Sci Eng Ethics
DOI 10.1007/s11948-017-9912-4

OPINION

Bankruptcy Prevention: New Effort to Reflect on Legal and Social Changes

Tomas Kliestik[1] · Maria Misankova[1] · Katarina Valaskova[1] · Lucia Svabova[1]

Received: 13 December 2016 / Accepted: 24 March 2017

Abstract Every corporation has an economic and moral responsibility to its stockholders to perform well financially. However, the number of bankruptcies in Slovakia has been growing for several years without an apparent macroeconomic cause. To prevent a rapid denigration and to prevent the outflow of foreign capital, various efforts are being zealously implemented. Robust analysis using conventional bankruptcy prediction tools revealed that the existing models are adaptable to local conditions, particularly local legislation. Furthermore, it was confirmed that most of these outdated tools have sufficient capability to warn of impending financial problems several years in advance. A novel bankruptcy prediction tool that outperforms the conventional models was developed. However, it is increasingly challenging to predict bankruptcy risk as corporations have become more global and more complex and as they have developed sophisticated schemes to hide their actual situations under the guise of "optimization" for tax authorities. Nevertheless, scepticism remains because economic engineers have established bankruptcy as a strategy to limit the liability resulting from court-imposed penalties.

Keywords Responsible management · Engineering economics · Bankruptcy prevention · Bankruptcy prediction tools

Introduction

In bankruptcy, usually many individuals are affected. Boettcher et al. (2014) claim that bankruptcy often violates human rights and the principle of justice—two criteria that are often used to examine whether actions are ethical. Estrin et al.

✉ Tomas Kliestik
tomas.kliestik@fpedas.uniza.sk

[1] Department of Economics, Faculty of Operation and Economics of Transport and Communications, University of Zilina, Univerzitna 8215/1, Zilina 010 26, Slovak Republic

Published online: 10 April 2017

(2009) believe bankruptcy is a normal, cyclic event with cathartic occurrences that will redress the existing policies and practices. In comparison, Kirkos (2015) views bankruptcy as an economic externality and bankruptcy prevention efforts as one of the most important activities for economic engineers. For a healthy corporation, the bankruptcy of a competitor presents an opportunity to purchase that competitor at a fraction of its value, reorganize it, sell it, and generate a profit. A different approach is presented by Boettcher et al. (2014) who advocate that bankruptcy is designed to provide the debtor another chance after a financial failure and that bankruptcy is an option that is both more ethical and more efficient than liquidation. Harper (2015) emphasizes the link between poor moral behaviour and bankruptcies; however, this link may not be deemed to be causal (Williams 2014). Credit is generally required to begin a new enterprise and is essential for the economic growth of a society (Boettcher et al. 2014). However, not all businesses succeed financially, so providing credit demands that the credit provider takes a risk. Everywhere there are investment opportunities, there are companies willing to assume financial liabilities and the associated inherent risks to maintain and develop their businesses (Mardoyan and Braun 2015). Analogies between countries, corporations and individuals can be traced through both free market and command economies (Hašková 2016). Boettcher et al. (2014) reminds us that throughout most of history, failure to pay a debt was considered a moral failure, and a creditor could place a delinquent debtor in prison or enslave a creditor's child. (Mutilation or death of the defaulting debtor can also be traced through history). However, it appears that the complete abolition of such harshly punitive approaches may lead to a different type of moral issue (Maroušek 2013). Subsequently, bankruptcy has become the most popular competitive strategy to limit liability from court-imposed penalties (Boettcher et al. 2014). False individual bankruptcies, strategic bankruptcies or bankruptcy frauds are also common (Regan 2010). Bankruptcy may be considered a financial success when it enables the corporation to use its corporate assets more efficiently (Boettcher et al. 2014). However, such a bankruptcy is not always ethical because the criteria for judging the financial and ethical success of a bankruptcy are different. Financial criteria anticipate the most efficient use of physical assets and capital. However, ethical criteria consider the natural and personal holistic impact (Maroušek et al. 2016). Only management who which emphasizes the importance of future developments and which makes appropriate and timely decisions can be considered ethical. Considering both the moral and the financial dimensions, the consensus is that it is better to prevent bankruptcies. As stated by Korol (2013), the best international companies must constantly monitor their financial situation and those of the companies with which they cooperate.

