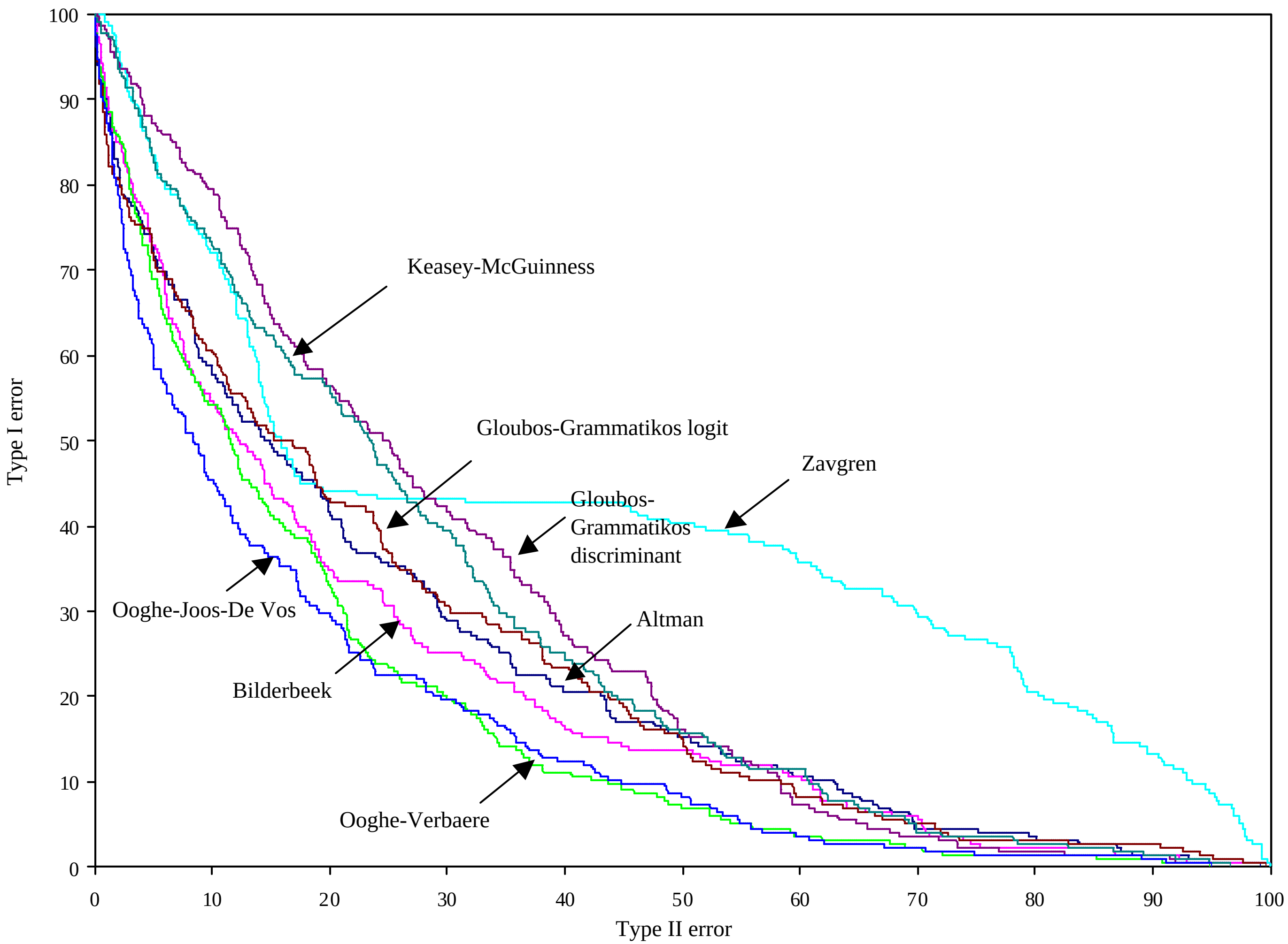

Figure 3 : Trade-off functions of the models 2 years prior to failure with their original coefficients

