doi: 10.36689/uhk/hed/2023-01-055

Using the Survival Analysis to Predict a Company's Creditworthiness

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Abstract: The boom in intra-group financing provoked a reaction from the OECD which requires the assessment of intra-group loans according to the principles of transfer pricing within the scope of activities aimed at limiting tax avoidance. The use of the group rating of MNEs is not unambiguous, for which reason the use of other methods of assessing a borrower’s creditworthiness, such as the use of scoring models, comes into consideration. The transfer of these models from other countries for application in the Czech Republic is debatable, which is why we consider the use of survival analysis methods for assessing a borrower’s creditworthiness, i.e. for the assessment of a company’s future ability to repay a loan provided and the interest related to it, in this paper. The possibility of using this approach was tested against the example of enterprises in one branch (NACE CZ 25). Enterprises with long-term negative equity were considered enterprises unable to repay a loan. We estimated a model with a high level of predictive power for the occurrence of financial distress risk using an extended Cox model with time varying covariates.

Keywords: transfer pricing of a financial transaction; creditworthiness assessment; financial ratio; survival analysis methods; extended Cox model

JEL Classification: G38; C41; H25

1. Credit Risk Assessment of Associated Enterprises

The provision of loans for the financing of corporate activities is shifting from bank financing to intra-group financing for large multinational companies. Multinational enterprises (MNEs) focus on the elimination of external indebtedness and more efficient use of funds within the holding company as part of their treasury management. The centralisation of free funds in a single account (master) makes it possible not only to achieve better appreciation of free funds, but also to reduce external indebtedness which is associated with significant savings on interest costs for the entire holding. They often use cash pooling, financial guarantees and, first and foremost, intra-group loans for this purpose. The efficient management of multinational enterprises can help optimise the cost of capital and support their value (and share price).

The OECD is responding to this trend as part of its activities aimed at limiting profit shifting to countries with lower taxation (base erosion and profit shifting – BEPS) – see Deloitte (2021). Transfer pricing guidance on financial transactions, which requires an assessment of a loan provided according to the principles of transfer pricing, was issued in

2020 (OECD, 2020). This means that it will be necessary to consider whether a loan has been made under conditions that would have applied between independent enterprises, and that the same commercial considerations such as creditworthiness, credit risk and economic circumstances are relevant. The given credit assessment will include understanding the business itself as well as the purpose of the loan, how it is to be structured and the source of its repayment, which may include analysis of the borrower’s cashflow forecasts and the strength of the borrower’s balance sheet (OECD, 2020, paragraph 10.54). Companies are not prepared for these steps and do not have an evidence base that would allow them to create their own models for the assessment of a borrower’s creditworthiness.

The basic question when providing intra-group financing is assessment of whether it is a loan or a hidden form of increase in equity (Brychta et al., 2021). If the business cannot prove that this involves a credit relationship, then the costs of the credit (interest and other expenses) are non-tax-deductible costs. This assessment is based both on the economic nature of the financial transaction (its purpose, maturity date, the right to recover the principal and interest, etc. are stipulated) and on assessment of the capital adequacy of the recipient of the loan, i.e. that the recipient is not over-indebted (and no independent company would, therefore, grant it a loan). Therefore, the arm's length principle is that before pricing the loan (interest rate), it must first be demonstrated that the company is not over-indebted and the level of its credit risk must be determined.

The ratings provided by independent credit rating agencies (CRAs) are a widely used and recommended credit risk assessment tool. In view of the time-consuming nature and financial demands of this process, however, the services of CRAs are generally used by MNEs to evaluate the holding as a whole (the MNE group), and are used only minimally to evaluate subsidiaries. Although the fact that a subsidiary is part of a group of multinational enterprises affects its credit rating, the same rating assessment as the assessment of the parent company cannot be applied to all subsidiary enterprises (Solilová et al., 2022). The following table presents a recommended adaptation of the rating of subsidiaries based on the rating of the parent company.

