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NEW APPROACHES FOR THE FINANCIAL DISTRESS CLASSIFICATION IN AGRIBUSINESS

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Abstract

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After the recent financial crisis the need for unchallenged tools evaluating the financial health of enterprises has even arisen. Apart from well-known techniques such as Z-score and logit models, a new approaches were suggested, namely the data envelopment analysis (DEA) reformulation for bankruptcy prediction and production function-based economic performance evaluation (PFEP). Being recently suggested, these techniques have not yet been validated for common use in financial sector, although as for DEA approach some introductory studies are available for manufacturing and IT industry. In this contribution we focus on the thorough validation calculations that evaluate these techniques for the specific agribusiness industry. To keep the data as homogeneous as possible we limit the choice of agribusiness companies onto the area of the countries of Visegrad Group. The extensive data set covering several hundreds of enterprises were collected employing the database Amadeus of Bureau van Dijk. We present the validation results for each of the four mentioned methods, outline the strengths and weaknesses of each approach and discuss the valid suggestions for the effective detection of financial problems in the specific branch of agribusiness.

agribusiness, DEA, financial distress, logistic regression, production functions, Z-score

The problem area of assessing the financial status of business entities has always been in the focus of research interests in economics. Apart from classical bankruptcy prediction models such as Altman's Z-Score, logistic regression or discriminant analysis (see Keasey, 1991), further approaches have been suggested that apply or modify the well-established methods for classification of business' entities financial distress. Let us mention methods employing chaos approach (Lindsay, 1996) or neural networks applications assessment usage (Platt, 1999). Premachandra *et al.* (2009) introduces DEA as a non-parametric approach for analysing enterprises performance and suggests that this approach can be used as a help for bankruptcy assessment. Recently a new alternative tool based on the estimates of production function's (PF) parameters has arisen (see Hampel, 2012). DEA and PF methods, being recently suggested, have not yet been validated for common use in business sector. In this paper we focus on thorough validation of these two methods compared to Z score and logistic regression in the specific agriculture industry.

The agricultural sector has witnessed two different tendencies in recent years: firstly, the long-term upward tendency of input prices and secondly, the downward tendency of output prices; both of them belong to the most unfavourable relations within the agricultural sector. This fact is supported by the decrease in value added in the whole EU agri-sector, see EC/2011. It is inevitable for agricultural enterprises to manage their business economic performance, because the public subsidies from the EU Common Agricultural Policy cannot guarantee them the sustainable economic viability, see Vavřina (2012). Unchallenged methods of evaluating the financial health of agriculture enterprises may be considered a crucial tool in managing the prosperous and sustainable agricultural sector.

In the presented validation study we focus on the agriculture enterprises running their business in the Visegrad Group member countries which have had similar conditions to sustain and develop their business activities since they entered the Common European market in 2004. For the validation calculations we use extensive data sets employing the database Amadeus of Bureau van Dijk. The objective of this work is to verify new approaches to bankruptcy prediction in the field of agribusiness and to provide the comparison to common methods of bankruptcy prediction.

RESOURCES AND METHODS

Analysed data

Datasets outsourced from the database Amadeus consisting of 2,581 active and 71 bankrupted Czech, Hungarian, Polish and Slovak enterprises from the years 1998–2012. For bankruptcy assessment within different approaches are utilized different sets of economic indicators mainly in the form of financial ratios, when the initial set of indicators is user defined. Variables for employing the logit model within the financial distress classification are suggested in (Parkin, 1990). Respecting the data availability the final set of variables has been slightly modified using book value of total debts instead of interest expenses as follows: ETA = EBIT / Total Assets; NITA = Net Income / Total Assets; ER = EBIT / Revenues; CFTA = Cash Flow / Total Assets; CLTA = Current Liabilities / Total Assets; WCTA = Working Capital / Total Assets; CATA = Current assets/ Total Assets; TDTA = Total debts/ Total Assets.

