DEA as a tool for bankruptcy assessment: the agribusiness case study

Jitka Janová[1], Jan Vavřina[2], David Hampel[3]

Abstract. Bankruptcy assessment provides valuable information for the governments and investors to base their decisions in order to prevent possible financial losses. Data envelopment analysis (DEA) has generally been used to assess relative efficiency of decision making units. Recently, several approaches have appeared that reformulate DEA as a bankruptcy prediction tool. However, only several studies have been published on evaluation of suggested approaches and, if so, the focus was given to manufacture industry and IT industry only.

In this paper we discuss the possibility of application of recent results in DEA bankruptcy prediction models in a specific field of agribusiness. Using the AMADEUS database, the Czech Farm Accountancy Data Network (FADN CZ) and the financial statements issued in the Czech Business Register, we collect primary data set on the Czech agriculture firms financial performance, apply the DEA based model, evaluate the results obtained and discuss the prediction power of the approaches in the agriculture industry.

Keywords: DEA, agriculture, bankruptcy assessment

JEL classification: C61
AMS classification: 90C90

1 Introduction

Bankruptcy assessment has already been an intensively studied problem, however, after recent financial crisis, the urgent need for unchallenged techniques evaluating properly the financial health of enterprises has even arisen. Apart form testing the applicability of classical Altman's bankruptcy prediction model, further approaches have been suggested that apply or modify the well established methods for bankruptcy assessment usage. Let us mention the logistic regression and the discriminant analysis that dominate the literature (for review see [9]) or more recent methods employing e.g a chaos approach [10] or neural networks applications [11]. However, the reliability of techniques can still be increased, hence the research in the field focuses on improving the known methods or suggesting and validating the new ones. One of the most distinguished methods from those recently arisen for the bankruptcy assessment is the DEA (data envelopment analysis) approach. Premachandra [12] introduces in 2009 (DEA) as a non-parametric approach for analysing enterprises performance and suggests that this approach can be used as a help for bankruptcy assessment. In our contribution we focus on introductory evaluation of this recently suggested technique in the specific field of agribusiness.

Originally, DEA was developed to analyze efficiencies of decision making units (see e.g. [6]) and the method has been applied in many different business branches. As for the agribusiness applications, DEA was applied only scarcely until the end of 20th century (see [5]). However, since then, DEA became a favorite tool for farm efficiency measurement and number of local studies applying the DEA methodology in agriculture have been elaborated (see e.g. [3]). DEA was used not only to evaluate the efficiencies of agriculture enterprises, but also the determinants of efficiency in agribusiness were studied ([2]) and some studies discussing DEA with respect to the problem of sampling variations existence were provided

[1]Mendel University in Brno/Department of statistics and operational analysis, Zemědělská 1, Brno 613 00, e-mail: janova@mendelu.cz
[2]Mendel University in Brno/Department of business economics, Zemědělská 1, Brno 613 00, e-mail: vavrina@node.mendelu.cz
[3]Mendel University in Brno/Department of statistics and operational analysis, Zemědělská 1, Brno 613 00, e-mail: qqhampel@node.mendelu.cz

for the specific field of agriculture (e.g. [1]). Especially, the local agribusiness DEA studies were carried out for which the national FADN databases were employed as data sources and this implied also the selection of DEA input and output variables used in particular studies (for Czech agribusiness problem see [7]). While the indices have already been investigated for the use in agribusiness before, application of recently theoretically developed DEA bankruptcy prediction represents a novel approach in the field. This new approach for financial distress prediction has not been studied for the agriculture industry so far.

2 Methods

Premachandra [12] selects for bankruptcy assessment the additive DEA model [4] which evaluates the relative efficiency of the specific oth firm as follows:

$$\begin{aligned} \max \quad & es^- + es^+ \\ \text{subject to:} \quad & X\lambda + s^- = x_o, \\ & Y\lambda - s^+ = y_o, \\ & e\lambda = 1, \\ & \lambda \geq 0, \\ & s^- \geq 0, \\ & s^+ \geq 0. \end{aligned} \tag{1}$$

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

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 (1) 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 [12], but note that using ratios in DEA analysis is currently being a matter of scientific discussion (see e.g. [8]). 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
   - CFTA = cash flow/total assets
   - WCTA = working capital/ total assets
   - ETA = EBIT/ total assets
   - ER = EBIT/revenues
   - ETD = book value of equity/ book value of total debt
   - NITA = net income/ total assets
   - CATA current assets/ total assets
2. outputs
   - TDTA = total debts/ total assets
   - CLTA = current liabilities/ total assets.