In view of the complexity of the rating determination procedure, the intention is to assess the default risk of an entity in a simplified manner. This leads to the creation of models assessing the risk of default, referred to as bankruptcy models. The principle of the construction

Table 1. Rating recommendation for a subsidiary in an MNE group (Fossati, 2020)

Category of subsidiary	Features	Rating
Core	Integral to the group’s current identity and future strategy.	Group rating
Highly strategic	Almost integral to the group’s current identity and future strategy.	One notch lower than group rating
Strategically important	Less integral to the group than “highly strategic” group members. The rest of the group is likely to provide support in most foreseeable circumstances. However, some factors raise doubts about the extent of group support.	Up to three notches above the stand-alone rating
Moderately strategic	Not important enough to warrant support from the rest of the group in most foreseeable circumstances. Nevertheless, there is potential for some support from the group.	One notch above the stand-alone rating
Non-strategic	No strategic importance to the group.	Stand-alone rating

of these models is the search for differences between the financial indicators of enterprises that are financially healthy and prosperous and those that are suffering from financial difficulties. These are known as scoring models and represent aggregated indices for evaluating the financial situation of an enterprise. The future development of an enterprise is estimated (in simplified form: prosperity, grey zone, risk of bankruptcy) by comparing it with the score values of other enterprises used to derive the model. Given that the value of these indicators depends on the given sector (taking on different values in different branches of enterprise) and also changes over time as a result of external conditions (first and foremost inflation, the prices of sources of financing, different levels of taxation in individual countries), their transferability from other countries for use in the Czech Republic is problematic. At the very least, they need to be updated with regards to external conditions.

The existing types of models differ mainly in the data they evaluate (accounting vs. market data) and the method in which they were derived. Historically, the following approaches have primarily been developed:

- Beaver's profile analysis, which is a univariate comparison of data on financially healthy enterprises and enterprises that have gone bankrupt. The greatest importance was attributed to the ratio of cash flow (profit after tax + depreciation) to total debts – see Beaver (1996).
- Altman-type models (Altman's model, IN05, Taffler's model). These models are based on multidimensional methods of assessing company risk. They most often combine around five financial ratios. In the case of the Altman model, the output is a Z-score value which is compared to a stipulated cut-off value. It must be added that the Z-score does not have any constrained domain – see Altman (1968).
- Zmijewski-type models. These models again combine a number of ratios calculated from a company's financial statements, though the output of the model takes the form of the probability of bankruptcy (within an interval of 0 to 1) – see Zmijewski (1984) or more generally Slavíček and Kuběnka (2016).
- Merton-type models. Unlike the preceding types of model, these are not based on comparison of the past data of healthy and bankrupt businesses. They are based on the application of the Black-Scholes option pricing model and derive the probability of bankruptcy based on the volatility of the stock value – see Merton (1974).

The first two models can be used to calculate a score that can take on almost any value (the value of the score is not limited in any way). The numbers can vary significantly, for which reason the average for the group may be distorted. This also has an impact on the estimated rating grade and the anticipated risk margin. In the second type of model the output takes the form of a probability, which is a number normalised within an interval from 0 to 1, meaning that the possibility of a result in the form of an outlier is extremely limited.

In this paper, we consider the question as to whether it is possible to use survival analysis methods for the purposes of assessing the debt capacity of a loan recipient and its credit risk. We begin from the assumption that a company that is over-indebted over the long term and that does not generate resources for its further development is not creditworthy, for which reason indebtedness ratios (primarily the debt-to-equity ratio and interest coverage ratio), indicators measuring the company's ability to generate resources to pay its liabilities (return on assets, operating cashflow to debt, earnings before interest, taxes, depreciation and amortisation to debt), assets turnover, net working capital ratios, and the age and size of the enterprise will be used to assess a borrower's creditworthiness. This is a highly topical issue due to high level of corporate indebtedness. While corporate debt (the debt securities, loans and financial derivatives and employee stock options of non-financial corporations) represented 100% of EU GDP in 2010 (or €11 trillion), it increased to 111% of EU GDP (or €14.9 trillion) in 2020 (see EU, 2022).

