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Improvements in rating models for the German corporate sector

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Abstract

Group-specific estimations can significantly improve the predictive power of accounting-based rating models. This is shown using a binary logistic regression model applied to the Deutsche Bundesbank's USTAN dataset, which contains 300,000 financial statements provided by German companies for the years 1994 to 2002, i. e. throughout a complete business-cycle. The robustness and the representability of this result is verified through out-of-sample tests and through comparisons with a benchmark model which applies the variables of Moody's RiskCalc^{TM} for Germany.

Keywords: Credit Risk, Credit Rating, Probability of Default, Logistic Regression

JEL: G21, G33, C52

Non technical summary

The prominent role of internal rating models in the first pillar of the New Basel Capital Accord (Basel II) means that rating models for commercial debt are becoming increasingly important for financial intermediaries. Accounting-based models can be directly used to assign a credit rating even to unlisted companies, such as most small and medium sized enterprises (SME).

The mathematical foundations of such rating models can be traced back to the seminal article of Altman (1968). Since then, research on their further improvement has mainly focused on four topics: the selection of regressors, a refined transformation of these variables, the use of enhanced empirical methods, and the use of market-based data as a supplement. A different method is analyzed in this paper: the underlying dataset is broken down according to a specific attribute, such as industry affiliation, size and legal form of companies and on this basis group-specific models are estimated. With more than 300,000 financial statements provided by German companies for the years 1994 to 2002, i. e. throughout a complete business cycle, the Deutsche Bundesbank USTAN database employed in this study is large enough to allow this simple approach.

Out-of-sample tests using random subsamples show that group-specific estimations can significantly improve the predictive power of a typical binary logistic regression model in each case. The representability of this result is verified through comparisons with a benchmark model which applies the variables of Moody's RiskCalc™ for Germany.

Nichttechnische Zusammenfassung

Statistische Ratingmodelle für Unternehmenskredite gewinnen - nicht zuletzt aufgrund der zentralen Rolle des IRB-Ansatzes in der ersten Säule des Neuen Baseler Akkords (Basel II) - zunehmend an Bedeutung für Finanzintermediäre. Auf Jahresabschlussdaten basierende Modelle können dabei auch nicht börsennotierten Unternehmen, insbesondere kleinen und mittleren Unternehmen (KMU) auf direktem Wege eine Bonitätsnote zuweisen.

Seit der grundlegenden Arbeit von Altman (1968) wurden vorwiegend vier Wege beschritten, um die Prognosegüte solcher Ratingmodelle zu verbessern: eine optimierte Auswahl von Regressoren (vorwiegend aus Finanz- und sonstigen Kennzahlen), eine verbesserte Transformation der Variablen, die Verwendung neuer empirischer Schätzverfahren und die Nutzung ergänzender Kapitalmarktdaten. Im Folgenden wird eine weitere Methode untersucht: Der zugrunde liegende Datensatz wird nach den Ausprägungen eines Merkmals, wie dem Wirtschaftszweig, der Größe und der Rechtsform der Unternehmen unterteilt und jeweils ein eigenes gruppenspezifisches Modell geschätzt. Die genutzte USTAN-Datenbank der Deutschen Bundesbank besitzt mit über 300.000 Jahresabschlüssen von 1994 bis 2002, d. h. über einen vollständigen Konjunkturzyklus hinweg, einen ausreichenden Umfang, um diesen einfachen Ansatz zu realisieren.

"Out-of-sample"-Tests auf der Basis von wiederholt gezogenen Stichproben zeigen, dass gruppenspezifische Schätzungen des verwendeten binären logistischen Regressionsmodells in allen untersuchten Fällen zu einer signifikanten Erhöhung der Prognosegüte führen. Der Vergleich mit einem Referenzmodell, das die Variablen der deutschen Version von Moody's RiskCalc™ verwendet, bestätigt die Repräsentativität dieses Ergebnisses.

Contents

Improvements in Rating Models for the German Corporate Sector[1]

1 Introduction

The recent financial crisis has underlined the importance of credit risk management. Credit categories such as commercial loans that have mostly been assessed on the basis of well-established rating models have shown a relatively robust performance. This provides support to the argument for the further development and implementation of internal rating models, as already proposed by the New Basel Capital Accord (Basel II).

Accounting-based models can be directly used to assign a credit rating even to unlisted companies, such as most small and medium sized enterprises (SME). Four approaches are commonly used to enhance such models: first, an optimized selection of variables, second, a refined transformation, third, the improvement of empirical estimation methods and fourth, the supplementation with additional, mostly market-based data. This paper analyzes a fifth method and breaks down the underlying dataset according to a specific attribute, such as industry affiliation, size and legal form of companies and on this basis group-specific models are estimated. With more than 300,000 financial statements provided by German companies for the years 1994 to 2002, i. e. throughout a complete business cycle, the Deutsche Bundesbank USTAN database employed in this study is large enough to allow this simple approach.

Out-of-sample tests using random subsamples show that group-specific estimations can significantly improve the predictive power of a typical binary logistic regression model in each case. The representability of this result is verified through comparisons with a benchmark model which applies the variables of Moody's RiskCalc^{TM} for Germany.

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2 General Methodology

The first multivariate accounting-based rating model was the Z-score model proposed by Edward Altman in 1968.[2] Since then, the basic principle of such models has remained unchanged. First, the historical statistical relationship between a set of financial ratios (and sometimes others, such as macro variables) and the future occurrence of a default on debt is explored. Second, the future probability of default (PD) for companies is forecast by entering the actual financial ratios into the estimated equation as appropriate.

In the late 1970s, Altman's multivariate discriminant analysis started to lose importance in favour of conditional probability analysis. Especially the use of logit models as proposed by Ohlson (1980) became a common standard.[3] Since the 1990s accounting-based models are strongly challenged by market-based approaches such as the commercial KMV-model.[4]

It is one of the main disadvantages of purely market-based models that they can only assign a credit rating directly to listed companies. However, market-based and accounting-based approaches are not mutually exclusive.[5] A current commercial hybrid model is Moody's Riskcalc™ v3.1 which supplements the former purely financial statement-based RiskCalc™ v1.0 model with market-based comparables at industry level.[6] In the academic literature Chava and Jarrow (2004) and Altman et al. (2011) have adopted a similar approach. The performance of all three models significantly improves by this upgrade, implying that different groups of companies show different patterns in business failure.

This paper analyzes the question of whether the estimation of group-specific models, as a simple purely financial-statement based method, is sufficient to yield similar improvements. The cited works of Chava and Jarrow (2004) and Altman et al. (2011) partly embrace this analysis by estimating a hybrid model on a sectoral basis.[7] However,

2 Cf. Altman (1968). For a brief overview of the evolution of rating models cf. Balcaena and Ooghe (2006) and Wang et al. (2010).
3 Efron (1975) and Lo (1986) compare discriminant analysis and the logistic regression model in detail. Hosmer and Lemeshow (2000) give a good introduction to the logistic regression model.
4 Based on the Merton-model (cf. Merton (1974)), such rating models use the Black/Scholes (1973) formula to derive the probability of default from equity prices, cf. Crouhy et al. (2000) and Crosbie and Bohn (2001).
5 In the strict sense, the first example of hybrid models is Altman's 1968 Z-Score model, which used the market value of equity as one of seven input variables.
6 Cf. Dwyer et. al. (2004), p. 16.
7 Earlier works by Altman and Izan (1984) and Izan (1984) propose to account for industry-specific characteristics by using company to industry relative ratios. Platt (1989) and Platt and Platt (1990 and 1991) implement this method.

both articles use a dataset of public companies to test the advantage of a private firm model. The Deutsche Bundesbank USTAN database employed in this study contains mostly unlisted companies, and it might therefore allow further insights. Additionally, this article analyzes the effect of group-estimations by size categories and legal forms.

To be advantageous, the proposed group-specific estimations need a sample large enough to guarantee robust estimates even when split into subsamples. The Deutsche Bundesbank's USTAN dataset used in this paper is considered to meet this condition. However, it seems crucial to check that each estimated model is not overfitted to the relatively small underlying pool of financial statements. The following measures of quality and robustness are defined to fulfil this task:

1. *Low pairwise correlations of the variables in each group.* Pairwise correlations between the variables in each model should not exceed a certain threshold.[8] High correlations, remaining below perfect multicollinearity, might lead to a higher explanatory power of the models if the correlations between the financial ratios remain stable out-of-sample. However, the dependence of the quality of the model on this condition is to be viewed critically. As a second disadvantage, it becomes less easy to interpret the coefficients of the model.

2. *Similar correlations of the variables in different groups.* As an indicator for robustness, the variables in a group-specific model should have similar covariances in the different sectors.

3. *Estimates of different group-specific models fluctuate within certain boundaries.* The estimates reflect group-specific differences, so they are expected to vary from model to model. However, extreme discrepancies might indicate a lack of robustness and are therefore seen as a warning sign.

4. *The performance of each model is measured out-of-sample.* Only a rating model's out-of-sample performance is an appropriate measure of its predictive power and should therefore be used to evaluate its usefulness in practice.

