Predicting Bankruptcy of Manufacturing Firms

Martin Grünberg and Oliver Lukason

***Abstract*—This paper aims to create bankruptcy prediction models using logistic regression and neural networks based on the data of Estonian manufacturing firms. The models are composed and tested on the whole population data of bankrupt firms and their vital counterparts for years 2005-2008. Composed models are also tested on the data of firms from economic recession years of 2009-2010. The results indicate that models based on different methods have similar predictive abilities, yet two and three years before bankruptcy they are not as good as for one year before bankruptcy. Also, the models do not perform as well when using data from economic recession years.**

***Index Terms*—Bankruptcy prediction, manufacturing firms.**

I. Introduction

Since 1960ies the failure prediction domain in literature has flourished. The main idea of failure prediction studies is to establish decision rules based on a set of variables (commonly financial ratios), which would facilitate to discriminate vital and failing firms. During past decades many literature reviews (e.g. [1]-[6]) have appeared, which list a myriad of different prediction studies and the amount of relevant research seems to be quickly increasing. The innovativeness of emerging studies mostly lies in novel statistical techniques, leaving other possibilities to contribute to literature in the background.

Still, for increasing the validity of a prediction model, more attention should be directed to the data applied. Therefore, this paper does not aim to make a contribution by elaborating a new statistical technique for failure prediction, but instead addresses to major limitations concerning the data used in prediction model composition. The objective of the paper is to compose bankruptcy prediction models by using one classical and one modern statistical technique, at the same time addressing a set of known data limitations. The novelty of the paper rises from the objective, namely an elaborate dataset will allow addressing multitude of limitations that are rarely viewed together in available empirical studies. As a classical technique, logistic regression, and as a modern technique, neural networks will be applied in empirical analysis. Because of that, literature review is mostly focused on given two methods and less attention is directed to others.

The paper is structured as follows. The introductory part is followed by a short review of literature, which specifically focuses on two methods chosen to model failure in current study and in addition addresses some of the general features of bankruptcy prediction models. The following empirical analysis is broken into two parts, of which the first addresses data and methodology, whereas the second outlines results of statistical analysis with relevant comments and discussion. The paper classically ends with conclusive remarks.

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Oliver Lukason and Martin Grünberg are with the Tartu University, Faculty of Economics and Business Administration, Narva road 4, Tartu 51009, Estonia (e-mail: oliver.lukason@ut.ee).

II. Summary of Relevant Literature

Bankruptcy prediction models have been actively composed since the seminal work by Altman (see [7]). The models are based on comparing two sets of firms, in broad terms “bad” and “good”. The “bad” firms are classically failed firms, but the failure can have different notions, as demonstrated in [8]. Still, the most common option is to use data of bankrupt firms in models, i.e. firms for which permanent insolvency has been declared by court. Of course, through different legal environments the content of permanent insolvency varies, although not in very large borders. Contrary to relatively clear definition of “bad” firm, the notion of “good” firm can vary to large extent. Literature can be divided into two sections, where the first one uses successful counterparts for bad firms, whereas the other section applies just vital firms functioning at the time of model composition. In practice, a lot of firms can be vital but not very well functioning.

The methodologies to compose given models can be broadly divided into two domains – classical and novel methods. Of classical methods, univariate analysis (e.g. [9]), discriminant analysis (e.g. [7], [10], [11]), logistic regression analysis (e.g. [12], [13]) have been the most widely used ones. Of given methods, logistic regression analysis is probably the best option, as univariate analysis is too simplistic and discriminant analysis has a lot of requirements for input data. The application of logistic regression analysis results in a score for each firm which allows determining the probability to be bankrupt [14]:

$$p = \frac{1}{1 + e^{-(b_0 + b_1 x_1 \,..+ b_n x_n)}}$$

where p is bankruptcy probability, b_i (i=0,…, n) are coefficients and n is the number of independent variables x_i (i=1,…, n).

When the set of classical approaches is quite narrow, then there are numerous novel ones, the rise of which is to a large extent connected with the development of computers. Of most commonly applied, survival analysis (e.g. [15], [16]), decision trees (e.g. [17]), neural networks (e.g. [18], [19]) can be brought out, although the spectrum of experimentations with different methods is very large. As different novel methods have positive and negative sides, none of them can directly be considered superior of others. In recent years, a myriad of bankruptcy prediction studies has been conducted based on neural networks (see [20]), which makes it most popular among novel approaches. In most general terms artificial neural networks is a nonlinear approach, which combines input data through different layers into a single output. As demonstrated in [20], numerous different approaches have been used for artificial neural network creation, the multilayer perceptron trained using a back-propagation method being most widely applied option. Still, genetic algorithm as method should lead to better results, but is more time consuming [25].