For the DEA approach, one more variable is defined: ETD = book value of equity / book value of total debt; for the PF approach we use Added Value as a product, Total Shareholder Funds and Liabilities as a Capital and Cost of Employees as labor factor. Note that an available Number of Employees characteristic is less accurate than used one.

Altman's Z-score

The Altman's Z-Score model that was developed in the year 1968 was modified by its author in 1983. There was employed the new variable, that substituted book value of equity for the market value in former variable X_4. The mentioned substitution led to discriminant function as follows (Altman, 2000):

$$\text{Z-Score1983} = 0.717X_1 + 0.847X_2 + 3.107X_3 +$$
$$+ 0.420X_4 + 0.998X_5,$$

where X_1 is Working Capital / Total Assets as the liquidity indicator, X_2 is Retained Earnings / Total Assets as the cumulative over time profitability indicator, X_3 is Earnings Before Interest and Taxes / Total Assets as the profitability indicator, X_4 is Book Value of Equity / Book Value of Total Debt as the solvency indicator, X_5 is Sales / Total Assets as the activity indicator (Altman, 1968). There is developed the classification according to Z-Score1983 results for classifying enterprises into the proper performance groups, namely Well performing enterprises with $Z > 2.9$; Indifferent performance enterprises ("gray zone") with $1.2 < Z < 2.9$ and Enterprises heading towards bankruptcy with $Z < 1.2$.

Logit model

So-called logit model is a popular tool for modeling of alternative data. These data take only two values (typically 0 and 1), which represent failure or success in general. For example, these can be interpreted as unpaid or properly paid credit, purchased or not purchased product and so on. Generally speaking, we can use the logit model for classifying selected entities, including companies. Logit model, nonlinear in parameters, can be introduced by the formula

$$Y_i = \frac{e^{Z_i}}{e^{Z_i}+1} = \frac{1}{1+e^{-Z_i}}, \quad i = 1,\ldots,n,$$

where $Z_i = \beta_0 + \beta_1 X_{1i} + \beta_2 X_{2i} + \ldots + \beta_k X_{ki}$ and $X_1, \ldots, X_k$ are factors (both qualitative or quantitative), which affects dependent alternative variable Y. In addition to the test of particular parameters significance, there is available output with number of correctly and incorrectly classified subjects.

DEA with bankruptcy frontier

Premachandra *et al.* (2009) selects for bankruptcy assessment the additive DEA model (see Charnes 1985) which evaluates the relative efficiency of the specific *o* th firm as follows:

$$\max es^- + es^+ \textit{ subject to}: X\lambda + s^- = x_0,$$

$$Y\lambda - s^+ = y_0,\ e\lambda = 1,\ \lambda = \geq 0,\ s^- \geq 0,\ s^- \geq 0.$$

Here

n .... the number of decision making units,
k .... the number of inputs,
m........... the number of outputs,
$X = (x_j)$ .. $k \times n$ matrix of inputs,
$Y = (y_j)$... $m \times n$ matrix of outputs,
e .... is a row vector with all elements equal to 1,
s^- .... a vector of input slacks,
s^+ .... a vector of output slacks,
x_0 .... a column vector of inputs of the oth decision making unit, and
$\lambda \in R^n$ ... a vector connecting inputs and outputs.

Note that the additive model allows negative values in inputs and outputs, which is useful in bankruptcy assessment where financial ratios (often negative) enter the calculations and, moreover, the additive model incorporates both input and output slacks in the efficiency measurement and the efficiency of a specific decision making unit is determined by examining slacks only. This feature seems comfortable for users who need not examine both DEA efficiency score and slacks.

For bankruptcy assessment, the role of inputs and outputs in the DEA model is played by financial variables (concretely by financial ratios), but as usually in DEA, the concrete selection is determined by a DEA user. In our study we will follow the input output choice suggested in Premachandra (2009). Respecting the data availability the final set of in/outputs has been slightly modified using book value of total debt instead of interest expense: 1. inputs: ETD, CFTA, CATA, ER, ETA, NITA, WCTA; 2. outputs: CLTA, TDTA.