All the above-mentioned conditions are supplementary to standard measures of quality and robustness, e.g. the need for the estimates to have certain levels of significance. The third condition can be viewed critically, as it limits the possible enhancement of the rating quality through groupwise estimations. Furthermore, it can be argued that

8 Following the proposal of Edmister (1972), p. 1484, the limit on the global level is set rather cautiously to 31%.

the out-of-sample measurement of the performance of a model is sufficient to guarantee robust results. However, I prefer the most conservative and robust approach, which additionally allows comparisons to existing rating models, although it limits the findings of this paper to a worst-case scenario. The quest for group-specific variables which show strongly differing estimates (and perhaps also pairwise correlations) for different groups of companies and which might greatly enhance the performance of rating models via group-specific estimations will be the subject of further research.

3 Data

3.1 Description

The Deutsche Bundesbank's USTAN database contains 718,927 financial statements for 143,991 German companies from 1989 to 2003. The financial statements were collected in the bill-rediscount business. Until 1997, the Deutsche Bundesbank could purchase commercial bills from other banks at the discount rate if three solvent companies guaranteed the payment. The Deutsche Bundesbank checked the solvency of the drawer by asking for the latest balance sheet, which was then incorporated into the USTAN database.[9] Later it was recorded whether insolvency proceedings had been initiated against these companies within the subsequent 24 months.[10] Since 1998, the Deutsche Bundesbank has only been able to accept commercial bills and credit claims as collateral for loans to the financial sector. Consequently, financial statements have been requisitioned much more rarely since then. In 2003, the Deutsche Bundesbank temporarily stopped updating USTAN and launched a new joint database with other institutions, called the Financial Statements Data Pool (or "Jahresabschlussdatenpool"). This database does not yet contain information about insolvent firms.[11]

9 To be precise, the Deutsche Bundesbank checked the solvency of two companies, usually the submitting bank as guarantor and the drawer. As data for banks were available from databases maintained by the banking supervision department, only the balance sheet of the drawer was requested and incorporated into the USTAN database.

10 The German Insolvency Code (Insolvenzordnung) defines several triggers that lead to insolvency proceedings such as a lack of liquidity, the inability to pay, and overindebtedness. In this paper, the initiation of insolvency proceedings is seen as a proxy for default.

11 See Deutsche Bundesbank (1998), p. 54, and Deutsche Bundesbank (2005), pp. 48f.

3.2 Data rectification

In this paper, fourteen commercial sectors (cf. Appendix I, Table 13), seven legal forms and four size categories are identified. In the USTAN database, sector information was specified for only a few companies before 1994. Using the individual identification number, this information can be obtained from later years for most companies. This procedure fails, however, if companies left the panel before 1994, which is typically the case with insolvencies. To avoid a quality bias, all financial statements before 1994 are therefore excluded from the sample.

Furthermore, only financial statements that have been prepared according to the German Commercial Code (HGB) or for taxation purposes are kept.[12] Subsequently, other questionable financial statements are eliminated, such as balance sheets with negative total assets, financial statements for a fiscal year (or a financial year in case of commercial financial statements) with less than 11 months, and income statements with sales and personnel costs that equal zero or are missing. The same applies to holding companies with investments exceeding 60% of total assets and companies with missing information about the initiation of insolvency proceedings.

The remaining sample is approximately half the size of the initial dataset and is still large compared to the samples in most other academic studies.[13] It is sufficient to develop different models for all size classes and legal forms, but not for all industries. The financial and the gastronomic sectors have to be excluded.[14]

3.3 Sample representativeness

It is a common concern about the USTAN database that banks might have tended to prefer submitting the bills of sound companies, leading to a sample bias. A comparison of the insolvency rate estimated by the Federal German Statistical Office (Statistisches

12 Table 15 in Appendix III contains an overview of all rectifications and shows that more than 99% of the companies submitted financial statements for tax purposes (tax) and less than 1% submitted commercial financial statements according to the German Commercial Code (HGB). As German financial statements for tax purposes are based on commercial financial statements, the two are viewed as equivalent in this paper.

13 According to Falkenstein et al. (2000), p. 14, the median sample size used in academic studies from 1932 to 2000 was forty defaults and forty-five non-defaults.

14 Table 14 in Appendix II shows the sectoral composition of the sample, broken down into non-defaulted and defaulted companies. As described above, the lack of data for the financial sector is the result of the process used for data generation. In the gastronomic sector, the number of recorded insolvencies only amounts to three, presumably because commercial bills are uncommon in this sector.

Bundesamt) with the corresponding sample parameter in Figure 1 shows that the former is indeed substantially lower than the latter in the first and in the last year. By contrast, in the vast majority of years from 1995 to 2001 the sample seems to be an adequate representation of the population of German companies.[15] This does not constitute hard proof, but is at least an indication that the hypothesis of a systematic sample bias can be rejected. Furthermore, it has to be stressed that even if there were a bias, this would not necessarily imply a distortion of the estimated relationship between financial ratios and the probability of default.

Figure 1: Insolvency rate estimated by the German Federal Statistical Office and that of the sample (in percent)

A different sample bias might result from disproportionate coverage of companies of different sizes. This can be controlled for using the total revenue reported by the German

15 A supplementary sectoral analysis was performed to test for noticeable sectoral patterns by visual inspection. It showed that the sectoral insolvency rates of the sample vary substantially from year to year, especially in the small sectors, but without obvious patterns.

Federal Statistical Office.[16] Figure 2 reveals that from 1994 to 1997, sample coverage of the total revenue of German companies increased from 35.7% to 37.8%. Coverage of the total revenue of small and medium-sized enterprises (companies with a revenue equal to or below EUR50 million per year) of about 20% is substantially lower than the coverage of large companies, which exceeds 50%. In the following years, the structural change in the rediscount business of 1998 has a large impact. From 1997 to 2003, total coverage declines from 37.8% to 24.3% (SME: 19.3% to 9.2%, large companies: 54.2% to 34.8%).[17] Given this bias, checks must be made to ensure that the statistical relationship between the number of insolvencies initiated and the models' financial ratios is constant for companies of all sizes.[18]

4 Model Estimation

4.1 Selection of variables

The relevant literature offers a wide range of financial ratios considered to contain information about different aspects of companies' operations. Baetge et al. (2004) present more than one hundred common variables that have been adjusted to the German Commercial Code and which have been used as a basic pool for the following search process.[19]

The multitude of different permutations of possible regressors of the model meant that a forward selection process had to be applied.[20] First, financial ratios were categorized as providing information either about corporate activity, capital structure, liquidity,

16 All German companies have to report their revenue to the local tax office if it exceeds a certain threshold. The data is aggregated by the Federal Statistical Office to estimate total revenue in different sectors. The sectors are differentiated on the one-digit sectoral level.

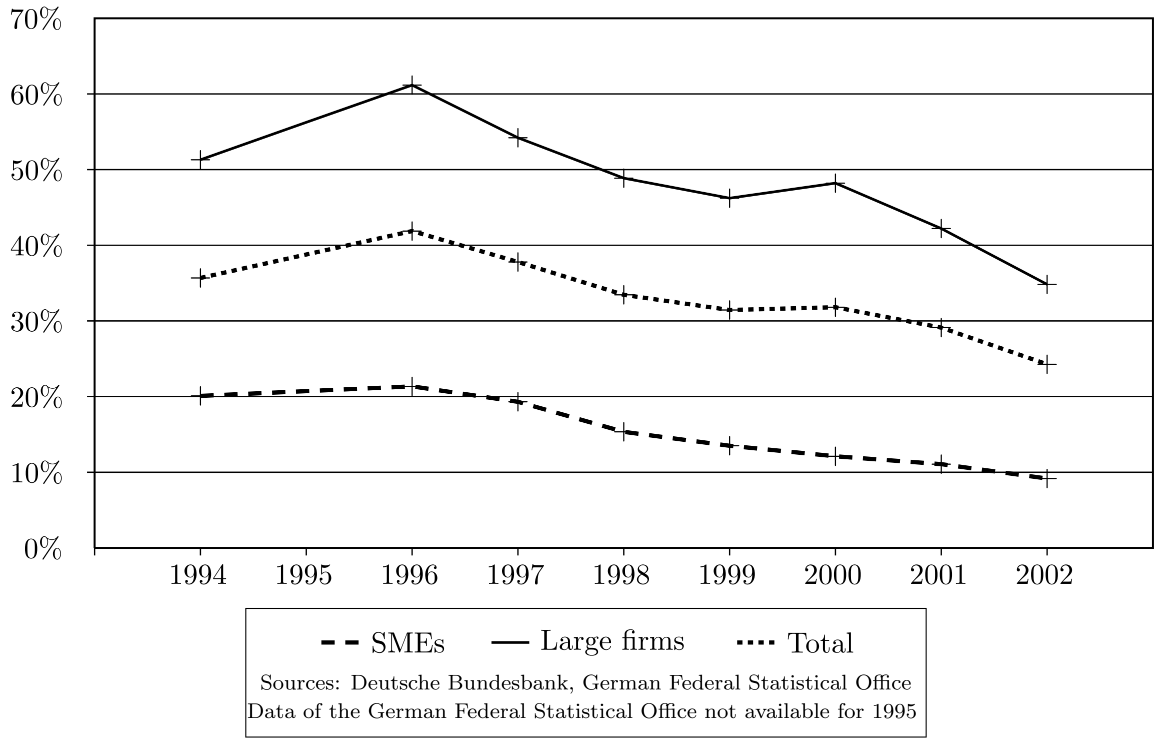
17 There are two structural breaks in the classification of enterprises. In 1994, the Federal Statistical Office's dataset covered companies with a revenue of at least DM25,000 (EUR12,782). In 1996, this threshold was lifted to DM32,500 (EUR16,167). Before the adoption of the euro in 2000, the line dividing SMEs and large companies had to be set at revenue of DM100 million (EUR51 million) instead of the EUR50 million mentioned in the text. The effects of both breaks seem to be negligible.