The classification accuracies have remarkably varied through studies (see [5]), so excellent and poor examples can be found. An important aspect is definitely the dataset based on which the accuracy is calculated. Commonly, predictive abilities on model composition data have been remarkably higher compared to test (control) data. Additionally important question is the accuracy in time, as it has been noted that models can lose a lot of their predictive power when applied for different time period (see [21]). The variation in prediction abilities could also be caused by different failure processes of firms (see [23], [24]).

The variables applied in models have classically been financial ratios (see [1]), which are easily accessible because of the publicly available financial information of firms and besides that have through firm failure theory the ability to notify of forthcoming decline. Still, on numerous occasions various other variables have been applied as well.

III. Data and Methodology

TABLE I: Number of Bankruptcies in Estonian Manufacturing Sector in 1998-2012.

Year	Number of bankruptcies	Year	Number of bankruptcies
1998	36	2006	60
1999	68	2007	57
2000	80	2008	78
2001	85	2009	157
2002	72	2010	134
2003	80	2011	73
2004	79	2012	52
2005	70		

Current paper applies data of Estonian bankrupt firms. A list of all bankruptcies with exact declaration date is provided to authors by Estonian Centre of Registers and Information Systems. From given organization annual financial reports of firms were also obtained. Annual reports are available since 1997, i.e. from the time the register was created in its current form. The first complete year the data is available for is 1998. The composition of bankruptcy prediction model over all sectors is not scientifically justified, as firms in different industries have large variation in their business processes, which in turn directly affects figures in financial reports. Mixing data over different sectors will likely result in a model with no predictive power. Therefore, for current study one specific sector will be chosen. Firstly, it is important to choose a sector with as many bankruptcy cases as possible, because the financial data of bankrupt firms is often missing and therefore in case of smaller sectors dataset can be limited to a point where statistical analysis is not possible. Because of that, two sectors (manufacturing, i.e. NACE C, and wholesale & retail, i.e. NACE G) are the candidates with the largest number of insolvency cases. Out of those two, manufacturing industry will be chosen, as firms from that sector have more sophisticated business processes and most of the classical models (e.g. [7], [12]) are also based on the example of manufacturing firms.

Table I lists the bankruptcies that occurred in Estonian manufacturing sector in 1998-2012. As the next step, years for analysis have to be chosen. The performance of bankruptcy prediction models is normally tested for several years before failure occurs, usually up to three years. Because of that, annual reports at least for four years before the bankruptcy must be downloaded, as some financial ratios must be calculated based on the data of two consecutive years. Also, in order to increase the comparability of cases, not all bankruptcies will be included in analysis. Namely, the ordinary limitation in studies has been the use of annual reports from previous years to bankruptcy without considering the exact bankruptcy date. This can be very misleading, as for instance bankruptcy can occur between 1st January and 31st December, spreading the possible difference in time between the last year's report and bankruptcy time up to one year. Therefore, firms that bankrupted only either in the first or last quarter will be included in analysis. For those that bankrupted in the last quarter, annual report from previous year will be used, whereas for those that bankrupted in the first quarter, the report from the one but previous year will be applied. In this way the maximum difference between bankruptcy time and information from last report is half an year, but the mean and median would of course be only a few months. It must also be noted, that according to Estonian law firms must submit reports the latest half a year after accounting year has ended, which means that there are practically no firms submitting it in the first quarter. Also, in case of bankruptcy the firm's management is not obliged to submit it. For those two reasons one but previous report can be applied in case of first quarter bankruptcies. As noted before, some financial ratios demand using data from two years and when the report from one but previous year is being used, data for five years before bankruptcy year must be obtained for firms that bankrupted in the first quarter. As Estonia radically changed its taxation system in the year 2000, namely profit taxation was abandoned and income tax from that on was imposed only on dividends, data from given year can therefore be the first one to be used to get comparable information. Because of previously given discussion, the first year when bankruptcies occurred can be year 2005. As during years 2009 and 2010 Estonia had severe economic recession and GDP seriously plummeted in comparison to previous periods, those years cannot be included in analysis. This also accounts for two forthcoming years (i.e. 2011 and 2012), as for bankruptcy cases from those years some financial data should still be obtained from given recession years. So bankruptcies that occurred in 2005-2008 will be used in current analysis and therefore financial data of firms comes from years 2000-2007, which were all economic growth years. In order to check whether bankruptcy models composed based on economic growth years' data are applicable during recession, year 2009-2010 bankruptcies will also be applied for testing.