Unlike in the conventional DEA based production analysis, where productive performers consist an efficiency frontier and insufficient performers exist within the production possibility set, in the approach considered here the frontier is "bankruptcy frontier". This means that the frontier contains the poor performers – the bankrupt firms, while the healthy firms are expected to exist inside a "bankruptcy possibility set". Hence, solving the additive DEA model for each firm we classify the firm based on whether all the slacks are zero on optimality of the DEA model. If all slacks are zero, the firm is on the bankruptcy frontier. Otherwise (at least one slack positive), the firm is not on the bankruptcy frontier.

Production function approach

Innovative concept of predicting companies' bankruptcy using production functions (PFs) is formulated in Hampel (2012). Cobb-Douglas PFs

$$Q = \gamma K^{\alpha} L^{\beta} \text{ and } Q = \gamma K^{\alpha} L^{(1-\alpha)}$$

and the CES PF of the form

$$Q = \gamma[\delta K^{-\rho} + (1-\delta)L^{-\rho}]^{(-v/\rho)},$$

are used for this purpose in our paper. All introduced PFs are nonlinear in parameters, so the nonlinear least squares method is used to estimate their parameters (this technique is deeply described for example in Bates, 2007). For testing differences of the PF parameters for bankrupted versus highly rated companies we use approach with dummy variable. We denote this variable D, $D_i = 0$, for a highly rated company and $D_i = 1$ for a bankrupted company. By this manner we obtain model based on Cobb-Douglas PF

$$Q = (\gamma_0 + \gamma_1 D)K^{(\alpha_0 + \alpha_1 D)} L^{(\beta_0 + \beta_1 D)},$$

where subscript 0 means parameters for highly rated companies and subscript 1 means parameters interpretable as increase or decrease of particular parameters for bankrupted companies. Adequate model for CES PF was established in a similar way. Prediction of an unknown company status can be established using parameters given by a model with known-status-companies (details in Hampel, 2012).

All the calculations were made using open source software Gretl 1.9.11, computational system Matlab R2012b and the Matlab script for cycle solution of DEA (source available from the www.mathworks.com/matlabcentral/fileexchange/19158-data-envelopment-analysis/ content/DEA.m).

RESULTS AND DISCUSSION

The results can be divided into two parts: correct classification of well performing companies and correct classification of the companies coming to bankruptcy. Having unbalanced number of well-performing and bankrupted companies in the dataset, we do not evaluate the total correctness of the classification. Note that this unbalance in the dataset is a reflection of the real situation in the business rather than shortcoming of the data. We define correct classification of bankrupted companies as a measure of the particular method validity since it is much harder task to correctly classify the company coming to bankrupt than the well performing company.

The ability of the Altman's Z-Score, as the reference method, to assess the financial distress of an agricultural business entity within the data sample was observed in different year period prior to bankrupt. Results can be seen in Tab. I.

I: *The power of Altman's Z-score to correctly classify the financial distress of agricultural enterprises*

Sample of enterprises	Classification in %	
	correct	**wrong**
1Y to bankrupt	62.1	37.9
2Y to bankrupt	58.7	41.3
3Y to bankrupt	58.3	24.0
4Y to bankrupt	57.8	19.0

As can be assumed, the Altman's Z-Score model's ability to correctly classify the financially distressed companies is decreasing as being prolonged the time period prior the bankrupt. Note that Altman's Z-Score classify onto 3 levels, so correctly estimated cases plus wrongly estimated cases not necessary give 100 %.

Results of the ability of the logistic regression to assess the financial distress of an agricultural business entity can be seen in Tab. II. Similarly to the Altman's Z-Score approach, the power of logistic regression to correctly classify the bankrupted companies decreases according to the prolonged period prior to the bankrupt status of the enterprise.