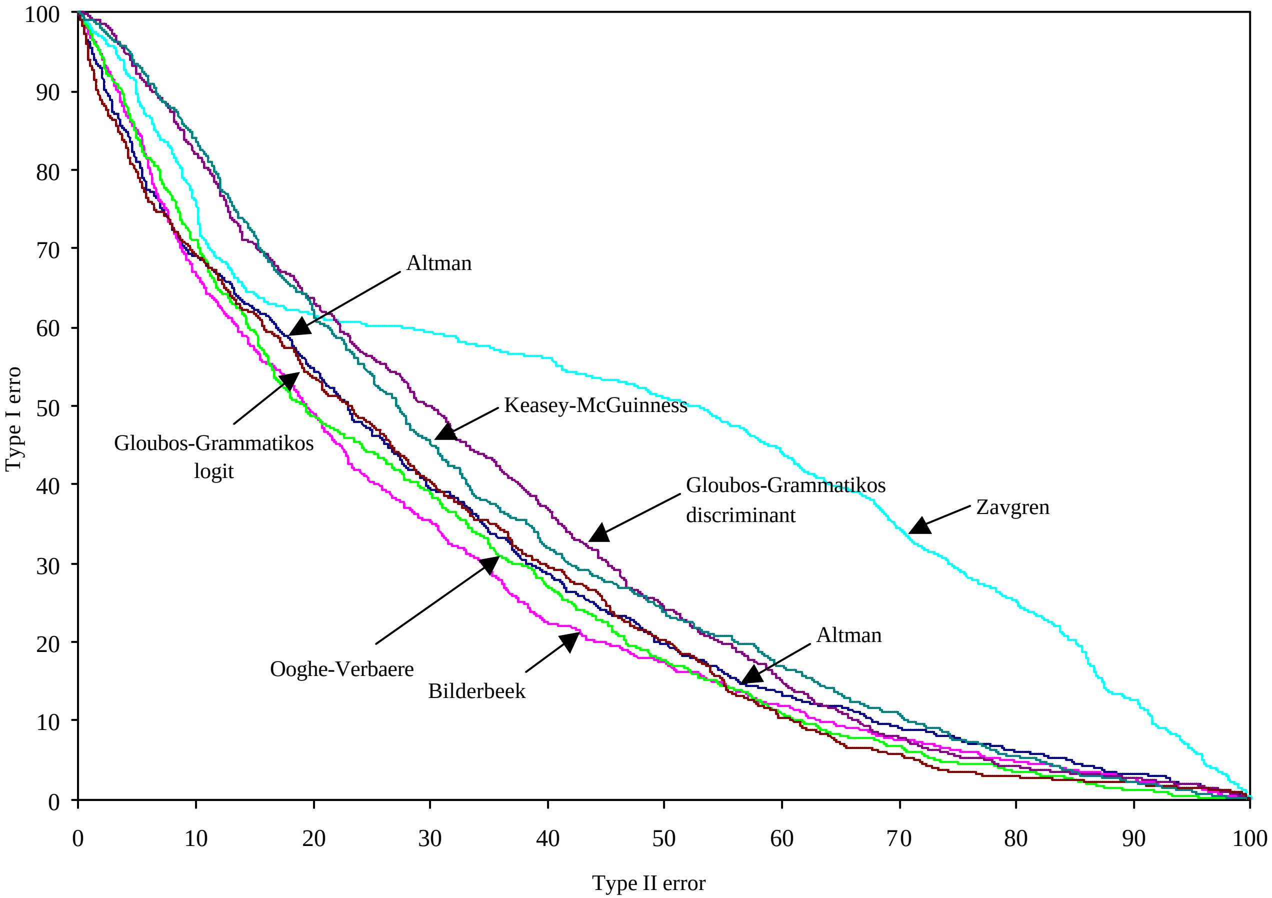

Figure 5 : Trade-off functions of the models 1 year prior to failure with their re-estimated coefficients