Many authors have dedicated their research to the issue of bankruptcy (do Prado et al. 2016), and they consider it crucially important to focus not only on the actual financial situation but also on the prediction of the future financial situation. Nevertheless, the number of bankruptcies worldwide has increased in recent years (Ogane 2016), and it is becoming much more challenging to predict it, as corporations have become more global, more complex and have developed sophisticated schemes to shield their actual situations. Similarly, the complexity involved in distinguishing between faithful customers and potentially fraudulent ones has also become more difficult (Maroušek et al. 2015). In the post-transitional economies of Central European countries, this situation is serious and more challenging (Svejnar 2002) because of persistent issues involving the legitimacy of the justice system as well as the corruption of public officials (Grochová and Otáhal 2011). Therefore, the owners of capital (corporations) are, in response to repeated bankruptcy cases, under constant suspicion that they acquired their businesses illegally or, at a minimum, unethically (Münich et al. 2005). In addition, the local nationalism boom (Dekker et al. 2016) has increased the general hostility directed to all who may be considered guilty (Estrin et al. 2009).

With the level of globalization, both macroeconomic and microeconomic changes have a nearly immediate impact on individuals. Moral concerns are also gaining global recognition. In earlier times, most authors understood the ethical aspects of bankruptcy only from the moment of bankruptcy declaration (Ardagh 2001). Therefore, because of all the difficulties noted above, the importance of early bankruptcy prediction is increasing, and the perception of ethical concerns has broadened (Maroušek 2014). Furthermore, economic engineers have developed an endless variety of general models that are currently used for estimating the bankruptcy probability of countries, corporations and individuals based on different principles, techniques and methodologies (Machek 2014). However, these efforts fail to reflect the complexity of local laws, regulations, or traditions or to reflect the specific behaviour of market sectors, communities and others. Furthermore, the predictive ability of most models may vary over time (Bauer and Agarwal 2014). Most of the tools derived for bankruptcy prediction can only be applied in the same sector and under the same economic situation for which the tools were originally modelled. Otherwise, these bankruptcy prediction tools provide far fewer accurate predictions.

First, economic engineers dedicated to the issue of bankruptcy and corporate failures gained stature as a profession in the 1930s. These individuals primarily focused on the comparison of financial ratios between bankrupt and non-bankrupt companies. Fitzpatrick (1932) published his work on the major differences between successful and unsuccessful businesses. This work became the inspiration for many applied studies that began to emerge in the mid-1960s. The breakthrough work of Beaver (1966) is considered the turning point. Beaver applied univariate discriminant analysis, which is based on various financial ratios fused into one final predictor to serve as a classification criterion. Despite the many limitations and reservations of this method, it inspired many studies devoted to the issue of bankruptcy prediction and corporate failure. Altman (1968) firstly applied multivariate discriminant analysis to construct bankruptcy prediction models. Altman's work is considered useful for the prediction of the financial health of companies. Another widespread mathematical—statistical method used for bankruptcy prediction is the logistic regression (logit) that was firstly applied by Ohlson (1980). Other mathematical statistical methods used for the prediction of financial health include: principal component analysis (Mures et al. 2012); rough sets (Huang and Tseng 2004); data envelopment analysis (Cielen et al. 2004); decision trees (Xu et al. 2014); support vector machines (Salehi et al. 2016); and others (Araghi and

Makvandi 2013). Odom and Sharda (1990) were pioneers in the highly accurate neural network application that is currently very popular (Tinoco and Wilson 2013).