II: *The power of Logistic regression to correctly classify the financial distress of agricultural enterprises*

Sample of enterprises	Classification in %	
	correct	**wrong**
1Y to bankrupt	71.9	28.1
2Ys to bankrupt	71.7	28.3
3Ys to bankrupt	61.0	39.0
4Ys to bankrupt	64.4	35.6

Success rate of the logit model is systematically higher than for the Altman's Z-Score model. It is because parameters of the logit model are estimated separately for each dataset. By this manner, for particular dataset we have the best estimates, but for Altman's Z-Score model parameters are prescribed (based on previous research). General validity of these parameters for agricultural business in V4 countries is questionable. Moreover, with logit model we use more parameters than Altman's Z-Score uses.

For the DEA approach, it is necessary to use slightly different practice. Financial data of bankrupted firms were collected in the year preceding the year of the bankrupt. According to non-significant difference between the values of CATA for bankrupted and non-bankrupted firms we decided to eliminate CATA from the set of inputs. The final set of inputs and outputs that are appropriate in classifying the agriculture firms as bankrupted and non-bankrupted consist of 6 inputs and 2 outputs, namely inputs CFTA, WCTA, ETA, ER, ETD, NITA and outputs TDTA, CLTA.

The capability of DEA approach in evaluating bankruptcy of agriculture enterprises is tested by using 60 different samples containing 1, 3, 5, or 8 bankrupt and 15, 30, or 45 healthy firms. For each sample the particular bankrupt and healthy firms were randomly selected from initial data set. This experiment enables to assess the strength of DEA in both identifying a single bankrupt firm and number of bankrupt firms from other firms in a sample.

As Tab. III shows, 163 of 255 bankrupt agriculture firms appeared in the bankruptcy frontier and in 80 of total 1800 cases the healthy firm appeared in bankruptcy frontier as well. Let us compute the four probabilities: P_1 = the number of bankrupt firms on the bankruptcy frontier divided by the total number of bankrupt firms; P_2 = the number of bankrupt firms not on the bankruptcy frontier divided by the total number of bankrupt firms; P_3 = the number of non-bankrupt firms not on the bankruptcy frontier divided by the total number of non-bankrupt firms; P_4 = the number of non-bankrupt firms on the bankruptcy frontier divided by the total number of non- bankrupt firms. Using the values from our experiment we obtain the rates

$$P_1 = 0.64, P_2 = 0.36, P_3 = 0.96, P_4 = 0.04.$$

Note, that the rate of overall correct predictions in our experiment is 0.92. In Tab. IV we can see the detailed DEA identification results with respect to the type of the sample.

The rates to for the samples (see Tab. V) indicate that the higher number of bankrupt firms in the sample the less correct classifications of bankrupt firms DEA provides. Let us discuss in a more detail the meaning of values of in Tab. V. DEA has perfectly detected a bankrupt firm if there was just one bankrupt in the sample. No matter if some healthy firms were classified wrongly in this case because we are interested in the evaluation of bankrupt firms only. Hence, for the purpose of prediction of bankruptcy for a single firm this DEA result seems to be very promising. Having an initial set of healthy enterprises one could evaluate the financial health of unknown firm by enlarging the initial set by the unknown one and apply the DEA tool. If unknown firm will lie on the bankruptcy frontier than one may conclude that financial problems should be expected in the future.

Finally, we try to predict status of the company using PF approach. The two-parameter Cobb-

III: *Summary of the DEA results, source: own work*

	Appeared in frontier	Not appeared in frontier	Total
No. of bankrupt firms	163	92	255
No. of non-bankrupt firms	80	1720	1800

IV: *Samples DEA results: The summary*

Number of bankrupt firms in the sample	1	3	5	8
NFNB (not on frontier – not bankrupt)	386	435	449	450
NFB (not on frontier – bankrupt)	0	11	21	60
FB (on frontier – bankrupt)	15	34	54	60
FNB (on frontier – not bankrupt)	64	15	1	0