2. Methodology

Data was retrieved from the Orbis Academic database. The study focused on a rather small sample in line with our goal. The data covers the ten-year period from 2009 to 2019. The dataset consists of accounting data on 906 companies. These are manufacturing firms belonging to the C.25 NACE classification "Manufacture of fabricated metal products, except machinery and equipment". During the analysed period, 378 of these companies were identified as "zombies", i.e. companies that had reported negative equity in three consecutive years (Blažková and Dvouletý (2022), for example, have labelled this type of firm "zombies").

The dataset was divided into a training and testing sample with a 75% to 25% data partition regarding company identification for out-of-sample predictive discrimination. The training sample consists, therefore, of 680 companies with 4,470 observations and the testing sample consists of 226 companies with 1,354 observations.

2.1. Research Method

Survival analysis methods have recently come to the forefront of interest for researchers in economic and financial fields. One of the most widely used of these methods is the semiparametric Cox proportional hazards model. Its general form is as follows (Kleinbaum & Klein, 2012):

$$h(t,X) = h_0(t)exp(\sum_{i=1}^{p} \beta_i X_i) \quad (1)$$

where $h(t,X)$ is the subject specific hazard at time *t,* which is the hazard related to an individual with a given specification of a set of predictors denoted by X, $h_0(t)$ is the baseline hazard function that changes over time *t,* and $exp(\sum_{i=1}^{p} \beta_i X_i)$ represents the relative hazard as a vector of *p* time invariant covariates, for which reason this part of the expression lacks the time element. This time-independent specification of the Cox model has been applied in previous studies with a similar research focus (e.g. Gemar et al., 2019; Karas, 2022; Kristanti et al., 2019), although we believe that the time variability of financial indicators also plays a role in predicting financial distress. We have therefore used an extended Cox model with time-varying covariates, which has enabled the use of annual financial ratios as predictors of an event – financial distress. The extension of the Cox model that respects both the time-independent and time-varying covariates can be written as (Ledwon & Jäger, 2020):

$$h(t, X) = h_0(t) exp(\sum_{i=1}^{p_1} \beta_i X_i + \sum_{j=1}^{p_2} \delta_j X_j(t)) \quad (2)$$

where $h(t, X)$ is hazard at the time t related to an individual with a given specification of a set of predictors denoted by the X, $h_0(t)$ is the baseline hazard function that changes over time *t*, β_i and δ_j represents coefficient for p_1 time invariant and p_2 time dependent covariates.

The statistical significance of covariates was evaluated using the Wald test with the null hypothesis that the covariate coefficient equals zero. The assumption of the proportionality of hazard was verified by Schoenfeld residuals with the null hypothesis of respecting the assumption about proportionality (Kleinbaum & Klein, 2012).

2.2. Variables

The variables employed in the survival analysis are presented in Table 2 along with the respective descriptive statistics and the expected sign of regression coefficients. The financial ratios and the expected sign for the survival analysis were based on the previous empirical

Table 2. Descriptive statistics of variables used for the full sample of 906 companies.