18 The bias becomes even more pronounced if one compares coverage in terms of the number of companies rather than in terms of revenue. This is due to the multitude of small and micro enterprises in Germany, which are generally not covered by the sample. This applies to most datasets, from the seminal work of Beaver (1966), pp. 72 f., to Moody's RiskCalc™ for Germany, which explicitly excludes all enterprises with a revenue of less than EUR500,000; cf. Escott et al. (2001), p. 4.

19 Additional sources of financial ratios were Chen and Shimerda (1981), who give an extensive overview of variables used in earlier research, Escott et al. (2001), Engelmann et al. (2003), and Mager and Schmieder (2009).

20 Cf. Falkenstein et al. (2000), pp. 27 ff., for a summary of this process and common mistakes in the selection of useful variables.

Figure 2: Sample coverage of German companies (Total revenue of sample companies as a percentage of total revenue of all German companies)



profitability or size. Second, all financial ratios in one category were inspected to detect any correlation with the occurrence of defaults. This was achieved by plotting the financial ratio of interest against the corresponding default rate.[21] All variables without an apparent relationship to the default rate were excluded. Figure 3 shows intersectoral graphs for the variables that were selected.

Finally, the remaining financial ratios were tested for their univariate explanatory power for future defaults in different sectors, using the area under the receiver operating characteristics curve (AUR) as a benchmark.[22] Where the results were similar, preference was given to variables that can be obtained from one financial statement (such as EBITDA) over variables that need two successive financial statements to be calculated (such as cashflows). The following variables were chosen:

1. EBITDA ROI: EBITDA / total assets,
2. Debt structure I: liabilities to financial institutions / total liabilities,
3. Debt structure II: current liabilities / total liabilities,
4. Total asset turnover: sales / total assets,
5. Equity ratio: equity / total assets,
6. Log total assets: log (total assets).

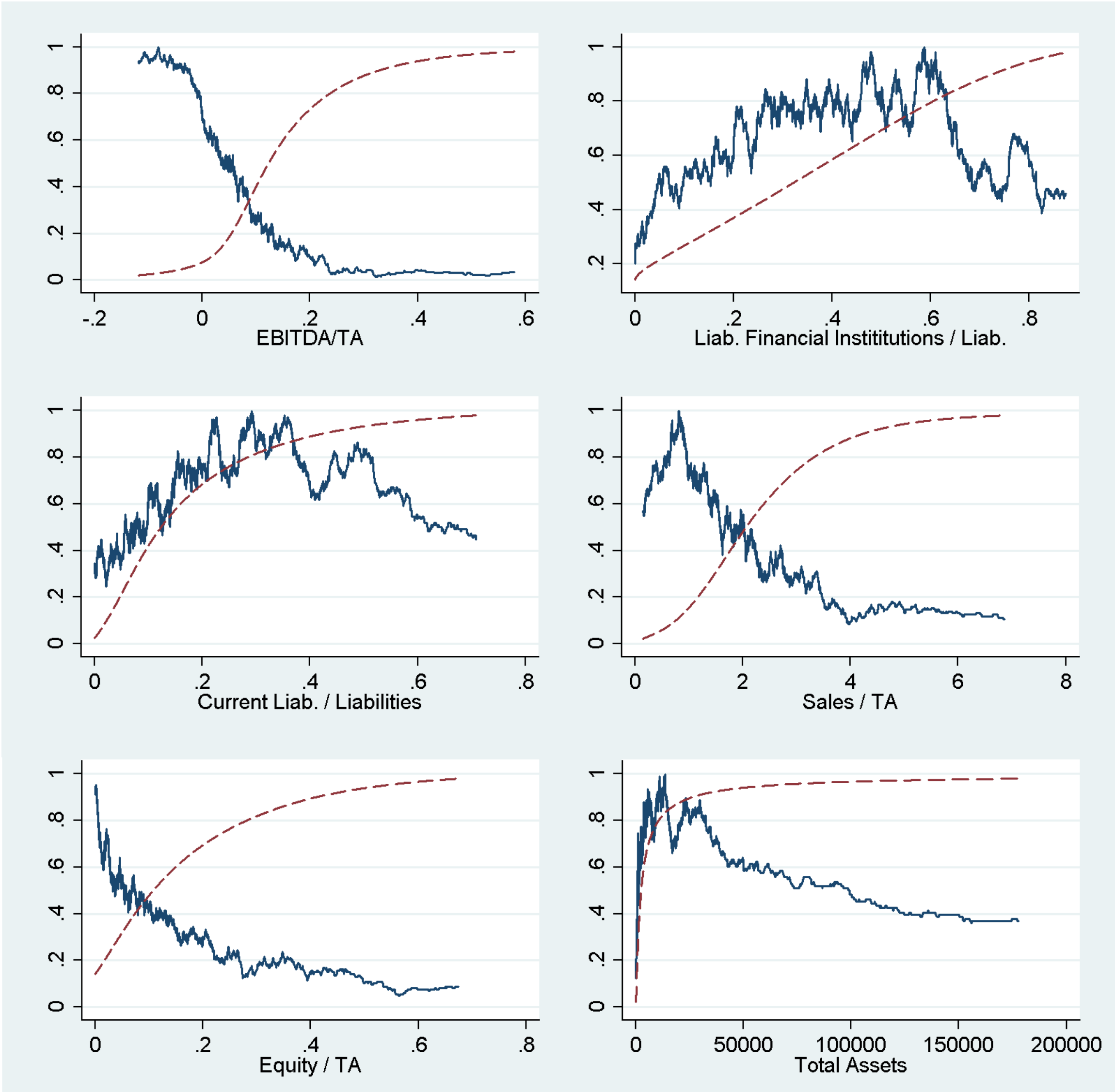
The use of relative ratios guarantees that large companies do not dominate the estimation and further accounts for the impact of inflation. Including the log of total assets as an additional exogenous variable allows taking size-specific differences into account.

It is apparent from Figure 3 that some relationships between the default rate and the chosen financial ratios are not strictly monotone. However, the cumulative distribution reveals that only about 10% of the data is affected. Given this fact and to obtain robust and interpretable results, I decided not to include quadratic terms in the regression. The only transformation ultimately made was to take the log of total assets, and this

21 The default rate was calculated using the number of defaults assigned to the adjacent 10,000 ordered financial statements. This procedure is a common standard, for example cf. Falkenstein et al.(2000).

22 See Hanley and McNeil (1982) and Sobehart and Keenan (2001) for an explanation of the ROC-curve and the AUR (often referred to as AUC in the literature) as an indicator. Stein (2002), p. 6 gives a good example of the limitations of the AUR.
The name "receiver operating characteristics curve" (ROC curve) originates from the first use of such graphs to describe the characteristics of radar receivers.

Figure 3: The default rate in percent subject to different financial ratios (continuous lines) and the cumulative distribution of the financial ratios (dotted lines).



The default rate in percent (continuous lines) was calculated using the number of defaults assigned to the adjacent 10,000 ordered financial statements.

Variables: EBITDA/TA: EBITDA per total assets, Liab. Financial Institutions / Liab.: liabilities to financial institutions per total liabilities, Current Liab. / Liab.: current liabilities per total liabilities, Sales / TA: sales per total assets, Equity / TA: equity per total assets, Total Assets: total assets.

does not address non-monotonicity.[23] To minimize the distorting influence of outliers, all variables are also modestly winsorized at the 1% level.[24]

4.2 Global estimation

A logistic regression using the full dataset yields that all estimates have the expected sign and are highly significant (cf. Table 1). The in-sample AUR of this global estimation amounts to 0.787, a value which is in line with other rating models.[25]

Table 1: Global estimation of the model.

Variable/Year	All sectors
EBITDA ROI	-5.403***
Debt structure I	0.869***
Debt structure II	1.888***
Total asset turnover	-0.313***
Equity ratio	-3.579***
Log TA	0.163***
Constant	-5.479***
N	318824
AUR	**0.787**

Variables: EBITDA ROI: EBITDA per total assets, Debt structure I: liabilities to financial institutions per total liabilities, Debt structure II: current liabilities per total liabilities, Total asset turnover: sales per total assets, Equity ratio: equity per total assets, Log TA: log(total assets).

Level of significance: * 10%, ** 5%, *** 1%

The global estimation of an alternative logit model based on the variables used in Moody's Risk Calc™ for Germany,[26] which is employed as a benchmark model to check

23 More sophisticated transformations are applied for example by Moody's, cf. Falkenstein et al. (2000), pp. 54 ff. To ensure that the results of this paper are reproducible, I only took into consideration the use of very basic transformations.