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 model (1) for each firm we classify the firm based on wheter all the slacks are zero on optimality of (1). 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.

3 Results

The data on 54 bankrupt and 21 healthy Czech agricultural firms were taken from 2007-2010 FADN and AMADEUS databases. The two sided Wilcoxon rank sum test for the median values of chosen inputs and outputs was applied in MATLAB to indicate significant difference between the bankrupt and non-bankrupt firms. The results can be seen in Table 1 where the medians for bankrupt ($median\, b$) and non-bankrupt ($median\, non{-}b$) firms are summarized. In line h there is the result of testing the null hypothesis that data in the vectors composed from bankrupt and non-bankrupt firm's financial characteristics are independent samples from identical continuous distributions with equal medians against the alternative that they do not have equal medians (h = 1 indicates a rejection of the null hypothesis at the 5% significance level, h = 0 indicates a failure to reject the null hypothesis at the 5% significance level). Since for all the in/outputs except CATA the medians were significantly different for bankrupt and non-bankrupt firms, we decide to choose the following final set of inputs and outputs that are appropriate in clasifying the agriculture firms as bankrupt and non-bankrupt:

1. inputs: CFTA, WCTA, ETA, ER, ETD, NITA
2. outputs: TDTA, CLTA.

in/output	TDTA	CLTA	CFTA	WCTA	ETA	ER	ETD	NITA	CATA
median b	1.114	0.511	-0.153	0.076	-0.073	-0.098	-0.104	-0.072	0.481
median non-b	0.275	0.115	0.202	0.223	0.194	0.158	2.642	0.166	0.517
h	1	1	1	1	1	1	1	1	0

Table 1: Financial characteristics for bankrupt and non-bankrupt firms

The capability of DEA approach in evaluating bankruptcy of agriculture enterprises is tested by using 54 different samples, each containing one bankrupt and several healthy firms. Sample sizes were 11, 16 and 21 and we had 20 samples containing 10 healthy firms, 17 samples containing 15 healthy firms and 17 samples containing 20 healthy firms. The healthy firms were randomly selected from the initial data set while each of the bankrupt firms was contained just in one of the 54 samples. This experiment enables to assess the strength of DEA in identifying a single bankrupt firm from other firms in a sample. The calculations were run in MATLAB using a script for cycle solution of DEA that employs the code [13].

	appeared in frontier F	not appeared in frontier NF	total
No. of bankrupt firms B	52	2	54
No. of non-bankrupt firms NB	214	581	795
total	266	583	849

Table 2: Summary of the DEA results

As Table 2 shows, 52 of 54 bankrupt agriculture firms appeared in the bankruptcy frontier and in 214 of total 795 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 (see Table 2) we obtain the rates

$$P_1 = 0.96,\ P_2 = 0.04,\ P_3 = 0.73,\ P_4 = 0.27 \tag{2}$$

Note, that the rate of overall correct predictions in our experiment is 0.75. In Table 3 we can see the detailed DEA identification results with respect to the type of the sample.

sample (number of non-bankrupt firms in a sample)	10	15	20
NFNB (not on frontier - not bankrupt)	155	183	243
NFB (not on frontier - bankrupt)	0	1	1
FB (on frontier - bankrupt)	20	16	16
FNB (on frontier - not bankrupt)	45	72	97

Table 3: Samples DEA results: The summary

The rates P_1 to P_4 for the samples (see Table 4) indicate that the bankrupt firms remain on the frontier even when the number of non bankrupt firms was increased, i.e. DEA approach seems to perform well in identifying agricultural bankrupt firms. On the other hand, DEA is less powerful in correctly evaluating non-bankrupt agricultural firms. Further we notice that in our experiment the DEA performance is getting slightly worse when increasing the sample volume (i.e. increasing the number of non-bankrupt firms in the sample): while the rates of correctly identified firms are 1 and 0.77 for bankrupt and non-bankrupt firms respectively in the samples with 10 healthy firms, these rates decreases to 0.94, 0.72, and to 0.94, 0.71 for the 15- and 20-healthy-firms-sample, respectively. These results (considering the values of P_1 to P_4 and the rate of overall correct predictions) of our introductory agribusiness experiment correspond to the industry-unspecific result values presented in [12], where these are considered to be promising for further DEA establishment in bankruptcy assessment.