Variable	Description	Exp. Sign	n	mean	sd	median	min	max
AGE	Initial Age (in years) of a Company (in 2011)	(-)	5,824	13.54	6.06	14.00	3.00	61.00
EVENT	Becoming a Zombie (1) or not (0)		5,824	0.06	0.25	0.00	0.00	1.00
EBIT	Earnings Before Interest and Tax*	(-)	5,824	9.86	35.40	0.37	-31.81	322.66
EBITDA	Earnings Before Interest, Tax, Amortisation and Depreciation*	(-)	5,824	15.75	48.87	0.78	-16.67	428.38
TA	Total Assets*	(-)	5,824	120.70	341.02	12.44	0.01	2,876.62
S	Sales*	(-)	5,824	149.71	409.63	14.29	0.00	3,653.88
ROA	EBIT to Total Assets	(-)	5,824	0.04	0.29	0.04	-2.37	0.86
ROS	EBIT to Sales	(-)	5,824	-3.03	28.32	0.05	-339.40	4.77
INTRS	Interests Paid	(+)	5,824	0.60	2.03	0.01	0.00	17.61
S/TA	Sales / Total Assets	(+)	5,824	1.46	1.33	1.25	0.00	8.41
NWC/TA	Net Working Capital / Total Assets	(-)	5,824	0.11	1.37	0.28	-15.61	1.00
CA/CL	Current Assets / Current Liabilities	(-)	5,824	3.91	7.52	1.66	0.00	60.70
St/TA	Stocks / Total Assets	(+)	5,824	0.14	0.17	0.07	0.00	0.88
IC	EBIT / Interests Paid	(-)	5,824	17.80	60.98	0.00	-56.58	509.39
OCF/S	Operating Cashflow / Sales	(-)	5,824	-2.44	24.71	0.09	-295.85	11.48
OCF/CL	Operating Cashflow / (Current Liabilities + Interests Paid)	(-)	5,824	0.68	4.55	0.26	-27.53	43.54
TL/TA	Total Liabilities / Total Assets	(+)	5,824	0.74	1.80	0.46	0.00	19.97

Note: Variables marked with an asterisk (*) are reported in mil. CZK, abbreviations used: Exp. Sign = expected sign of coefficient; n = number of observations; sd = standard deviation.

research (e.g. Altman et al., 2010; Chava & Jarrow, 2004; Gupta et al., 2018; Karas et al., 2021; Kramoliš & Dobeš, 2020; Ledwon & Jäger, 2020; Shumway, 2001). The financial variables earnings, sales and assets are considered proxies for the size of a company. A third reporting of negative equity in a row was considered the occurrence of an event. The survival analysis was applied on the follow-up period from 2011 to 2019, since the two preceding years served for the identification of the financial distress of firms in later years.

The preliminary exploratory analysis showed the presence of extreme outlier values for most of the variables, for which reason all variables were Winsorised at the 0.5 or 99.5 percentile level. The threshold for Winsorising was set at such a low level to prevent the bias of regression results caused by extreme outliers on one hand, while retaining the outliers that are believed to be characteristics of firms in financial distress on the other hand.

Correlation was checked by Pearson's correlation coefficient; the respective results are depicted in Figure 1. The correlation analysis revealed strong positive correlation between earnings, assets and sales, as well as between ROS and the cashflow to sales ratio. Strong negative correlation was identified between the TL/TA ratio and the net working capital to assets ratio.