24 For the global estimations, a winsorization at the 0.5% level, which had initially been used, would already lead to robust results, but at the sectoral level, more rigorous winsorization appeared necessary in some small sectors.

25 Higher in-sample AUR values in other models using the same dataset mainly result from the use of a smaller fraction of the data, a heavier truncation of the variables and/or the use of variables which are correlated to each other beyond the upper threshold of 31% used in this paper.

26 Unlike under the Moody's methodology, these variables have not been transformed. None of the following results therefore represent the performance of the full model of Moody's Risk Calc for Germany™.

the robustness of the results, yields an in-sample AUR of 0.764 (cf. Table 2).[27] In both cases, the pairwise correlations between the incorporated variables (not reported in detail here) are low. In the model they always remain below the chosen threshold of 31%; in the benchmark model, they do so with one exception.

Table 2: Global estimation of the benchmark model based on the variables of Moody's Risk Calc for Germany™.

Variable / Year	All sectors
Payables payment period	0.002***
Capital structure	1.065***
Net debt ratio	0.742***
Equity ratio	-0.683***
Cashflow per liabilities	-0.335***
EBITD ROI	-5.209***
Net profit ratio	0.151***
Personnel cost ratio	0.132***
Sales growth	-0.049
(Sales growth)^2	0.002
Constant	-5.479***
N	239034
AUR	**0.764**

Variables: Payables payment period: (Trade payables per sales)·360, Capital structure: (current liabilities and liabilities to financial institutions) per total liabilites, Net debt ratio: (current liabilites – current assets) per total assets, Equity ratio: (equity – intangible assets) per (total assets – intangible assets – cash and cash equivalents – land and buildings), Cashflow per liabilities: cash flow per total liabilities, EBITD ROI: EBITD per total assets, Net profit ratio: operating profit per sales, Personnel cost ratio: wages and salaries per sales, Sales growth: sales per sales last year.

Level of significance: * 10%, ** 5%, *** 1%

27 The quality of the two models cannot be directly compared using the AUR because the benchmark model covers fewer observations (N) than the model. If one compares the AUR only for those data for which all variables can be calculated for both models, the performance of the model improves even more.

4.3 Estimation per industrial sector

As the first means of distinction between various groups, the model is estimated separately for different industries. Table 3 shows that the vast majority of estimates are highly significant and that all significant variables have the expected sign and plausible coefficients. For the final estimations, the set of variables of the sectoral models was slightly reduced to include only the significant ones (cf. Table 4). In the service sectors, a more robust measure of equity per total assets was applied. The estimates and the in-sample AUR change only very little as a result of this reduction of variables.

Likewise, the benchmark model is estimated for all sectors to check the representativeness of the results. Again, the vast majority of all significant variables are of the expected sign and have comparable values in all sectors. The in-sample AUR of the model and the benchmark model show similar sectoral patterns, indicating that they are sectorally balanced. None of the variables of one model should be able to improve the performance of the other model when applied to certain industries only.

In-sample AUR are only a weak indicator for the real performance of rating models, especially if these exhibit different degrees of freedom.[28] Consequently, the predictive power of the model resulting from different estimations is measured out-of-sample. The easiest approach is to split the dataset into a training set to estimate the model, and a validation set (or test set) to evaluate and compare the resulting performance.[29] More sophisticated resampling methods deliver more information about the models' performance through a more exhaustive use of the available data.[30] Therefore a random subsampling procedure with one hundred repetitions is applied in this paper. Each time, 20% of the observations of each sector of the sample are split off as a test set. The remaining 80% of observations are used as a training set for the global and the sectoral estimations. The discriminative power of the sectorally and globally estimated model is surveyed on

28 The risk of overfitting a model increases with its degrees of freedom.

29 Various articles address the questions how compare the resulting AUR. DeLong et al. (1988) is the most prominent nonparametric approach, which is summarized by Engelmann et al. (2003) in the context of statistical rating models.

30 Stein (2002), p. 20 illustrates that the application of such methods is typical in the rating industry, Demšar (2006), p. 4 shows the same for the related but more general discipline of machine-learning.

Table 3: Sectoral estimation of the model using the full set of variables.

Variable / Year	01 Agr	02 Min Energy	03 Man Met	04 Man CMC	05 Man Other	06 Cons	07 Trade	09 Transport	12 Real Est	13 Service	14 Service Other
EBITDA ROI	-4.584 **	-4.685 **	-5.141 ***	-4.587 ***	-6.247 ***	-4.253 ***	-7.192 ***	-3.117 ***	-5.408 ***	-4.118 ***	-3.146 ***
Debt structure I	-0.206	0.723	1.005 ***	2.215 ***	1.618 ***	1.416 ***	1.147 ***	0.998	-0.784	0.451	-0.432
Debt structure II	2.265 *	5.438 ***	3.919 ***	5.280 ***	2.705 ***	3.951 ***	1.338 ***	1.596	1.534	1.987 **	2.090
Tot. asset turnover	-0.190	-0.670 *	-0.368 ***	-0.550 ***	-0.306 ***	-0.116	-0.259 ***	-0.004	-0.292	-0.277 *	-0.162
Equity ratio	-4.753 ***	-7.619 **	-2.994 ***	-2.642 ***	-3.190 ***	-4.017 ***	-3.494 ***	-2.600	-3.797 **	-1.008	-1.684
Log TA	0.627 ***	-0.338	0.253 ***	0.222 ***	0.196 ***	0.263 ***	0.258 ***	-0.095	0.075	0.050	0.106
Constant	-8.960 ***	-1.857	-6.473 ***	-6.751 ***	-5.939 ***	-6.531 ***	-6.585 ***	-4.847 ***	-4.352 ***	-5.239 ***	-5.390 ***
N	4463	4125	22812	36057	59974	24310	139041	8642	6501	10679	2220
AUR	**0.820**	**0.922**	**0.81**	**0.824**	**0.813**	**0.744**	**0.787**	**0.704**	**0.759**	**0.745**	**0.857**

Variables: EBITDA ROI: EBITDA per total assets, Debt structure I: liabilities to financial institutions per total liabilities, Debt structure II: current liabilities per total liabilities, Total asset turnover: sales per total assets, Equity ratio: equity per total assets, Log TA: log(total assets).

Sectors: 01 Agr: Agriculture and forestry & fishing, 02 Min Energy: Mining industry, energy and water supply, 03 Man Met: Manufacturing (metal), 04 Man CMC: Manufacturing (chemicals, machines and vehicles), 05 Man Other: Manufacturing (other), 06 Cons: Building / construction, 07 Trade: Trade, maintenance and repair of vehicles and durables, 09 Transport: Transportation and communications, 12 Real Est: Real estate, renting, leasing etc., 13 Service: Business activities, 14 Service Other: Other public and personal services.

Level of significance: * 10%, ** 5%, *** 1%

Table 4: Sectoral estimation of the model with a reduced set of variables.

Variable / Year	01 Agr	02 Min Energy	03 Man Met	04 Man CMC	05 Man Other	06 Cons	07 Trade	09 Transport	12 Real Est	13 Service	14 Service Other
EBITDA ROI	-5.117 ***	-4.636 **	-5.141 ***	-4.587 ***	-6.247 ***	-4.253 ***	-7.192 ***	-2.977 ***	-5.907 ***	-4.132 ***	-3.439 ***
Debt structure I			1.005 ***	2.215 ***	1.618 ***	1.416 ***	1.147 ***				
Debt structure II		5.145 ***	3.919 ***	5.280 ***	2.705 ***	3.951 ***	1.338 ***				
Total asset turnover		-0.720 **	-0.368 ***	-0.550 ***	-0.306 ***	-0.116	-0.259 ***				
Equity ratio	-4.683 ***	-8.011 ***	-2.994 ***	-2.642 ***	-3.190 ***	-4.017 ***	-3.494 ***	-3.097 *	-3.976 **	-0.596 **	-0.544 ***
Log TA	0.574 ***	-0.356 *	0.253 ***	0.222 ***	0.196 ***	0.263 ***	0.258 ***	-0.112	0.059	0.075	0.049
Constant	-8.382 ***	-1.294	-6.473 ***	-6.751 ***	-5.939 ***	-6.531 ***	-6.585 ***	-3.960 ***	-4.596 ***	-5.460 ***	-5.144 ***
N	4466	4125	22812	36057	59974	24310	139041	8642	6501	10695	2219
AUR	**0.813**	**0.921**	**0.81**	**0.824**	**0.813**	**0.744**	**0.787**	**0.697**	**0.761**	**0.728**	**0.876**

Variables with insignificant coefficients in several related sectors in Table 3 were excluded here.

Variables: EBITDA ROI: EBITDA per total assets, Debt structure I: liabilities to financial institutions per total liabilities, Debt structure II: current liabilities per total liabilities, Total asset turnover: sales per total assets, Equity ratio: equity per total assets, Log TA: log(total assets).