sample (number of non-bankrupt firms in a sample)	10	15	20
P_1	1	0.94	0.94
P_2	0	0.06	0.06
P_3	0.77	0.72	0.71
P_4	0.23	0.28	0.29
overall correct predictions	0.80	0.73	0.73

Table 4: Samples DEA results: The conditional probabilities estimation

4 Conclusion

This contribution aims to provide an entrance validation calculations testing the applicability of a recently suggested DEA bankruptcy assessment technique in agribusiness. According to the results discussed in the previous section, we can conclude that the small test case study provides us with promising numbers. In our future research, further validation calculations using a larger dataset will be done. Using particularly FADN and AMADEUS databases, the dataset can be enlarged to more than 500 agriculture enterprises from central and eastern Europe to provide a base for thorough validation calculations based on evaluating the method performance for sets including increasing number of bankrupted local enterprises and varying in total number of enterprises considered. Further, a detailed comparison with other methods (namely logistic regression) should be provided to arrive to final decision on the effectiveness of suggested method for agribusiness bankruptcy assessment.

Acknowledgements

The research is supported by the grant MSM6215648904 of the Ministry of Education, Youth and Sports of the Czech Republic.

References

[1] Balcombe K., Davidova S., Morrison J.A.: The use of bootstrapped Malmquist indices to reassess productivity change findings: an application to a sample of Polish farms, *Applied Economics*, **40** (16) (2008), 2055–2061.

[2] Bojnec, S., Latruffe, L: Productivity Change in Slovenian Agriculture During the Transition: A Comparison of Production Branches, *Ekonomicky casopis*, **57** (4) (2009), 327–343.

[3] Cesaro, L. et al.: Methodology for analysing competitiveness, efficiency and economy of scale. Use and applications of DEA, *Farm Accountancy Cost Estimation and Policy Analysis of European Agriculture*, Accessible via http://www2.ekon.slu.se/facepa/documents/Deliverable_ D5-1-3_ CUB.pdf

[4] Charnes, A., Cooper, W.W. Golany, B., Seiford, L.: Foundations of data envelopement analysis for Pareto Koopmans efficient empirical production functions, *Journal of Econometrics*, **30** (1985), 91-107.

[5] Coelli, T. J. : Recent developments in frontier modelling and efficiency measurement, *Australian Journal of Agricultural Economics*, **39** (3) (1995), 219–245.

[6] Cooper, W.W., Seiford L.M., Tone, K.: *Data Envelopment analysis.* Springer, New York 2007.

[7] Davidova, S., Latruffe, L.: Relationships between Technical Efficiency and Financial Management for Czech Republic Farms, *Journal of Agricultural Economics*, **58** (2) (2007), 269–288.

[8] Emrouznejad, A ., Amin, G. R.: DEA models for ratio data: Convexity consideration, *Applied Mathematical Modelling*, **33** (1) (2009), 486–498.

[9] Keasey, K., Watson, R.: Financial distress prediction models: A review of their usefulness, *British Journal of Mnagement*, **2** (1991), 89–101.

[10] Lindsay, D., Campbell, A.: A chaoss approach to bunkruptcy prediction, *Journal of Applied Business Research*, **12** (1996), 1–9.

[11] Platt, D., Platt, B., Yang, Z.: Probabilistic neural networks in bunkruptcy prediction, *Journal of Business Research*, **44** (1999), 67–74.

[12] Premachandra, I.M., Bhabra G.S., Sueyoshi T.: DEA as a tool for bankruptcy assessment: A comparative study with logistic regression technique, *European Journal of Operational REserach*, **193** (2009), 412–424.

[13] program available at http://www.mathworks.com/matlabcentral/fileexchange/19158-data-envelopment-analysis/content/DEA.m