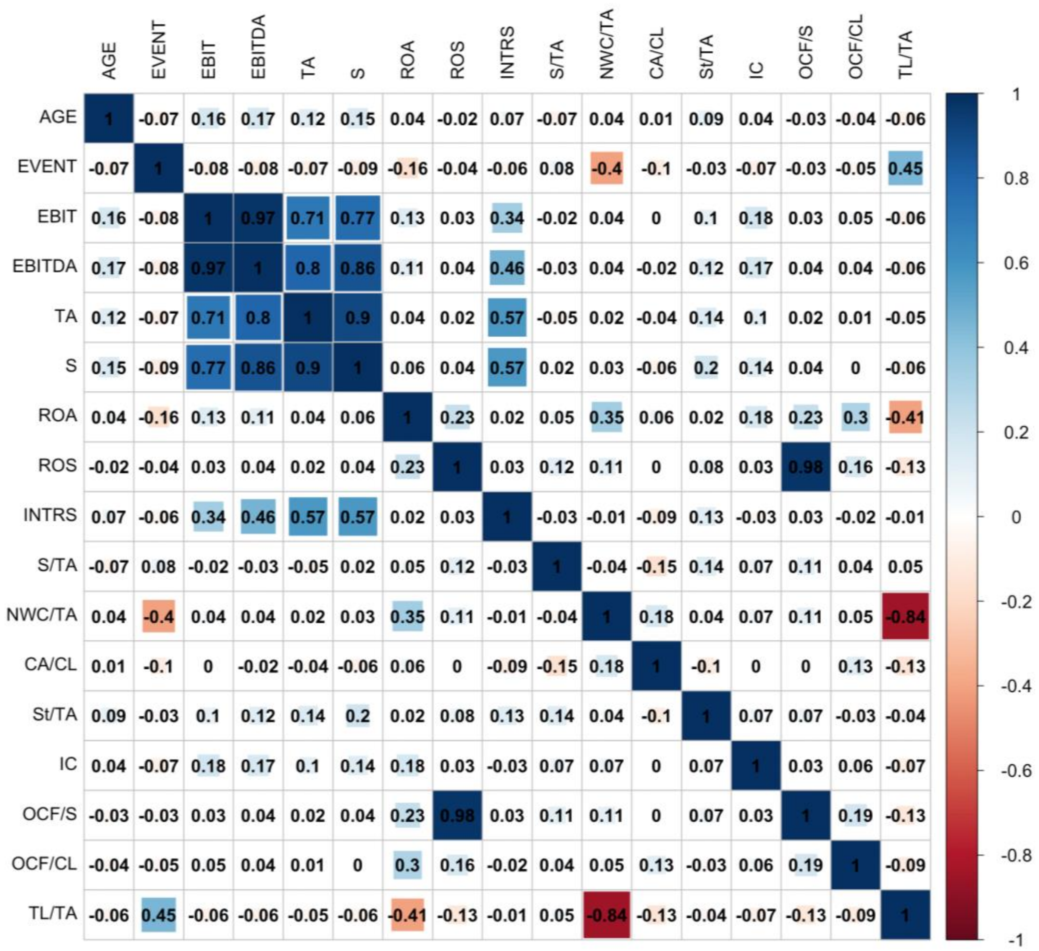

Figure 1. Correlation plot including correlation coefficients.

Four variables were excluded from further analysis, namely EBIT, EBITDA, sales, and NWC/TA, to prevent multicollinearity problems.

3. Results

The model was estimated using a stepwise procedure based on Bayesian information criterion (BIC). Table 3 shows the results of several steps of model fitting. The results suggest exclusion of five variables (ROA, ROE, S/TA, OCF/CL and OCF/S) which do not significantly contribute to the model. The p-value for Schoenfeld residuals for the entire model (not for individual covariates) is reported in the table as GLOBAL. Values above a significance level of 0.05 indicate that the assumption of proportionality holds true. For interpretational reasons, the respective coefficients (β, δ) are reported in its exponents (exp(coef)).

Table 3. Results of the extended Cox model for four steps of model fitting

	COX1		COX2		COX3		COX4	
Var	exp(coef)	se(coef)	exp(coef)	se(coef)	exp(coef)	se(coef)	exp(coef)	se(coef)
TL/TA	1.149***	0.010	1.151***	0.011	1.148***	0.010	1.157***	0.011
TA	0.990***	0.002	0.990***	0.002	0.990***	0.002	0.99***	0.002
CA/CL	0.875***	0.035	0.874***	0.036	0.875***	0.035	0.873***	0.036
IC	0.987***	0.004	0.986***	0.004	0.987***	0.004	0.987***	0.004
St/TA	2.114*	0.314	2.127*	0.314	2.116*	0.314	2.066*	0.316
AGE	0.979*	0.011	0.978*	0.011	0.979	0.011	0.979*	0.011
ROA			1.059	0.110				
ROE			1.000	0.000				
S/TA							1.045	0.037
OCF/CL					0.995	0.010		
OCF/S							1.002	0.002
GLOBAL (sch.resid.)		p=0.164		p=0.156		p=0.189		p=0.0406
BIC	3,073.76		3,084.65		3,079.09		3,081.88	

Significance codes: *significant at the 5% level, **significant at the 1% level, ***significant at the 0.1% level