To extend the knowledge on bankruptcy prediction and mitigate its negative societal impact this study attempts to analyse and improve the unpleasant scenarios encountered with the previously noted general models through a robust and deep analysis of data from local corporations to subsequently design and assess a novel tool for bankruptcy prediction. To achieve these goals, two hypotheses were built:

1. Variables included in the current bankruptcy prediction tools are statistically significant.
2. The prediction tools of Slovak companies are statistically significant.

Methods

The data for the study were obtained from the financial statements of Slovak corporations (Register of financial statements, Ministry of Finance of the Slovak Republic) during the period from 2012 to 2015. The Slovak legal system understands insolvency as the moment when the total amount of payable and non-payable liabilities of a corporation is higher than the value of corporate assets and there is no prospect of a future profitable operation. Therefore, for each year, these corporations were initially divided into two groups: bankrupt and non-bankrupt companies (see Table 1). Subsequently, a review of highly predictive bankruptcy prediction studies was conducted (similar to Korol 2013), and the most commonly used explanatory variables were summarized (see Table 2). Eleven explanatory variables (X_{1-11}) were chosen to serve as the basis on which to designate the bankruptcy prediction model. Multiple Discriminant Analysis was used (according to Altman 1968) to classify the observation into one of several a priori groups. Fundamental of Discriminant Analysis (FDA) was applied (according to Stankovicova and Vojtkova 2007) to examine the dependence of one qualitative (classification) variable upon several quantitative variables to determine the optimal assignment criterion. (This process minimizes the probability of incorrect classification of elements; therefore, it minimizes the mean value of an incorrect decision.) The descriptive tasks of discriminant analysis determine the appropriate

Table 1 An introductory overview of the processed data indicates that the number of bankruptcies in Slovakia has been increasing steeply for several years and has become a nationwide social issue with moral implications

Year	Bankrupt	Non-bankrupt	Total	Bankrupt (%)
2012	12,974	44,586	57,560	22.54
2013	14,886	49,046	63,932	23.28
2014	17,854	51,024	68,878	25.92
2015	19,636	55,321	74,957	26.20

Table 2 Overview of 11 currently most commonly used explanatory variables (X_{1-11}) and the number of studies

Explanatory variable		Number of studies
$Cuurent\ ratio = \frac{Current\ assets}{Current\ liabilities}$	X_1	51
$Cash\ ratio = \frac{Cash+short-term\ investment}{Current\ liabilities}$	X_2	22
$Return\ on\ assests = \frac{EBIT}{Total\ assets}$	X_3	54
$Return\ on\ equity = \frac{EBIT}{Equity}$	X_4	18
$Debt\text{-}to\text{-}assets\text{-}ratio = \frac{Total\ debt}{Total\ assets}$	X_5	27
$Debt\text{-}to\text{-}equity\text{-}ratio = \frac{Total\ debt}{Equity}$	X_6	15
$Number\ of\ days\ of\ receivables = \frac{Receivables}{(Sales/360)}$	X_7	8
$Number\ of\ days\ of\ payables = \frac{Current\ liabilities}{(Sales/360)}$	X_8	13
$Inventory\ turnover = \frac{Inventory}{(Sales/360)}$	X_9	10
$Net\ assets = \frac{Net\ working\ capital}{Total\ assets}$	X_{10}	45
$Retained\text{-}earnings\text{-}to\text{-}total\text{-}asset\text{-}ratio = \frac{Retained\ earnings}{Total\ assets}$	X_{11}	42

discriminant function that identifies the existence of statistically significant differences between the means of predefined groups; this can be derived using two alternative calculations. Subsequently, stepwise discriminant analysis was applied. Using the SPSS Statistics 20 advanced analytics tool (IBM, New York, USA), the data were processed in the following order: a test of the statistical significance of all the initial explanatory variables; a determination of the relative contributions of each explanatory variable; and an examination of the inter correlations among the relevant variables accompanied by an examination of the predictive accuracy of each independent variable. Because of the high number of independent variable predictors entering the analysis (11), the stepwise discriminant analysis was applied to find the linear combinations of those variables that best separate the groups of cases. These combinations formed discriminant functions with a coefficient vector, A, (α_1, α_2,…, α_n—standardized classification coefficients) and a constant term, $\alpha0$, per the general form displayed in Eq. 1.

$$Z_i = \alpha_0 + \alpha_1 x_{i1} + \alpha_2 x_{i2} + \alpha_3 x_{i3} + \ldots + \alpha_n x_{in} \quad (1)$$

where Z_i is the value of the discriminant function for corporation i, a_{0-n} are values of discriminant coefficients of the prediction function. $x_{i1\text{-}in}$ are n predictors for corporation i.