TABLE II: CASES IN CURRENT ANALYSIS.

Firm status \ Dataset type	Total cases (2005-2008 vital vs bankruptcies)	Model composition dataset (2005-2008 vital vs bankruptcies)	Test dataset (2005-2008 vital vs bankruptcies)	Test dataset (2009-2010 vital vs bankruptcies)
Vital	16360	11542	4908	8990
Bankrupt	83	58	25	190

TABLE III: VARIABLES USED IN STATISTICAL ANALYSIS.

Variable group	Variable formula
Solvency ratios	cash / current liabilities (X_1)
	current assets / current liabilities (X_2)
Capital structure ratios	equity / total assets (X_3)
	total liabilities / total assets(X_4)
	retained earnings / total assets (X_9)
Profitability ratios	operating profit / total sales (X_5)
	net profit / total sales (X_6)
	net profit / total assets (X_8)
Liquidity ratios	cash / total assets (X_{10})
	current assets / total assets (X_{11})
Efficiency ratio	total sales / average total assets of two years (X_7)
Size	Ln(total sales) (X_{12})
	Ln(total assets) (X_{13})
Other	Firm age at time of bankruptcy (X_{14})

Unlike in many previous studies which have used successful firms for comparison, current paper applies all vital firms to compare with bankrupt firms, whereas vitality is defined followingly. The firm should not be in liquidation or deleted/liquidated from register as of 31.12.2012. Also, the vital firm should be active, i.e. firms without turnover or very low turnover (below ten thousand euros) will be excluded. For each bankruptcy year all firms meeting before mentioned criteria will be included in vital group, because of what firms can be represented up to four times in the dataset, although their data is always unique. Table II lists the number of cases for analysis in current study. As often the prediction accuracy is not brought out on model composition dataset, but instead on test dataset, such approach will also be followed in current study. Out of the whole population, 70% of cases will be applied for model composition and 30% for testing the composed model. As noted earlier, the models will also be tested on the dataset of firms that bankrupted during economic recession. Bankrupted firms will be coded with 1 and vital with 0 for following analysis.

The variables for analysis will be based on most commonly used predictors listed in literature review of Dimitras *et al.* [1]. They represent seven different domains, whereas five of them are classical domains of ratios (solvency, profitability, capital structure, liquidity, efficiency). In total 14 variables are applied in the analysis and they have been listed in Table III.

TABLE IV: ANOVA TEST OF THE SIMILARITY OF MEANS FOR VARIABLES IN ANALYSIS.

Variable	Median		Mean		p-value
	Bankrupt	Vital	Bankrupt	Vital	
cash / current liabilities (X_1)	0.06	0.38	0.21	32.68	0.836
current assets / current liabilities (X_2)	0.66	1.74	0.78	44.95	0.929
equity / total assets (X_3)	-0.10	0.58	-221.32	0.43	<0.001
total liabilities / total assets(X_4)	1.78	1.03	223.03	1.17	0.012
operating profit / total sales (X_5)	-0.08	0.05	-2.04	-0.09	0.163
net profit / total sales (X_6)	-0.08	0.04	-3.38	-0.08	<0.001
total sales / average total assets of two years (X_7)	2.05	1.87	3.23	2.26	0.006
net profit / total assets (X_8)	-0.19	0.09	-5.82	0.11	<0.001
retained earnings / total assets (X_9)	0.00	0.22	-227.29	-0.10	<0.001
cash / total assets (X_{10})	0.07	0.12	0.13	0.21	<0.001
current assets / total assets (X_{11})	0.76	0.61	0.71	0.60	0.008
ln(total sales) (X_{12})	14.80	14.75	14.62	14.67	0.435
ln(total assets) (X_{13})	13.54	14.16	13.84	14.27	0.004
firm age at time of bankruptcy (X_{14})	6.50	8.00	7.16	8.06	0.182

TABLE V: CORRELATIONS BETWEEN VARIABLES IN ANALYSIS.