Sectors: 01 Agr: Agriculture and forestry & fishing, 02 Min Energy: Mining industry, energy and water supply, 03 Man Met: Manufacturing (metal), 04 Man CMC: Manufacturing (chemicals, machines and vehicles), 05 Man Other: Manufacturing (other), 06 Cons: Building / construction, 07 Trade: Trade, maintenance and repair of vehicles and durables, 09 Transport: Transportation and communications, 12 Real Est: Real estate, renting, leasing etc., 13 Service: Business activities, 14 Service Other: Other public and personal services.

Level of significance: * 10%, ** 5%, *** 1%

Table 5: Sectoral estimation of the benchmark model based on the variables of Moody's Risk Calc for Germany™ using a logit estimation.

Variable / Year	01 Agr	02 Min Energy	03 Man Met	04 Man CMC	05 Man Other	06 Cons	07 Trade	09 Transport	12 Real Est	13 Service	14 Service Other
Pay. paym. period	-0.003 *	0.007 ***	0.012 ***	0.013 ***	0.006 ***	0.006 ***	0.003 ***	-0.006	-0.000	-0.000	0.007 ***
Capital structure	1.100	1.571	1.210 ***	2.004 ***	1.564 ***	1.137 ***	1.387 ***	2.434 **	0.465	0.699	-1.153
Net debt ratio	1.336 *	2.491 ***	1.517 ***	0.484	0.147	0.759 ***	0.902 ***	2.209 **	0.942	0.196	1.075
Equity ratio	-0.526 **	-1.287	0.417	-0.215	-0.601 ***	-0.110	-0.678 ***	-0.416	-0.602 ***	-0.238	-0.430 **
Cashflow per Liab.	-0.862 **	-1.500	-0.785 *	-0.439	-0.920 ***	-0.053	-0.148	0.373	-0.554	-0.277	-1.271
EBITD ROI	-11.483 ***	-1.242	-4.710 ***	-2.566 **	-3.480 ***	-2.835 ***	-6.041 ***	-2.613	-5.209 ***	-3.820 ***	-0.467
Net profit ratio	7.755 ***	0.664	0.486	-0.811	-1.285	-2.312 **	-1.632	-0.741	-0.205 **	0.081	-0.511
Personnel cost ratio	2.449 *	4.510 ***	1.327 **	1.667 ***	2.162 ***	0.207	1.992 ***	0.037	-0.544	0.009	0.915 *
Sales growth	2.709 *	1.024	-1.196	-0.310	-1.012	0.976 ***	-1.925 ***	-1.933	1.183	0.513	0.151
(Sales growth)^2	-0.486	-0.008	0.397	0.048	0.237	-0.165 *	0.524 ***	0.602	-1.009	-0.094	-0.000
Constant	-8.551 ***	-10.240 ***	-5.944 ***	-6.593 ***	-5.319 ***	-6.030 ***	-5.316 ***	-6.316 ***	-4.760 ***	-5.586 ***	-5.954 ***
N	3091	3177	17415	27850	46029	17161	105858	5932	4022	6984	1515
AUR	**0.852**	**0.915**	**0.821**	**0.826**	**0.811**	**0.719**	**0.791**	**0.758**	**0.845**	**0.739**	**0.922**

Variables: Pay. paym. period: (Trade payables per sales)·360, Capital structure: (current liabilities and liabilities to financial institutions) per total liabilites, Net debt ratio: (current liabilites – current assets) per total assets, Equity ratio: (equity – intangible assets) per (total assets – intangible assets – cash and cash equivalents – land and buildings), Cashflow per Liab.: cash flow per total liabilities, EBITD ROI: EBITD per total assets, Net profit ratio: operating profit per sales, Personnel cost ratio: wages and salaries per sales, Sales growth: sales per sales last year.

Sectors: 01 Agr: Agriculture and forestry & fishing, 02 Min Energy: Mining industry, energy and water supply, 03 Man Met: Manufacturing (metal), 04 Man CMC: Manufacturing (chemicals, machines and vehicles), 05 Man Other: Manufacturing (other), 06 Cons: Building / construction, 07 Trade: Trade, maintenance and repair of vehicles and durables, 09 Transport: Transportation and communications, 12 Real Est: Real estate, renting, leasing etc., 13 Service: Business activities, 14 Service Other: Other public and personal services.

Level of significance: * 10%, ** 5%, *** 1%

the test set.[31] Only the out-of-sample observations for which a probability of default is obtained *in all estimations* are used to compare the models' predictive power.

The main result of the random subsampling procedure is that the total average AUR increases from 0.784 to 0.804 when using sectoral estimations (cf. Table 6). This rise is substantial, given that the scale for useful models only lies between 0.5 (random guess) and 1.0 (perfect prediction). Both, paired t-tests (two one-sided tests and one two-sided test) and the non-parametric Wilcoxon rank sum test show that the difference between the AUR is statistically significant, too.[32]

Figure 4 gives a visual impression of this difference between both AUR in the random subsamples. The upper subfigure (a) depicts the kernel density estimates of the area under the ROC-curve (AUR) of the global estimation and of the AUR of the sectoral estimations. Even if the graph does not reflect the paired character of these subsamples, it already indicates that the difference is substantial and statistically significant. The lower subfigure (b) shows that the difference between the AUR of the sectoral estimations and the AUR of the global estimation has an estimated bimodal distribution which only covers a positive range with a high peak at 0.02.

At the sectoral level, the out-of-sample AUR are higher for the group-specific estimation in eight of eleven sectors at the 1% level of significance and in one more sector at the 5% level. In two sectors, there are no significant differences between the AUR of both estimations. In the small agricultural sector, the sectoral AUR are significantly lower than the AUR of the global estimation.

It is apparent from Table 6 that groupwise estimations only slightly improve the prediction of defaults in large sectors. This result appears intuitive as the corresponding subsamples, such as those of the manufacturing sectors, can be expected to be the main drivers of the estimates of the global estimation. In the smaller industries greater ameliorations can be achieved if the occurence of defaults deviates from other sectors and

31 The random subsampling method as portrayed here is a weak indicator of the predictive power of a model in the event of structural breaks. One of the merits of a walk-forward testing approach as summarized in Stein (2000), pp. 15 f. is that it helps to detect these cases. However, the yearly in-sample estimations already show that there are no such breaks in the concrete dataset as the estimates and the performance do not vary in a systematic way over the years (see Appendix IV, Tables 16 and 17).

32 Demšar (2006) points to the weaknesses of a paired t-test to compare the performance of classifiers (such as the AUR) in the context of resampling. He analyzes alternatives such as the 5x2cv t-test and corrected resampled t-test, and comes to the conclusion that the rank sum test of Wilcoxon (1945) is superior.

Table 6: The area under the ROC-curve (AUR) of the sectoral estimations and of the global estimation.

	Total	01 Agr	02 Min Energy	03 Man Met	04 Man CMC	05 Man Other
AUR sectoral	**0.804**	0.798	0.896	0.806	0.826	0.802
AUR global	**0.784**	0.807	0.829	0.801	0.810	0.803
p_l	**1.000**	0.002	1.000	1.000	1.000	0.094
p	**0.000**	0.005	0.000	0.000	0.000	0.188
p_u	**0.000**	0.998	0.000	0.000	0.000	0.906
$p_{Wilcoxon}$	**0.000**	0.020	0.000	0.000	0.000	0.435

	06 Cons	07 Trade	09 Transport	12 Real Est	13 Service	14 Service Other
AUR sectoral	0.737	0.789	0.696	0.743	0.725	0.854
AUR global	0.707	0.785	0.646	0.708	0.720	0.816
p_l	1.000	1.000	1.000	1.000	0.811	0.997
p	0.000	0.000	0.000	0.000	0.379	0.006
p_u	0.000	0.000	0.000	0.000	0.189	0.003
$p_{Wilcoxon}$	0.000	0.000	0.000	0.000	0.997	0.003

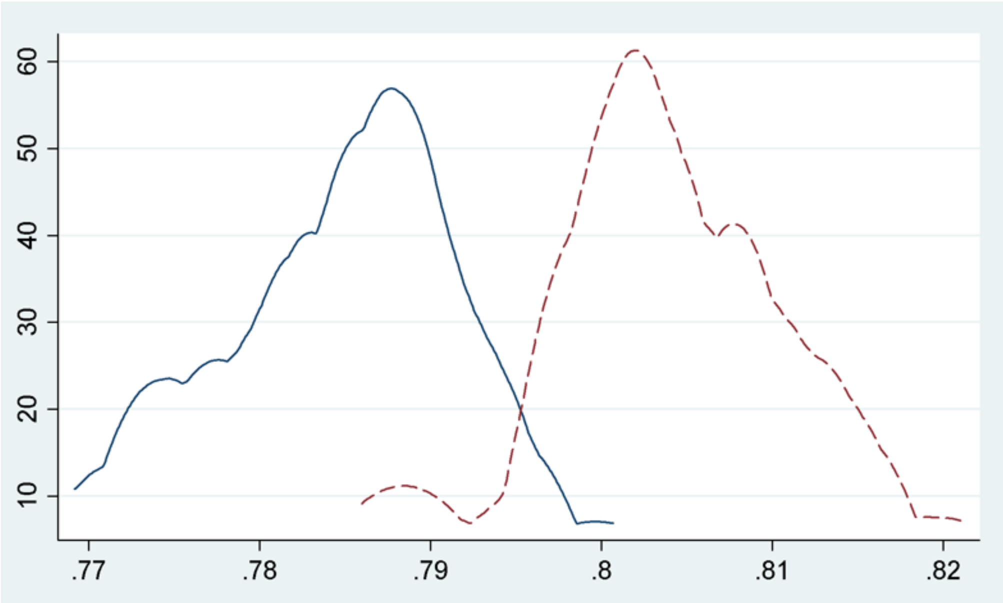
The first column Total shows results from the groupwise estimations (per sector) and from the global estimation *for all groups*. All other columns contain the corresponding performance per subgroup.