The final estimated model is considered the COX1 model and its results are depicted in Figure 2. The signs of all coefficients are in line with expectations. Variables with a positive effect on the risk of financial distress are the ratio total liabilities to total assets (TL/TA) and the ratio stock to total assets (St/TA). A unit change in TL/TA results in 1.15-fold increase of hazard. Similarly, a unit change in St/TA results in a 2.11-fold increase in the risk of financial distress. Variables having a negative effect on hazard, i.e. decreasing the risk of financial distress, are total assets (TA), interest coverage (IC) as a ratio of EBIT to interest expenses, the ratio current assets to current liabilities (CA/CL) and the initial age of the company (AGE). The results suggest a 2% decrease in the risk of financial distress with every additional year in the initial age of a company. In other words, the younger the company is, the higher the risk of financial distress. Every additional million of total asset accounting value also reduces the risk of financial distress by one percent. Although a risk reduction of one unit change seems negligible, considering the total assets variable as a measure of company size and regarding its range in the sample, it outlines a significant difference in the risk of financial distress between, for example, small and large companies in favour of the latter. Finally, one unit change in the financial ratios CA/CL and IC results in a 13% and 1% reduction in the risk of financial distress, respectively.

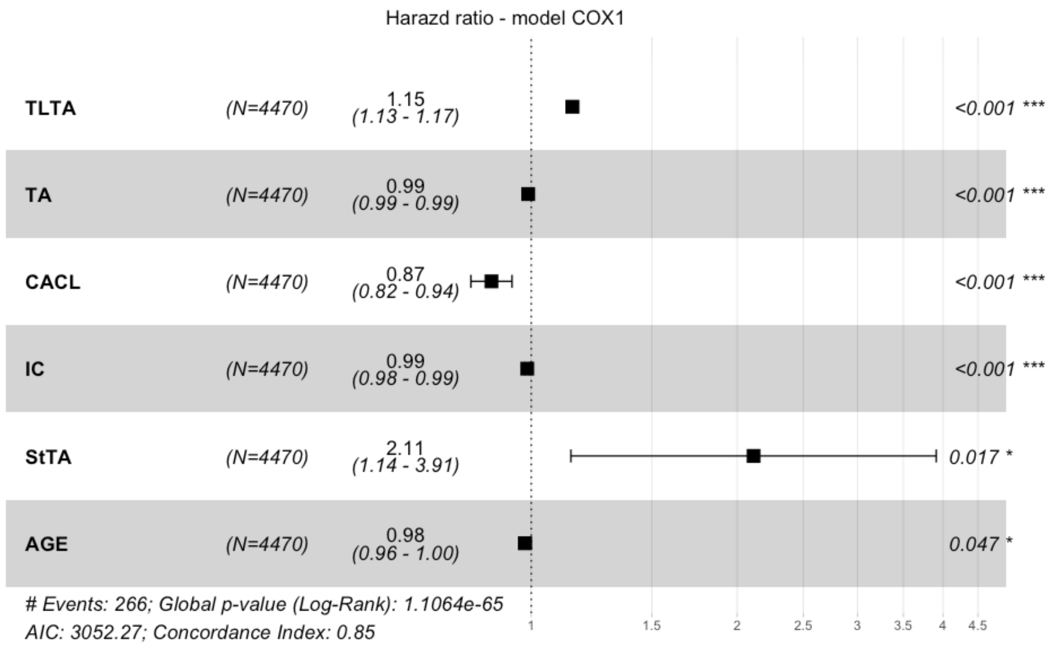

Figure 2. Forest plot for the estimated COX1 model.

The predictive performance of the model was evaluated by the area under the ROC (receiver operating characteristic) curve using the inverse probability of censoring weighting estimates of the time-dependent AUC as suggested by Suresh et al. (2022). The AUC is a scale-invariant measure, with 1 indicating perfect discrimination and 0.5 indicating chance-like accuracy. Out-of-sample validation was performed on a testing sample of 25% of the companies in the collected dataset. The results are depicted in Figure 3 for the whole follow-up period with the results of the AUC (in %) for the first year of the follow-up period.