Based on Eq. 1, each case obtained a discriminant Z-score; on its basis the centroid was obtained for each group. Classification was then performed using cutting scores derived from these centroids. The statistical significance of the discriminant function is provided by Wilks λ (smaller values indicate a greater discriminatory ability of the function). Then, steps were taken to develop the new bankruptcy model. The appropriateness of the existing methods for bankruptcy prediction (equality of variances and the equality of group means) was analysed using the one-way analysis of variance (ANOVA) as stated in Table 3. Before the initial process of stepwise selection, the null hypothesis of the equality of covariances across groups was tested using the Box's M tests (Table 4). The stepwise selection statistic of multivariate discriminant analysis was initially begun with the most significant explanatory variable, continued with the subsequent inclusion of one variable in each step based on the value of Wilks λ and finally provided the number of financial ratios that best discriminate between bankrupt and non-bankrupt corporations in each year (Table 5). Because the accuracy and reliability of the selected variables have been confirmed, the linear MDA function (Z-score function) is developed as follows (Eqs. 1–5):

$$Z\text{−score}_{\mathrm{SK}}^{2012} = -0.080 + 0.018\mathrm{X}_2 + 0.003\mathrm{X}_6 + 0.003\mathrm{X}_4 + -0.000000957\mathrm{X}_8 \tag{2}$$

$$\begin{aligned} Z\text{−score}_{\mathrm{SK}}^{2013} = {} & -0.009 + 0.002\mathrm{X}_1 + 0.003\mathrm{X}_6 - 0.015\mathrm{X}_3 - 0.006\mathrm{X}_4 \\ & - 0.00000191\mathrm{X}_8 + 0.015\mathrm{X}_{10} \end{aligned} \tag{3}$$

$$Z\text{−score}_{\mathrm{SK}}^{2014} = -0.006 + 0.004\mathrm{X}_2 + 0.000199\mathrm{X}_6 - 0.004\mathrm{X}_3 + -0.005\mathrm{X}_{10} \tag{4}$$

$$Z\text{−score}_{\mathrm{SK}}^{2015} = -0.024 + 0.003\mathrm{X}_2 + 0.000448\mathrm{X}_6 - 0.004\mathrm{X}_3 + 0.000311\mathrm{X}_{10}. \tag{5}$$

Based on the calculated Z-score of the company, the company was subsequently classified into the bankrupt or non-bankrupt company group. The value of the Z-score was compared to the calculated functions at the group centroids (Table 6). The prediction accuracy was determined for different years (Table 7).

Results and Discussion

In every corporation, economic engineers have a legal responsibility to obey government regulations and laws. According to Boettcher et al. (2014), the corporation also has an economic and moral responsibility to stockholders to perform well financially. A comparison of the results summarized in Table 1 revealed significant financial differences between groups of bankrupt and non-bankrupt companies. In response to the actual performance of the Slovak economy (Kotulic et al. 2015), the number of corporations going bankrupt is probably excessively large with no apparent macroeconomic cause. Therefore, it is possible to argue that increasingly more managers in Slovakia rarely behave responsibly and definitely do not behave ethically. According to Koyuncugil and Ozgulbas (2012), incompetent economic engineering can produce substantial losses for all parties such as creditors, investors, auditors, financial institutions, stockholders, employees, and customers; this undoubtedly reflects the economics of the countries concerned. Regarding Table 2, the results revealed that the *Results on assets* is probably the most popular tool for bankruptcy prediction. This result is interesting because Korol (2013) claims that decisional trees usually outperform similar conventional tools, including methods of discriminant analysis or sophisticated artificial neural