The two upper rows denote the average AUR from a random subsampling procedure, which repeatedly uses 80% of the dataset to estimate PDs for the remaining 20% companies. The three middle rows give the results of a paired t-test. They note the probability of an error of type I rejecting the null hypothesis that the AUR resulting from a groupwise estimation is lower than (p_l), different from (p) or higher than (p_u) the AUR resulting from the global estimation. The bottom row shows the result of the nonparametric Wilcoxon rank sum test with the null hypothesis that both AUR are different. Accordingly, p and $p_{Wilcoxon}$ are different test statistics regarding the same hypothesis.

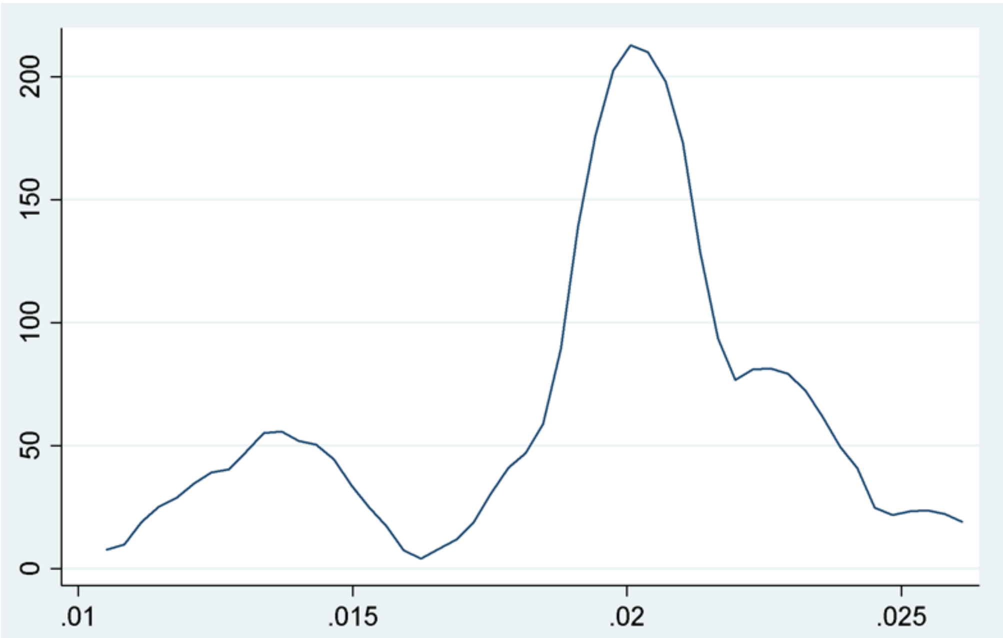
The definition of the sectors corresponds to that in Tables 3, 4 and 5.

Figure 4: Distribution of the area under the ROC-curve (AUR) of the global estimation and of the sectoral estimation using random subsampling.

(a) Kernel density estimates of the AUR of the global estimation (continuous line) and of the AUR of the sectoral estimation (dotted line).



(b) Kernel density estimate of the difference between the AUR of the sectoral estimation and the AUR of the global estimation.



if the data is sufficiently extensive to guarantee robust results in the sectoral estimations. This is the case in all but the agricultural and service sectors.

4.4 Estimation per company size

As a second groupwise distinction, the model and the benchmark model are re-estimated for groups of firms of different sizes.[33] Again, both models yield quite similar results. Both show a better in-sample performance when applied to medium-sized and large companies.

Interestingly, many estimates display systematic patterns in both models. For example, liabilities to financial institutions and current liabilities relative to total liabilities have a stronger impact on the probability of default the larger the company is. The non-linear relationship between size and the probability of default becomes obvious from the estimate for the log total assets. Within the class of micro companies, the size effect is positive; for small companies, it is not significantly different from zero; for medium-sized and large companies, it is negative. Obviously, the inclusion of the non-transformed variable increases the predictive power for medium-sized and large companies and reduces it for micro companies in the case of a single global estimation.

The random subsampling validations (cf. Table 9) illustrate that group-specific estimations improve the average out-of-sample AUR significantly from 0.785 to 0.797. At the group level, the effect is significantly positive on the 5% level in all size categories. The average AUR rises mainly for large companies. This is further evidence that the ratings of small groups of companies with specific characteristics, which are otherwise dominated by the majority, can be in particular enhanced by group-specific estimations.

33 The definition of micro, small and medium-sized enterprises is based on the classification used by the European Commission. Micro enterprises need to have revenue and/or total assets below EUR2 million, small companies have revenue and/or total assets of EUR10 million and must not have been classified as micro companies, medium-sized companies have revenue below EUR50 million and/or total assets below EUR43 million and must not have been classified as micro or small companies. All companies that do not fall into one of these categories are classified as large companies.

Table 7: Model estimated per company size.

Variable/Company Size	Micro	Small	Medium	Large
EBITDA ROI	-4.658 ***	-6.132 ***	-5.974 ***	-6.070 ***
Debt structure I	0.018	0.978 ***	1.845 ***	2.342 ***
Debt structure II	1.081 ***	2.027 ***	3.531 ***	4.134 ***
Total asset turnover	-0.191 ***	-0.457 ***	-0.682 ***	-0.613 ***
Equity ratio	-3.254 ***	-3.752 ***	-3.516 ***	-2.116 **
Log TA	0.317 ***	0.000	-0.419 ***	-0.451 **
Constant	-6.455 ***	-3.695 ***	0.397	0.470
N	145230	113124	43975	16495
AUR	0.767	0.796	0.835	0.824

Variables: EBITDA ROI: EBITDA per total assets, Debt structure I: liabilities to financial institutions per total liabilities, Debt structure II: current liabilities per total liabilities, Total asset turnover: sales per total assets, Equity ratio: equity per total assets, Log TA: log(total assets).

Size categories: Micro enterprises have revenues and/or total assets below EUR2 million, small companies have revenues and/or total assets below EUR10 million and must not have been classified as micro companies, medium-sized companies have revenues below EUR50 million and/or total assets below EUR43 million and must not have been classified as micro or small companies. All remaining companies are classified as large companies.

Level of significance: * 10%, ** 5%, *** 1%

Table 8: Benchmark model using the variables of Moody's Risk Calc™ for Germany estimated per company size.

Variable / Company Size	Micro	Small	Medium	Large
Payables payment period	0.001 ***	0.002 ***	0.002 ***	0.004 ***
Capital structure	0.144	1.433 ***	2.826 ***	2.768 ***
Net debt ratio	0.914 ***	0.503 ***	0.906 ***	0.383
Equity ratio	-0.692 ***	-1.394 ***	-1.225 ***	-0.547 ***
Cashflow per liabilities	-0.380 *	-0.154	-0.439 **	0.426
EBITD ROI	-4.349 ***	-5.888 ***	-5.177 ***	-4.933 ***
Net profit ratio	0.117 ***	0.429	-0.327	0.271
Personnel cost ratio	0.086 ***	0.739 ***	1.211 ***	1.519 **
Sales growth	0.146	-0.128	-0.040	-0.402
(Sales growth)^2	-0.015	0.002	0.003	0.011
Constant	-5.465 ***	-5.451 ***	-6.501 ***	-6.500 ***
N	100770	88871	35762	13631
AUR	0.747	0.781	0.825	0.797

Variables: Payables payment period: (Trade payables per sales)·360, Capital structure: (current liabilities and liabilities to financial institutions) per total liabilites, Net debt ratio: (current liabilites – current assets) per total assets, Equity ratio: (equity – intangible assets) per (total assets – intangible assets – cash and cash equivalents – land and buildings), Cashflow per liabilities: cash flow per total liabilities, EBITD ROI: EBITD per total assets, Net profit ratio: operating profit per sales, Personnel cost ratio: wages and salaries per sales, Sales growth: sales per sales last year.

Size categories: Micro enterprises have revenues and/or total assets below EUR2 million, small companies have revenues and/or total assets below EUR10 million and must not have been classified as micro companies, medium-sized companies have revenues below EUR50 million and/or total assets below EUR43 million and must not have been classified as micro or small companies. All remaining companies are classified as large companies.

Level of significance: * 10%, ** 5%, *** 1%

Table 9: The AUR of estimations per company size and of the global estimation.

	Total	Micro	Small	Medium	Large
AUR size	**0.797**	0.763	0.794	0.835	0.806
AUR global	**0.785**	0.755	0.793	0.822	0.775
p_l	**1.000**	1.000	0.983	1.000	1.000
p	**0.000**	0.000	0.034	0.000	0.000
p_u	**0.000**	0.000	0.017	0.000	0.000
$p_{Wilcoxon}$	**0.000**	0.000	0.016	0.000	0.000

The first column Total shows results from the groupwise estimations (per company size) and from the global estimation *for all groups*. All other columns contain the corresponding performance per subgroup.