	X_1	X_2	**X_3**	X_4	X_5	**X_6**	**X_7**	X_8	X_9	**X_{10}**	**X_{11}**	**X_{12}**	X_{13}	**X_{14}**
X_1	1.00	**0.95**	0.00	0.00	0.00	0.00	-0.01	0.00	0.00	0.05	0.01	-0.02	-0.01	0.00
X_2		1.00	0.00	0.00	0.00	0.00	-0.01	0.00	0.00	0.04	0.01	-0.02	-0.01	0.01
X_3			1.00	**-1.00**	-0.01	-0.01	0.08	**0.93**	**1.00**	0.08	-0.12	0.09	**0.41**	0.10
X_4				1.00	0.01	0.01	-0.08	**-0.93**	**-1.00**	-0.08	0.12	-0.09	**-0.41**	-0.10
X_5					1.00	**0.95**	0.11	0.02	-0.01	0.05	-0.07	0.29	0.11	-0.09
X_6						1.00	0.13	0.01	-0.01	0.08	-0.06	0.34	0.12	-0.10
X_7							1.00	0.09	0.08	0.03	0.31	0.23	-0.18	-0.12
X_8								1.00	**0.92**	0.11	-0.16	0.11	**0.44**	0.08
X_9									1.00	0.07	-0.12	0.09	**0.41**	0.10
X_{10}										1.00	0.31	-0.19	-0.22	-0.09
X_{11}											1.00	-0.10	-0.35	-0.01
X_{12}												1.00	**0.77**	0.15
X_{13}													1.00	0.16
X_{14}														1.00

Two statistical techniques will be applied to create bankruptcy models in current study. Firstly, classical logistic regression analysis will be applied. Before given analysis, ANOVA test will be conducted to study which variables are significantly different through two groups (bankrupt and vital). Table IV shows ANOVA results and it can be seen that only a few variables have similar means in given groups. Noteworthy is the fact that values of both solvency measures are similar, whereas p-value indicates the similarity to be very large. Table IV shows some anomalous values, especially in case of mean, which is caused by the fact that extreme values have not been excluded (i.e. there is no exclusion of outliers). Therefore median values have been presented as well. None of the variables will be excluded from analysis as a result of ANOVA test, as they might still be significant discriminators in the logistic regression model.

Secondly, as multicollinearity can be an issue in logistic regression models, then those variables that have correlation with another variable exceeding 0.4 will be excluded from analysis. Table V lists correlations of variables. Correlations exceeding 0.4 have been bolded and underlined, except when the variable has been correlated with itself (the main diagonal). It can be seen, that high correlation is often between very similar variables, i.e. there is often the same denominator. Excluded are those variables, the exclusion of which reduces the number of correlations exceeding 0.4 the most. The variables used for logistic regression modelling have been underlined in Table V. For logistic regression model, the VIF values are also checked to discover possible multicollinearity issue.

The logistic regression analysis is conducted by using freeware statistical package R. As there are very large differences in the number of bankrupt and vital cases, they must be weighed to be equal in current analysis. Otherwise the result will be directed towards classifying the vital firms as correctly as possible, whereas the classification accuracy of bankrupt firms will not matter in model. The neural networks analysis is free of presumptions about variables, so all given in Table III have been applied. For neural networks analysis, genetic algorithm with a novel option of extreme learning machines (ELM) will be applied, which unlike classical neural networks does not demand validation dataset (see [22]).

IV. Results of Empirical Analysis

The resulted logistic regression model has been summarized in Table VI. Three variables are significant in discriminating between vital and bankrupted firms. Rise in equity to total assets ratio reduces bankruptcy probability, which is also a very commonly cited predictor in literature before. Bankruptcy probability is increased with the rise in turnover, for which there is not any direct logical explanation and it could be suspected that there is some hidden dimension that connects the significant variables. Interestingly, the higher proportion of liquid assets decreases survival possibilities, which could probably point to the fact that during financial distress firms start to reduce their fixed assets to increase liquidity. Still, such phenomenon needs to be studied further during future research.

TABLE VI: Variables in the Logistic Regression Model.