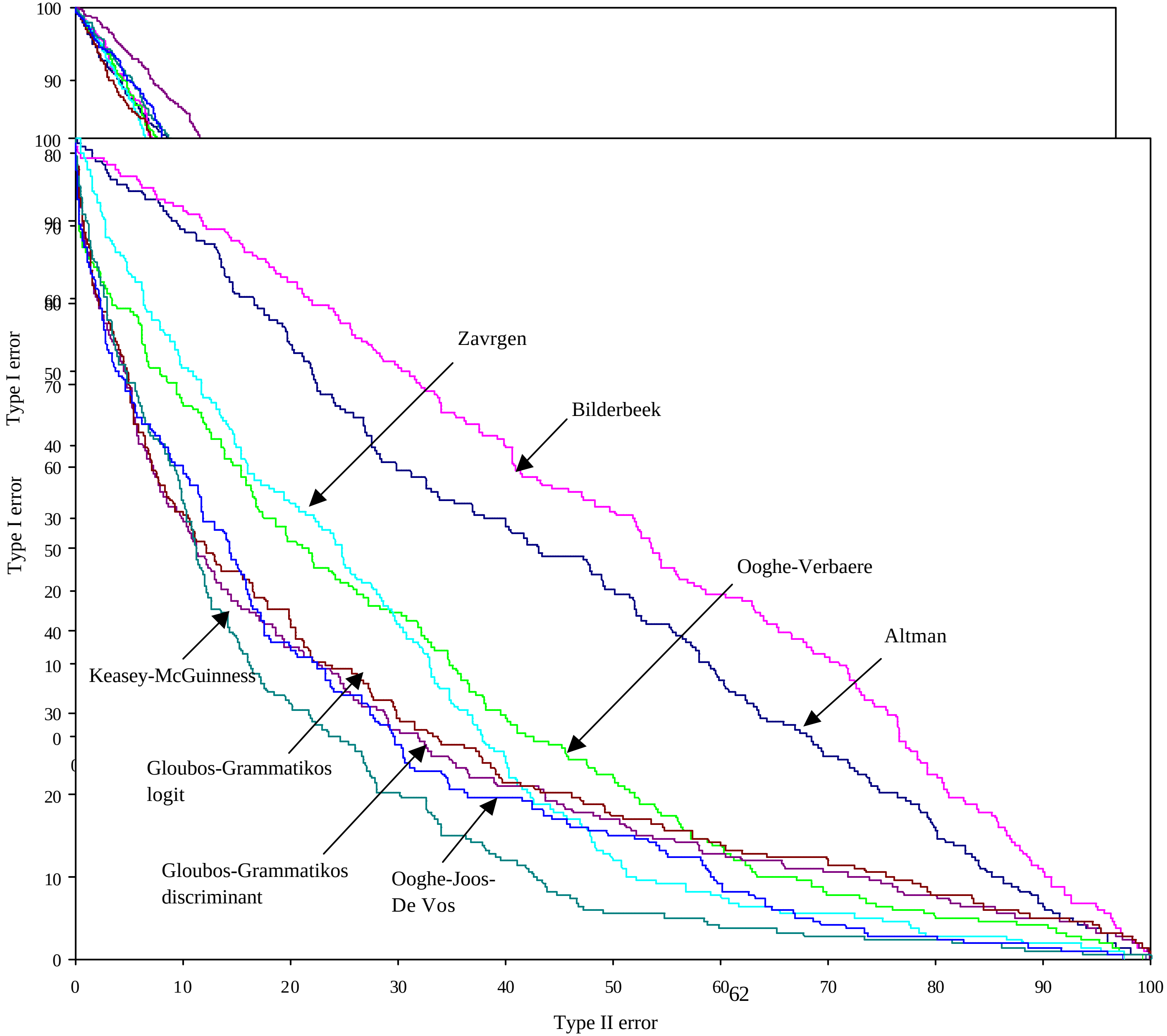

Figure 6 : Trade-off functions of the models 2 years prior to failure with their re-estimated coefficients