The two upper rows denote the average AUR from a random subsampling procedure, which repeatedly uses 80% of the dataset to estimate PDs for the remaining 20% companies. The three middle rows give the results of a paired t-test. They note the probability of an error of type I rejecting the null hypothesis that the AUR resulting from a groupwise estimation is lower than (p_l), different from (p) or higher than (p_u) the AUR resulting from the global estimation. The bottom row shows the result of the nonparametric Wilcoxon rank sum test with the null hypothesis that both AUR are different. Accordingly, p and $p_{Wilcoxon}$ are different test statistics regarding the same hypothesis.

The definition of the sectors corresponds to that in Tables 7 and 8.

4.5 Estimation per legal form

As a third distinction, the model and the benchmark model are re-estimated for companies with different legal forms. The first group consists of stock corporations (AG and KGaA), the second group of German limited liability companies (GmbH), (GmbH), the third group constitutes cooperative societies (Geno), the fourth group limited partnerships with a German limited liability company as general partner (GmbH & Co KG), the fifth group limited commercial partnerships (KG), the sixth group general partnerships (OHG), and the seventh group one-man companies (One man).

All significant variables in the model show the expected sign. This is not always the case for the benchmark model, for example appertaining to the variables short-term liabilities minus short-term assets per total assets and cashflow per liabilities. Nevertheless, both models again yield the same order of the AUR per group.

Astonishingly, few patterns in the estimates follow the general separation of legal forms into private companies with full owner liability (KG, OHG, One Man) and incorporated companies with restricted owner liability (AG/KGaA, GmbH, Geno, GmbH & Co KG). Only liabilities to financial institutions per total liabilities and current liabilities per total liabilities show higher estimates for incorporated companies. This finding is in line with the results from the previous estimation based on size categories, as these companies tend to be larger. Additionally, the influence of the equity ratio on the probability of default appears more stable for private companies. It seems worth noting that the performance of both models is much worse for limited liability companies (GmbH and GmbH & Co KG) than for all other groups. This result is especially remarkable as this legal form is of great importance for the German corporate sector. For example, it accounts for nearly half of all observations in the sample.

The random subsampling validation shows that group-specific estimations increase the average out-of-sample AUR (cf. Table 12) from 0.785 to 0.794. This is almost exactly the same amount as in the case of size-specific estimations. At the group level, the increase is significant at the 1% level for all but limited commercial partnerships (KG) and general partnerships (OHG). The increase in discriminatory power is particularly marked for stock corporations, which is in line with the strong increase in the average AUR for large companies described in the previous section. Again, the prevalent group (in this case, limited liability companies) hardly benefits from group-specific estimations.

Table 10: Model estimated per legal form.

Variable / Legal Form	AG_KGaA	GmbH	Geno	GmbH & Co KG	KG	OHG	One_man
EBITDA ROI	-4.708***	-4.077***	-10.378***	-6.094***	-8.979***	-4.244**	-6.193***
Debt structure I	2.003***	1.043***	0.600	1.226***	0.628	0.210	0.246
Debt structure II	3.794***	2.028***	-0.655	2.146***	1.546**	1.130	0.494
Total asset turnover	-0.401***	-0.382***	-0.138*	-0.330***	-0.196*	-0.809***	-0.308**
Equity ratio	-2.707***	-4.057***	-6.261***	-2.844***	-4.268***	-4.195***	-3.827***
Log TA	-0.111	0.101***	-0.144	0.079**	0.231***	-0.047	0.563***
Constant	-3.071***	-4.871***	-1.634	-4.808***	-5.662***	-3.051	-8.476***
N	6919	167451	4392	72362	12889	4865	48456
AUR	0.841	0.780	0.851	0.795	0.819	0.840	0.826

Variables: EBITDA ROI: EBITDA per total assets, Debt structure I: liabilities to financial institutions per total liabilities, Debt structure II: current liabilities per total liabilities, Total asset turnover: sales per total assets, Equity ratio: equity per total assets, Log TA: log(total assets).

Legal forms: AG and KGaA: stock corporations, GmbH: limited liability companies, Geno: cooperative societies, GmbH & Co KG: limited partnerships with a limited liability company as general partner, KG: limited commercial partnerships, OHG: general partnerships, One man: one-man companies.

Level of significance: * 10%, ** 5%, *** 1%

Table 11: Benchmark model using the variables of Moody's Risk Calc™ for Germany estimated per legal form.

Variable / Legal Form	AG_KGaA	GmbH	Geno	GmbH_&_Co_KG	KG	OHG	One_man
Payables payment period	0.001	0.002***	-0.003	0.002***	0.000	0.002**	0.004***
Capital structure	2.414***	1.517***	4.082**	1.360***	0.737	-0.051	0.297
Net debt ratio	1.330*	0.555***	2.096	0.634***	0.564	-2.213**	-0.011
Equity ratio	-1.176	-1.474***	-0.917	-0.770***	-1.134***	-1.642***	-0.493**
Cashflow per liabilities	-1.764***	-0.320**	2.873**	0.186	0.201	-0.050	-1.457***
EBITD ROI	-3.439***	-3.635***	-15.727***	-6.308***	-7.593***	-7.097***	-6.298***
Net profit ratio	0.075	0.114	0.084	0.489**	0.065	-0.920	1.633***
Personnel cost ratio	0.026	0.147***	4.427***	0.322***	0.090	1.091	0.758***
Sales growth	0.217	-0.004	23.141*	-0.236	-0.749	-1.421	1.245
(Sales growth)^2	-0.047	-0.005	-9.605*	0.009*	0.045	0.594	-0.293
Constant	-5.923***	-5.635***	-22.367***	-5.308***	-4.298***	-2.933	-6.455***
N	5486	125557	3356	56978	9783	3561	33418
AUR	0.840	0.761	0.891	0.787	0.799	0.858	0.786

Variables: Payables payment period: (Trade payables per sales)·360, Capital structure: (current liabilities and liabilities to financial institutions) per total liabilites, Net debt ratio: (current liabilites – current assets) per total assets, Equity ratio: (equity – intangible assets) per (total assets – intangible assets – cash and cash equivalents – land and buildings), Cashflow per liabilities: cash flow per total liabilities, EBITD ROI: EBITD per total assets, Net profit ratio: operating profit per sales, Personnel cost ratio: wages and salaries per sales, Sales growth: sales per sales last year.

Legal forms: AG and KGaA: stock corporations, GmbH: limited liability companies, Geno: cooperative societies, GmbH & Co KG: limited partnerships with a limited liability company as general partner, KG: limited commercial partnerships, OHG: general partnerships, One man: one-man companies.

Level of significance: * 10%, ** 5%, *** 1%

Table 12: The AUR of estimations per legal form and of the global estimation.

	Total	AG_KGaA	GmbH	Geno	GmbH&Co KG	KG	OHG	OneMan
AUR legal form	**0.794**	0.822	0.778	0.811	0.793	0.810	0.798	0.813
AUR global	**0.785**	0.789	0.777	0.778	0.788	0.811	0.802	0.802
p_l	**1.000**	1.000	1.000	0.999	1.000	0.197	0.261	1.000
p	**0.000**	0.000	0.000	0.002	0.000	0.394	0.521	0.000
p_u	**0.000**	0.000	0.000	0.001	0.000	0.803	0.739	0.000
$p_{Wilcoxon}$	**0.000**	0.000	0.000	0.002	0.000	0.877	0.659	0.000

The first column Total shows results from the groupwise estimations (per legal form) and from the global estimation *for all groups*. All other columns contain the corresponding performance per subgroup.

The two upper rows denote the average AUR from a random subsampling procedure, which repeatedly uses 80% of the dataset to estimate PDs for the remaining 20% companies. The three middle rows give the results of a paired t-test. They note the probability of an error of type I rejecting the null hypothesis that the AUR resulting from a groupwise estimation is lower than (p_l), different from (p) or higher than (p_u) the AUR resulting from the global estimation. The bottom row shows the result of the nonparametric Wilcoxon rank sum test with the null hypothesis that both AUR are different. Accordingly, p and $p_{Wilcoxon}$ are different test statistics regarding the same hypothesis.

The definition of the sectors corresponds to that in Tables 10 and 11.

5 Conclusion

Accounting-based rating models for commercial debt are typically estimated without considering the specific characteristics of different types of companies. This paper analyzed whether and to what extent their predictive power can be ameliorated by using group-specific estimations. It used the Deutsche Bundesbank's USTAN database, which includes enough observations to deliver robust estimates even after being split into subsamples.

The main finding is that group-specific differences do matter. Especially estimations at industry level can considerably improve the total performance of common rating models for commercial debt, at least for German companies. If the models are estimated per size or per legal form, the amelioration is less strong, but still significant. In each case, the most considerable improvements in rating quality can be achieved for small groups of companies with specific characteristics, which are otherwise dominated by the prevalent groups. This applies despite the fact that no group-specific variables were used in this paper.