Variable	Estimate	Std. Error	p-value
Intercept	-0.92021	0.11202	< 2e-16
Equity / Total assets	-1.81482	0.03642	< 2e-16
Current assets / Total assets	0.86870	0.05391	< 2e-16
Ln (Total sales)	0.04563	0.00699	6.64e-11

TABLE VII: Classification Accuracies of Logistic Regression Model.

Firm status	2005 – 2008			2008 –2009
	One year before bankruptcy	Two years before bankruptcy	Three years before bankruptcy	One year before bankruptcy
Bankrupt	72%	43%	38%	51%
Vital	88%	88%	88%	88%

TABLE VIII: Classification Accuracies of Neural Networks model.

Firm status	2005 – 2008			2008 - 2009
	One year before bankruptcy	Two years before bankruptcy	Three years before bankruptcy	One year before bankruptcy
Bankrupt	84%	57%	62%	65%
Vital	85%	84%	83%	77%

Table VII lists the classification accuracies for logistic regression model. It can be seen that the model is more efficient in classifying correctly the vital firms, namely 88%. In case of more costly classification errors (Type 1 error), the misclassification is 28% (100%-72%). As cases from two groups were weighed to be equal in current analysis, the average classification accuracy is 80%. It can also be seen, that classification accuracy of bankrupt firms dramatically falls when to use financial ratios for two or three years before failure occurs. This can point to the presence of acute failure process as brought out in [23]. Also, the model is not as efficient in classifying bankrupt firms from recession time. The finding is curious, as for recession time classification accuracy falls only for bankrupt firms. The VIF values for logistic regression model variables were all below two, pointing to the fact that multicollinearity is not an issue.

As the next stage, the best neural network model will be searched based on all variables given in Table III. In the modelling process, the 14 variables are combined into 60 different networks initially, which is followed by combing the networks having best predictive abilities through hundred iterations. The best model emerged during 83 iteration. The five most frequent variables in different created neural network models were net profit to total assets, total liabilities to total assets, equity to total assets, cash to current liabilities, current assets to total assets. All given variables except for cash to current liabilities are variables that according to ANOVA test have significantly different means in two groups of firms. Due to its size, the neural network model will not be presented here and only the classification accuracies are brought out in Table VIII for the best neural network model created. The best neural network model consists of five variables: cash to current liabilities, total liabilities to total assets, net profit to total assets, retained earnings to total assets, cash to total assets. As Table IV demonstrates, all given variables except for the last one have very different median values.

It can be seen, that the prediction accuracy for vital firms in neural network model is a bit lower than for logistic regression model, but due to remarkably higher accuracy of bankrupt firm classification the overall accuracy is therefore better than for the logistic regression model. Table VIII also shows that during recession years the model is not as efficient as for economic growth years, which is analogical finding to logistic regression model.

V. Conclusion

Current paper was focused on a topic that has been elaborated a lot in literature, namely bankruptcy prediction. Through decades hundreds of prediction models have been composed to study firms' collapse. Although there has been constant improvement in the methodologies used, the prediction accuracies have not changed remarkably in time. Less attention has been paid on the data issues in analysis, namely the application of comparable data.

In the empirical analysis of current study the whole population of Estonian manufacturing firms was applied. The bankrupt manufacturing firms originated from years 2005-2008, whereas bankrupt firms from two severe recession years (2009-2010) were applied to validate the models. Also, data was processed in a way that the time between bankruptcy declaration and last annual report would be similar for all firms.

Two models were established, namely a classical logistic regression model and a novel neural networks model. The logistic regression model includes only three variables, of which some are not classical predictors of failure. The neural networks model includes all 14 variables available and is modelled with a novel technique that does not demand a validation dataset. Although for vital firms slightly lagging behind, the overall prediction accuracy was better for neural networks model when compared with logistic regression model. Still, the prediction accuracies for some years and firm groups are quite comparable through models established with two different methods. During the recession years the models created based on the data from economic growth years did not perform similarly well. The paper can be developed in many ways, for instance the usage of additional methods can be introduced and more sectors included in analysis.

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Oliver Lukason has received his MA degree from Tartu University and is currently working as a researcher at Tartu University, Faculty of Economics and Business Administration in Estonia. His previous research has mainly concerned different facets of firm failure, e.g. firm bankruptcies and reorganization, survival and performance of start-up and spin-off firms, violation of different legal requirements by firms.

Martin Grünberg has received MBA degree from Tartu University and is currently working as IT manager in a manufacturing firm. His research has focused on different facets of computer programming.