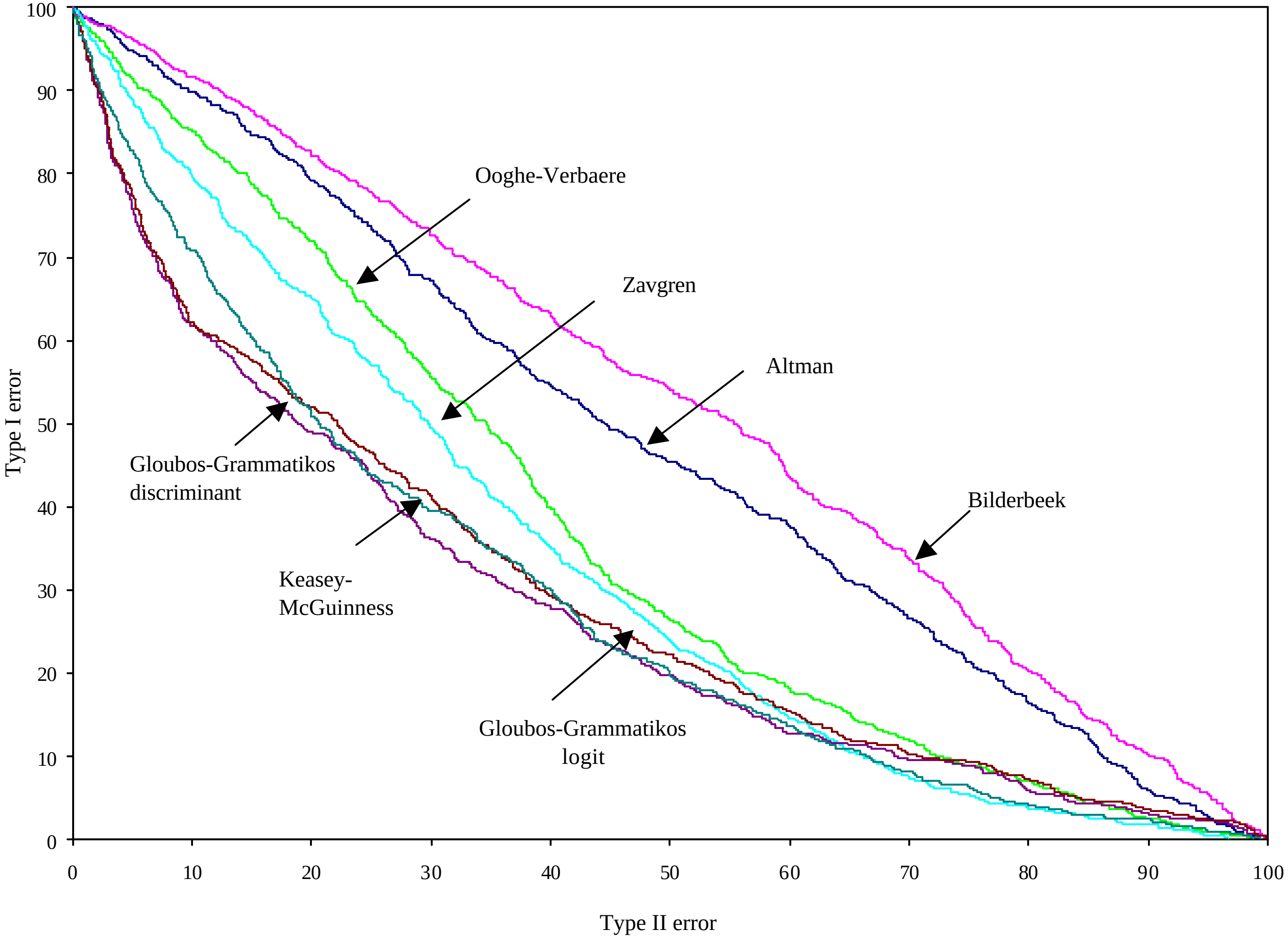

Figure 7 : Trade-off functions of the models 3 years prior to failure with their re-estimated coefficients