The result provides grounds for optimism that group-specific estimations are a simple means of further enhancing accounting-based rating models, implying a reduction of unexplained credit risk and a better allocation of scarce resources.

Appendix I: Classification of sectors.

Table 13: Classification of sectors.

Sector	Abbreviation	Classification (NACE)	Classification (WZ1993)
1. Agriculture and forestry & Fishing	01 Agr	A, B	01-05
2. Mining industry, energy and water supply	02 Min Energy	C, E	10-14, 40-41
3. Manufacturing (metal)	03 Man Met	DJ	27-28
4. Manufacturing (chemicals, machines and vehicles)	04 Man CMC	DG, DK	24-25, 29, 34-35
5. Manufacturing (other)	05 Man Other	D without DJ, DG, DK	15-23, 26, 30-33, 36-37
6. Building / construction	06 Cons	F	45
7. Trade, maintenance and repair of vehicles and durables	07 Trade	G	50-52
8. Hotels and restaurants	08 Hotel	H	55
9. Transportation and communications	09 Transport	I	60-64
10. Financial intermediation, except insurance and pension funding	10 Bank	J65	65
11. Insurance and pension funding, activities auxiliary to financial intermediation	11 Insurance	J66-J67	66-67
12. Real estate, renting, leasing etc.	12 Real Est	K70	70
13. Business activities	13 Service	K71-74	71-74
14. Other public and personal services	14 Service Other	M, N O, P95	80-95

Appendix II: Sectoral composition of the final sample.

Table 14: All companies and defaulted companies per sector and year.

All Companies									
Sector / Year	1994	1995	1996	1997	1998	1999	2000	2001	2002
01 Agr	618	703	751	676	457	381	345	306	229
02 Min Energy	555	581	575	531	449	404	375	357	298
03 Man Met	3,501	3,743	3,676	3,128	2,326	1,937	1,742	1,542	1,219
04 Man CMC	5,322	5,785	5,583	4,857	3,745	3,198	2,889	2,603	2,077
04 Man Other	9,087	9,836	9,791	8,487	6,232	5,165	4,502	3,890	2,988
06 Cons	4,038	4,615	4,473	3,654	2,421	1,821	1,431	1,104	754
07 Trade	19,813	21,869	22,490	20,208	14,815	12,376	10,796	9,352	7,325
08 Hotel	64	77	108	108	69	51	43	43	32
09 Transport	1,360	1,544	1,503	1,190	805	711	625	528	378
10 Bank	17	24	29	31	23	25	26	28	20
11 Insurance	14	20	21	17	14	26	24	15	11
12 Real Est	618	703	751	676	457	381	345	306	229
13 Service	555	581	575	531	449	404	375	357	298
14 Service Other	3,501	3,743	3,676	3,128	2,326	1,937	1,742	1,542	1,219

Defaulted Companies									
Sector / Year	1994	1995	1996	1997	1998	1999	2000	2001	2002
01 Agr		3	3	6	2	3	4	1	
02 Min Energy		1	1	1	2	4	1		
03 Man Met	3	23	16	24	19	13	28	19	7
04 Man CMC	6	50	23	36	38	32	35	32	16
04 Man Other	7	58	58	94	63	71	75	36	14
06 Cons	12	72	49	78	46	60	39	23	12
07 Trade	12	72	71	99	79	73	120	77	19
08 Hotel				1	1			1	
09 Transport	1	3	2	5	4	5	4	4	
10 Bank									
11 Insurance									
12 Real Est	1	6	3	8	4	6	4	3	1
13 Service		9	3	9	1	9	13	3	2
14 Service Other		2		4	1	1	3	2	

Appendix III: Data rectification.

Table 15: Data rectification.

Adjustment	Remaining companies	Remaining financial statements	Of which: HGB	Of which: Tax
0. Initial dataset	143,991	718,927	6,804	711,511
1. Drop if year < 1994 or year > 2002	94,801	410,382	4,132	405,640
2. Drop if balance sheet not according to HGB, Tax	94,668	409,772	4,132	405,640
3. Drop if total assets <= 0	94,668	409,769	4,132	405,637
4. Drop if financial year / fiscal year < 11 months.	82,186	351,571	3,170	348,401
5. Drop if sales = 0 or missing	80,385	343,320	3,038	340,282
6. Drop if personnel costs = 0 or missing	75,780	323,598	2,895	320,703
7. Drop if investments > 60% of total assets	75,753	323,396	2,893	320,503
8. Drop if dummy for the initiation of insolvency proceedings missing	75,438	319,841	2,865	316,976

Appendix IV: Robustness Check: Estimation per year.

An estimation per year is useful for identifying potential structural breaks in the data. The following tables clearly show that there are no such problems in the underlying dataset as all significant variables show the expected sign and similar values over the years, without displaying obvious patterns or trends. Again, both models perform quite similarly, with a relatively weak performance in the years 1999 to 2001. This might be explained by the dotcom bubble of those years, when enthusiasm about the growing role of the internet led to a boom in companies being set up. During this upturn and the following crash, the survival of some companies and the insolvency of others might not have followed typical patterns.

Table 16: Model estimated per year.

Variable/Year	1994	1995	1996	1997	1998	1999	2000	2001	2002
EBITDA ROI	-6.125***	-5.182***	-5.723***	-5.988***	-6.086***	-5.509***	-4.559***	-4.643***	-6.826***
Debt structure I	0.811	0.560**	1.121***	0.763***	1.046***	0.940***	0.718***	0.601**	0.689*
Debt structure II	2.025***	1.711***	2.732***	2.143***	2.025***	1.935***	1.590***	1.591***	1.931***
Total asset turnover	-0.143	-0.405***	-0.423***	-0.312***	-0.367***	-0.249***	-0.245***	-0.319***	-0.431***
Equity ratio	-5.958***	-3.612***	-4.571***	-3.991***	-4.842***	-3.565***	-2.866***	-4.155***	-4.066***
Log TA	0.382***	0.180***	0.296***	0.155***	0.153***	0.108***	0.070**	0.031	0.024
Constant	-9.399***	-5.462***	-7.039***	-5.159***	-5.041***	-4.696***	-4.079***	-3.747***	-4.195***
N	46429	51118	51401	45027	33080	28126	24812	21793	17038
AUR	0.812	0.799	0.828	0.795	0.804	0.769	0.755	0.777	0.825

Level of significance: * 10%, ** 5%, *** 1%

Variables: EBITDA ROI: EBITDA per total assets, Debt structure I: liabilities to financial institutions per total liabilities, Debt structure II: current liabilities per total liabilities, Total asset turnover: sales per total assets, Equity ratio: equity per total assets, Log TA: log(total assets).

Table 17: Benchmark model using the variables of Moody's Risk Calc^{TM} for Germany, estimated per year.

Variable/Year	1995	1996	1997	1998	1999	2000	2001	2002
Payables payment period	0.000	0.002 ***	0.001 ***	0.002 ***	0.001 *	0.002 ***	0.003 ***	0.001
Capital structure	1.181 ***	1.300 ***	1.366 ***	1.267 ***	1.283 ***	1.018 ***	1.125 ***	1.000 **
Net debt ratio	1.425 ***	0.617 *	0.910 ***	0.728 **	0.896 ***	0.486 **	0.780 **	0.338
Equity ratio	-0.248	-0.483 **	-0.753 ***	-0.798 ***	-0.495 ***	-1.011 ***	-1.126 ***	-1.006 ***
Cashflow per liabilities	-0.091	-0.358	-0.099	-0.898 ***	-0.049	-0.600 **	-0.092	-0.498 **
EBITD ROI	-5.077 ***	-6.785 ***	-5.404 ***	-5.452 ***	-6.096 ***	-4.644 ***	-4.165 ***	-6.147 ***
Net profit ratio	0.401 **	0.441 *	0.491 ***	0.326 **	0.244 **	0.351 **	-0.192	0.092
Personnel cost ratio	0.936 ***	0.735 ***	1.301 ***	0.315 ***	0.269 ***	0.187 ***	-0.078	0.048
Sales growth	0.354	0.275	0.463 **	-0.399	0.049	-0.016	-0.314	-1.253
(Sales growth)^2	-0.028	-0.098	-0.036 *	0.014 *	-0.007	-0.044	0.028	0.086
Constant	-6.870 ***	-6.524 ***	-6.605 ***	-5.237 ***	-5.437 ***	-4.618 ***	-4.987 ***	-4.425 ***
N	44867	42368	39573	29566	24648	22228	19528	16256
AUR	0.769	0.802	0.784	0.779	0.764	0.768	0.777	0.803

Level of significance: * 10%, ** 5%, *** 1%

Variables: Payables payment period: (Trade payables per sales)·360, Capital structure: (current liabilities and liabilities to financial institutions) per total liabilites, Net debt ratio: (current liabilites – current assets) per total assets, Equity ratio: (equity – intangible assets) per (total assets – intangible assets – cash and cash equivalents – land and buildings), Cashflow per liabilities: cash flow per total liabilities, EBITD ROI: EBITD per total assets, Net profit ratio: operating profit per sales, Personnel cost ratio: wages and salaries per sales, Sales growth: sales per sales last year.

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