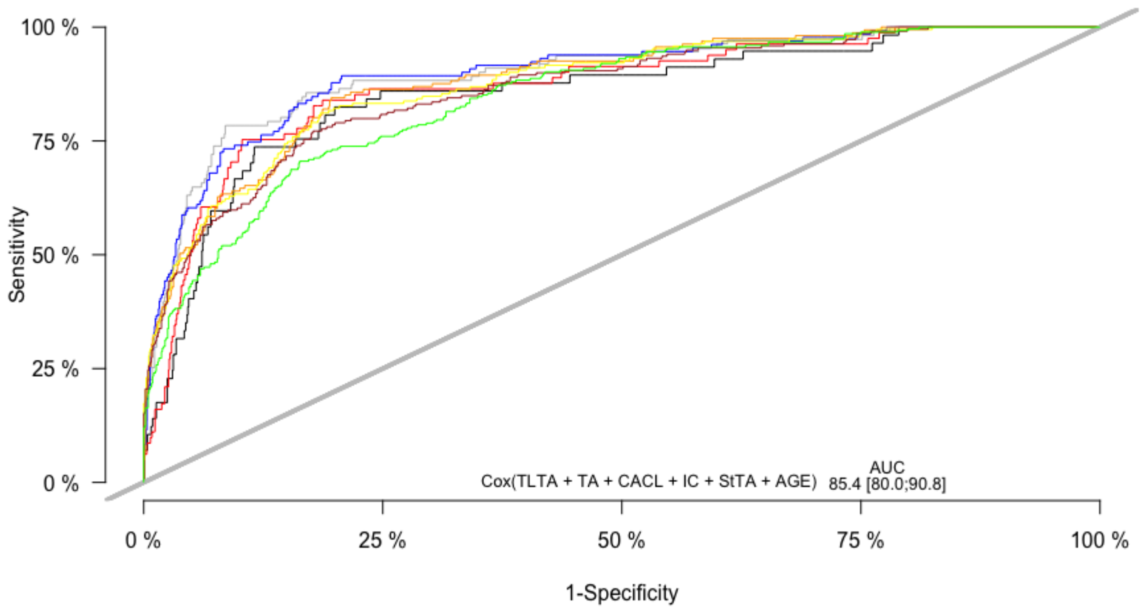

Figure 3. The ROC curve and time-dependent AUC for every year of follow-up (black t=1, red t=2, grey t=3, blue t=4, orange t=5, yellow t=6, brown t=7, green t=8).

The lowest value of the AUC was 0.846 in the eighth year, the highest value was 0.899 for both the third and fourth year of the follow-up period. This suggests, therefore, a relatively high level of predictive discrimination of the model.

4. Discussion

The high level of predictive discrimination of the model entitles us to conclude that the use of an extended Cox model with time-varying covariates is a suitable tool for predicting financial distress when using annual financial ratios as predictors. The model predicts the probability with which a company will face financial distress in the following year. The model predicts the probability with which a company will fall into financial distress in the following period. This makes this type of model suitable for the prediction of creditworthiness. It is surprising that the predictors used did not include the indicator debt-equity ratio, which is used by the financial authorities as a criterion for assessing a financial transaction between connected persons to adjudge whether it is a loan or a hidden increase in equity. Similarly, it is also surprising that neither of the indicators EBITDA and OCF/CL (operating cashflow to current liabilities and interests paid), which are considered indicators of a company's ability to pay its liabilities, were included among the predictors. In further research, it will be necessary to devote attention to testing the predictive ability of other indicators and their economic justification.

The selected approach is original in that it does not only consider companies that have officially gone bankrupt, but also companies that are over-indebted over the long term to which no independent company would provide a loan. The data does not relate merely to companies forming a holding, as we preferred to analyse companies in the same branch of enterprise. Its originality also lies in the methodology we used for the assessment of credit risk. The limitations of the study are twofold – the sample analysed was limited to the field of metal manufacturing and covered a short period, the beginning of which was, in addition, also affected by the economic crisis. However, the sample served well for the goal of the paper to be achieved. The results provide a basis to be built on in further research.

Acknowledgments: This paper was supported by the Technology Agency of the Czech Republic within project No. TL05000328 "Setting the Market Price for Financial Transactions Using the Arm's-length Principle".

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