Table 3 The results of one-way analysis of variance (ANOVA) according to the calculated *p* value of the appertain F-statistic for each explanatory variable

	2012			2013			2014			2015		
	Wilkś λ	F	Sig.	Wilkś λ	F	Sig.	Wilkś λ	F	Sig.	Wilkś λ	F	Sig.
X_1	.999	31.732	.000	.999	46.869	.000	.999	37.584	.000	.999	43.803	.000
X_2	.997	175.77	.000	.999	37.245	.000	.999	66.884	.000	.999	45.315	.000
X_3	1.000	3.754	.053	.999	32.308	.000	1.000	14.216	.000	1.000	29.726	.000
X_4	1.000	6.737	.009	1.000	7.595	.006	1.000	.354	.552	1.000	3.501	.061
X_5	1.000	4.847	.028	.998	103.378	.000	1.000	7.384	.007	1.000	16.723	.000
X_6	.998	131.10	.000	.997	208.128	.000	1.000	9.117	.003	1.000	33.939	.000
X_7	1.000	.127	.722	1.000	9.909	.002	1.000	.502	.479	1.000	.160	.690
X_8	1.000	17.996	.000	.999	55.832	.000	1.000	3.146	.076	1.000	1.992	.158
X_9	1.000	7.635	.006	1.000	.342	.558	1.000	.312	.577	1.000	.103	.749
X_{10}	.999	67.893	.000	.998	96.050	.000	.999	40.811	.000	1.000	17.980	.000
X_{11}	1.000	2.558	.110	1.000	17.600	.000	1.000	4.671	.031	1.000	3.592	.058

Table 4 Box's M test

Box́s M		2012 286,381.753	2013 865,338.241	2014 987,805.080	2015 1,272,430.495
F	Approx.	28,634.804	41,200.302	98,771.858	127,232.897
	Df1	10	21	10	10
	Df2	2,626,788,657.465	2,875,935,957.412	5,299,451,663.857	6,444,963,460.436
	Sig.	0.000	0.000	0.000	0.000

Table 5 Results of the stepwise MDA. The canonical discriminant functions coefficient

2012		2013		2014		2015	
	Function 1		Function 1		Function 1		Function 1
X_2	.018	X_1	.002	X_2	.004	X_2	.003
X_6	.003	X_6	.003	X_6	1.99E−04	X_6	4.48E−04
X_4	.003	X_3	−.015	X_3	−.004	X_3	.004
X_8	−9.57E−07	X_4	−.006	X_{10}	.005	X_{10}	3.11E−04
Constant	−.080	X_8	−1.91E−06	Constant	−.006	Constant	−.024
		X_{10}	.015				
		Constant	−.009				

Table 6 Functions at group centroids

2012		2013		2014		2015	
	Function		Function		Function		Function
Default	1	Default	1	Default	1	Default	1
Non-bankrupt	−.152	Non-bankrupt	.046	Non-bankrupt	.026	Non-bankrupt	.024
Bankrupt	.044	Bankrupt	−.150	Bankrupt	−.074	Bankrupt	−.066

networks (Tinoco and Wilson 2013). The results of the ANOVA analysis shown in Table 3 indicate that each explanatory variable that is traceable in Table 2 is statistically significant. This result is another notable development because it demonstrates that, although economic engineers may choose one of the less appropriate tools for bankruptcy prediction, they still would have received warning information. The MDA results (Table 5) shows that four financial ratios are significant in discriminating between bankrupt and non-bankrupt Companies in 2012, 2014 and 2015, while in 2013 there are six financial ratios that are significant. *Debt-to-equity-ratio* is included in each year as a significant explanatory variable.