V: *Samples DEA results: The conditional probabilities estimation*

Number of bankrupt firms in the sample	1	3	5	8
P_1	1.00	0.75	0.72	0.50
P_2	0.00	0.25	0.28	0.50
P_3	0.86	0.96	1.00	1.00
P_4	0.14	0.04	0.00	0.00
Overall correct predictions	0.86	0.95	0.96	0.89

Douglas production function cannot predict status of companies at sufficient level and seems to be unusual for us purpose. When splitting data according to years-to-bankrupt, we obtain low number of bankrupted companies in each set. Numerical problems arise in this case and it is impossible to estimate parameters of the CES PF for the set of bankrupted companies. Generally, when focus on three parameter Cobb-Douglas PF, in the case of one year to bankrupt we have 53.1% of correct classification, for four years to bankrupt it is 50.0%. When we do not distinguish among different years-to-bankruptcy and use all the data, prediction power increases to 56.5% for the three-parameters Cobb-Douglas PF. Moreover, in this case it is possible to calculate estimates for the CES PF, which gives 62.9% of correct classifications. In all cases, the results are less valuable than ones obtained using logit model. On the other hand, only three variables are used for the task, what can be an advantage if we have only limited data.

CONCLUSION

The validity of classification of well performing and bankrupted agricultural enterprises within the observed sample was verified via employing both widely known and rather novel approach. It can be stated that all the utilized approaches have got their pros and cons related to proper classification of financial health status. On the one hand the Z-Score approach from the year 1983 which can be very easily applied by users on the financial statement data of an company is criticized mainly due to its methodology, which is based on the stepwise multiple discriminant analysis of 33 bankrupt and 33 non-bankrupt US corporations from manufacturing branch only. On the other hand the employed approaches: logistic regression, DEA and PF methodology, which cannot be applied without a special statistical software using bigger dataset of only agricultural enterprises outperforms the Altman's Z-Score in the overall correct classification of bankrupted companies only in several percentage points. But we have obtained very promising result for the case of evaluating only one firm if a set of healthy firms is available. Then, DEA tool provides us with perfect identification of bankrupt firm. The potential decision maker who employs methodology for classification of financial health status should consider the aim of such a classification, i.e. the need for the level of the financial distress classifications' significance. Subsequently employment of different approaches for different required information content should be well considered. This article presents possible approaches for predicting the bankruptcy or financial distress of enterprises, which were identified by authors and were based on previous study of this problem area. The given results will be continuously verified and the following studies will be broadened to identify and analyze particular factors, which can influence validity of bankruptcy classification approaches.

SUMMARY

Financial analysis of corporate economic performance and its sustainability is a multi-disciplinary science field area using various methodological approaches. Tools and techniques of prediction of corporate financial distress or failure bring together outputs of financial analysis related to past economic performance of company and future estimates concerning further respective enterprises' performance. Bankruptcy prediction models were employed on the data sample of identified bankrupt and non-bankrupt Czech, Hungarian, Polish and Slovak agricultural enterprises. The managed enumerations of Z-score and the logistic regression approaches revealed that the most efficient approach for predicting the bankruptcy of agricultural enterprises within the observed enterprises sample was the logistic regression approach, which correctly classified nearly 72% of bankrupted enterprises one year prior the bankruptcy, concurrently to the Z-Score approach with correct classification of 62% companies one year prior to bankrupt, respectively. The decreasing power of correct classification of the business entities' financial distress was revealed regarding the prolongation of the time period before the bankrupt. Namely, the logistic regression approach was able to correctly identify only about 64% of bankrupted companies compared to the Altmans' Z-score model with the result of about 58% correctly classified bankrupted agricultural companies, respectively. Beside this, results of DEA and production function approach are given. Comparing to the logit model, these methods have some limitations, but in particular cases they can be more efficient than logit model or Altman's Z-Score. PF approach is based on the three characteristics only, what can be advantageous in the case of limited information about companies. DEA seems to be superior method for classification of a small subsample of bankrupted companies. The presented basic utilization and results of classification of financial distress of business entities are the motive for authors to carry on further next research in this area using the corporate data from EU member states and other industry sectors.

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