Table 7 Prediction accuracy of discriminant classification

		Predicted group membership 2012			Predicted group membership 2013		
		Non-bankrupt	Bankrupt	Total	Non-bankrupt	Bankrupt	Total
Count	Non-bankrupt	12,630	344	12,974	48,521	525	49,046
	Bankrupt	23,322	21,264	44,586	10,334	4552	14,886
%	Non-bankrupt	97.3	2.7	100.0	98.9	1.1	100.0
	Bankrupt	52.3	47.7	100.0	69.4	30.6	100.0
a 58.9% of the original grouped cases were correctly classified					a 83.0% of the original grouped cases were correctly classified		
		Predicted group membership 2014			Predicted group membership 2015		
		Non-bankrupt	Bankrupt	Total	Non-bankrupt	Bankrupt	Total
Count	Non-bankrupt	50,722	302	51,024	38,851	16,470	55,321
	Bankrupt	15,537	2317	17,854	806	18,830	18,636
%	Non-bankrupt	99.4	.6	100.0	70.2	29.8	100.0
	Bankrupt	87.0	13.0	100.0	4.1	95.9	100.0
a 77.0% of the original grouped cases were correctly classified					a 77.0% of the original grouped cases were correctly classified		

Table 8 Summary of canonical correlation function coefficients

2012				
Eigenvalues				
Function	Eigenvalue	% of variance	Cumulative %	Canonical correlation
1	.007[a]	100.0	100.0	.082
a. First 1 canonical discriminant functions were used in the analysis				
Wilks' Lambda				
Test of function(s)	Wilks' Lambda	Chi square	df	Sig.
1	.993	386.843	4	.000
2013				
Eigenvalues				
Function	Eigenvalue	% of variance	Cumulative %	Canonical correlation
1	.007[a]	100.0	100.0	.083
a. First 1 canonical discriminant functions were used in the analysis				
Wilks' Lambda				
Test of Function(s)	Wilks' Lambda	Chi square	df	Sig.
1	.993	437.003	6	.000
2014				
Eigenvalues				
Function	Eigenvalue	% of variance	Cumulative %	Canonical correlation
1	.002[a]	100.0	100.0	.044
a. First 1 canonical discriminant functions were used in the analysis				
Wilks' Lambda				
Test of function(s)	Wilks' Lambda	Chi square	df	Sig.
1	.998	131.484	4	.000
2015				
Eigenvalues				
Function	Eigenvalue	% of Variance	Cumulative %	Canonical Correlation
1	.002[a]	100.0	100.0	.039
a. First 1 canonical discriminant functions were used in the analysis				
Wilks' Lambda				
Test of Function(s)	Wilks' Lambda	Chi square	df	Sig.
1	.998	116.568	4	.000

The results of the Z-score calculations depicted in Table 6 confirm that the financial crisis experienced by the majority of the analysed corporations begins several years before the bankruptcy itself. This finding is in accordance with Korol (2013) who claims that the process of going bankrupt is not a sudden phenomenon that is impossible to predict; in fact, it may take as long as 5–6 years. Statistics also revealed that MDA can correctly classify 98.9% of the non-bankrupt companies but only 30.6% of bankrupt companies. As is shown in Table 7, the MDA can correctly classify 97.3% of the non-bankrupt companies and 47.7% of bankrupt companies in 2012 in the Slovak Republic. Higher prediction accuracy was achieved in 2013 when MDA correctly classified 98.9% of the non-bankrupt companies but only 30.6% of bankrupt companies. The highest results in both groups of companies were achieved in 2015 when MDA correctly classified 70.2% of the non-bankrupt companies and nearly 96% of the bankrupt companies. In 2014 the MDA model correctly classified more than 99% of non-bankrupt companies; however, only 13% of the bankrupt companies were classified correctly.

In general, these models appear to be more effective in classifying non-bankrupt companies than bankrupt ones. An explanation may be that the financial ratios of non-bankrupt companies are more stable than those of bankrupt companies. The overall prediction accuracy of models to identify bankrupt companies from the non-bankrupt companies changed from 58.9% in 2012, to 83% in 2013, to 77.0% in 2014 and 2015. However, the low values of canonical correlations are all created by bankruptcy prediction models and are statistically significant per the appertain p value, which is lower than 0.05 (defined level of significance $\alpha = 0.05$) in all cases. The results of these calculations are shown in Table 8.

Conclusion

There should be a continuous focus on the issue of bankruptcy predictions to ensure business continuity and to further sustainable and ethically responsible economic development. The robust analysis of Slovak corporate performance in recent years revealed that, in many cases, there are indications of financial troubles several years before the bankruptcy itself; in addition, in most cases, it is possible to detect these troubles using conventional bankruptcy prediction tools.

A new bankruptcy prediction tool was proposed that outperforms conventional tools. This tool's higher sensitivity originates primarily from the fact that it was modelled on local legal and business aspects. However, the conclusion is that these tools are either not used competently or the bankruptcies are affected by financially unpredictable factors; an alternative conclusion is that economic engineers work with false financial data.

Acknowledgements This work was supported by the Slovak Research and Development Agency under Grant number APVV-14-0841: Comprehensive Prediction Model of the Financial Health of Slovak Companies.

References

Altman, E. (1968). Financial ratios, discriminant analysis and the prediction of corporate bankruptcy. *The Journal of Finance*, *23*(4), 589–609.

Araghi, M. K., & Makvandi, S. (2013). Comparing logit, probit and multiple discriminant analysis models in predicting bankruptcy of companies. *Asian Journal of Finance and Accounting, 5*(1), 48–59.

Ardagh, D. (2001). The ethics of bankruptcy. *Australasian Journal of Philosophy*, *79*(4), 589–591.

Bauer, J., & Agarwal, V. (2014). Are hazard models superior to traditional bankruptcy prediction approaches? A comprehensive test. *Journal of Banking and Finance, 40,* 432–442.
Beaver, W. H. (1966). Financial ratios as predictors of failures. *Empirical Research in Accounting Supplement to Journal of Accounting Research*, *4*, 71–111.
Boettcher, J., Cavanagh, G., & Xu, M. (2014). Ethical issues that arise in bankruptcy. *Business and Society Review, 119*(4), 473–496.
Cielen, A., Peeters, L., & Vanhoof, K. (2004). Bankruptcy prediction using a data envelopment analysis. *European Journal of Operational Research*. doi:10.1016/S0377-2217(03)00186-3.
Dekker, H., Farnen, R. F., German, D. B., & Meyenberg, R. (Eds.). (2016). *Democracy socialization and conflicting loyalties in east and west: Cross-national and comparative perspectives*. Berlin: Springer.
do Prado, J. W., de Castro Alcântara, V., de Melo Carvalho, F., Vieira, K. C., Machado, L. K. C., & Tonelli, D. F. (2016). Multivariate analysis of credit risk and bankruptcy research data: a bibliometric study involving different knowledge fields 1968. *Scientometrics, 106*(3), 1007–1029.
Estrin, S., Hanousek, J., Kočenda, E., & Svejnar, J. (2009). The effects of privatization and ownership in transition economies. *Journal of Economic Literature, 47*(3), 699–728.
Fitzpatrick, P. (1932). A comparison of ratios of successful industrial enterprises with those Of failed firms. *Certified Public Accountant, 1*(1), 598–605.
Grochová, L., & Otáhal, T. (2011). Corruption in the Czech and the Slovak Republics: Did the EU pressure improve legal enforcement? MENDELU Working Papers in Business and Economics 4/2011. doi:10.2139/ssrn.2246008.
Harper, S. J. (2015). Bankruptcy and bad behavior-The real moral hazard: Law schools exploiting market dysfunction. *American Bankruptcy Institute Law Review, 23*(1), 347–365.
Hašková, S. (2016). Holistic assessment and ethical disputation on a new trend in solid biofuels. *Science and Engineering Ethics*, pp. 1–11.
Huang, Ch Ch., & Tseng, T. L. (2004). Rough set approach to case-based reasoning application. *Expert Systems with Applications*. doi:10.1016/j.eswa.2003.09.008.
Kirkos, E. (2015). Assessing methodologies for intelligent bankruptcy prediction. *Artificial Intelligence Review*. doi:10.1007/S10462-012-9367-6.
Korol, T. (2013). Early warning models against bankruptcy risk for Central European and Latin American enterprises. *Economic Modelling, 31,* 22–30.
Kotulic, R., Vozarova, I. K., Nagy, J., Huttmanova, E., & Vavrek, R. (2015). Performance of the Slovak economy in relation to labor productivity and employment. *Procedia Economics and Finance, 23,* 970–975.
Koyuncugil, A. S., & Ozgulbas, N. (2012). Financial early warning system model and data mining application for risk detection. *Expert Systems with Applications, 39*(6), 6238–6253.
Machek, O. (2014). Long-term predictive ability of bankruptcy models in the Czech Republic: Evidence from 2007–2012. *Central European Business Review, 3*(2), 14.
Mardoyan, A., & Braun, P. (2015). Analysis of Czech subsidies for solid biofuels. *International Journal of Green Energy, 12*(4), 405–408.
Maroušek, J. (2013). Study on agriculture decision-makers behavior on sustainable energy utilization. *Journal of Agricultural and Environmental Ethics, 26*(3), 679–689.
Maroušek, J. (2014). Economically oriented process optimization in waste management. *Environmental Science and Pollution Research*, *21*(12), 7400–7402.
Maroušek, J., Hašková, S., Zeman, R., & Vaníčková, R. (2015). Managerial preferences in relation to financial indicators regarding the mitigation of global change. *Science and Engineering Ethics, 21*(1), 203–207.
Maroušek, J., Hašková, S., Zeman, R., Žák, J., Vaníčková, R., Maroušková, A., et al. (2016). Polemics on ethical aspects in the compost business. *Science and Engineering Ethics, 22*(2), 581–590.
Münich, D., Svejnar, J., & Terrell, K. (2005). Returns to human capital under the communist wage grid and during the transition to a market economy. *Review of Economics and Statistics, 87*(1), 100–123.
Mures, J. Q., Garcia, A. G., & Vallejo, E. P. (2012). Cross-industry analysis of business failure: Differential factors. *Pecvnia Monográfico*. doi:10.18002/pec.v0i2012.1107.
Odom, M. & Sharda, R., (1990) A neural network model for bankruptcy prediction. In *Proceedings of the International Joint Conference on Neural Networks*, part II, pp. 163–168.
Ogane, Y. (2016). Banking relationship numbers and new business bankruptcies. *Small Business Economics, 46*(2), 169–185.

Ohlson, J. A. (1980). Financial ratios and the probabilistic prediction of bankruptcy. *Journal of Accounting Research*. doi:10.2307/2490395.

Regan, M. C. (2010). *Eat what you kill: The fall of a Wall Street lawyer*. Ann Arbor: University of Michigan Press.

Salehi, M., Shiri, M. M., & Pasikhani, M. B. (2016). Predicting corporate financial distress using data mining techniques: An application in Tehran Stock Exchange. *International Journal of Law and Management*. doi:10.1108/IJLMA-06-2015-0028.

Stankovicova, I., & Vojtkova, M. (2007). *Viacrozmerne statisticke metody s aplikaciami* (p. 261). Bratislava: Iura Edition.

Svejnar, J. (2002). Transition economies: Performance and challenges. *The Journal of Economic Perspectives, 16*(1), 3–28.

Tinoco, M. H., & Wilson, N. (2013). Financial distress and bankruptcy prediction among listed companies using accounting, market and macroeconomic variables. *International Review of Financial Analysis, 30,* 394–419.

Williams, J. F. (2014). The Archaeology of professional ethics in bankruptcy (Part II). *AIRA Journal*.

Xu, Z., Kusner, M. J., Weinberger, K. Q., Chen, M., & Chapelle, O. (2014). Classifier cascades and trees for minimizing feature evaluation cost. *Journal of Machine Learning Research*, *15*(1), 2113–2144.