Original scientific paper
UDC: 658.14/65.012
Paper Received: 12/07/2018
Paper Accepted: 22/08/2018

DEFAULT PROBABILITY OF THE MEDICAL IMAGING SERVICE PROVIDERS IN HUNGARY

Dr. habil. Gábor Dávid Kiss, PhD
Faculty of Economics and Business Administration, University of Szeged, Szeged, Hungary
kiss.gabor.david@eco.u-szeged.hu

ABSTRACT

Medical imaging, providing Magnetic Resonance Imaging (MRI) services have a special, oligopolistic market in Hungary. A majority of the MRI machines are operated by private contractors in a Public Private Partnership form in major healthcare centres with defined machine-hours for public healthcare services while they can sell their remaining capacities on the market as well. Current paper analyses the default probability of this firms via Ohlson-O and Altman-Z' ratios, based on their annual financial report data. Then, default ratios are compared to market segment- and macro-specific variables trough panel regression analysis to identify the key factors of this technology-intense sector. Finally, results are compared to public default-rate databases.

Key words: *MRI, bankruptcy ratio, Altman-Z', Ohlson-O*

1. INTRODUCTION

This paper analyses which factors affect default probability of the set of major Hungarian MRI service provider companies. This subject involves the calculation of the Ohlson-O default ratio, and it's back testing by Altman-Z' score. Different panel regression methods were applied to test the impact of technological, healthcare-sector and economic variables on the default probability.

The analysis was mainly motivated both by the special symbiosis between the private service providers and the public healthcare system and the need for the calibration of the Ohlson and Altman scores. Despite of their evergreen popularity in the literature, they were defined in the 1960's and 1970's on US data, so it is necessary to test their accuracy and responses on the business environment.

2. THEORETICAL BACKGROUND

Bankruptcy forecasting was initiated by the multivariate discriminant analysis of Altman (1968) as the Altman-Z model for public traded enterprises. Later on other approaches were published like the logit model of Ohlson (1980), Taffler's (1984) modified Z and Zmijewski's (1984) probit model. Since then, these are the most popular methods next to the neural networks and contingent claims analysis (Jackson – Wood 2013) and they provide similar results for the companies (Agarwal – Taffler 2008, Altman 2017).

The Altman-Z (1968) model was the first multivariate default-model for public-listed enterprises in the manufacturing sector – based on their liquidity, profitability and funding conditions. Later on, it was modified to study private firms as well (Altman 1977, Altman 2000), often referred as Altman-Z' (1):

$$Z' = 0.717X1 + 0.847X2 + 3.107X3 + 0.420X4 + 0.998X5 \quad (1)$$

X1 = (current assets – current liabilities) / total assets

X2 = retained earnings / total assets

X3 = earnings before interest and taxes / total assets

X4 = book value of equity / total liabilities

X5 = sales / total assets

Companies under $Z'<1.23$ have 95% chance to go default in the next business years (it is 72% two years later and 48% three years later), while this chance is minimal above 2.9 (Altman 2000, Betts 1987, Kotormán 2009).

The original Altman-Z score has been modified many times in the last 50 years to fit private or non-manufacturing enterprises (Altman 2000). Despite it's American origin, the model was successfully tested on different European samples: it was validated on 57% of the Slovakian construction industry (Rybárová et al. 2016), an N=521 Lithuanian sample was analysed between 2009 and 2013 (Marcinkevicius – Kanapickiene 2014) and nearly 60 thousand manufacturing and construction enterprises were compared between 2008 and 2013 (Karasa és Režňáková 2015). The banking sector was also a subject of different articles: international banks (N=34) between 2007-2010 (Altman et al. 2017) as well as public owned investment banks (N=34) were studied (Brou

– Krueger 2016). The model was able to stand the test of big data analysis: samples like one thousand British enterprises between 2000-2013 (Almamy et al. 2016) or nearly nine thousand Czech companies with more than 10 employees (Machek 2014). The popularity of the method in the last two decades underlines its validity – however, some author (Tian – Yu 2017, Altman et al. 2017, Brou – Krueger 2016, Almamy et al. 2016, Grice – Ingram 2001, Wu et al. 2010, Qi 2014) suggests that a sectorial fine-calibration or the inclusion of macro-variables like inflation, interest rate or lending can enhance the predictive power ever further. The predictability of defaults one year earlier are varying on a narrow scale: 75 for Altman et al. (2017), 95-75% for Berzkalne – Zelgalve (2013), 74.5% for Marcinkevicius – Kanapickiene (2014), 88% for Salimi (2015) and 91% for Karasa – Režňáková (2015). Recession periods can bias the accuracy downwards according to Berzkalne – Zelgalve (2013).

The Ohlson-O model (2) based on a logistic regression (Ohlson 1980), and it represents the probability of default within the next two years for P>0,5 under 96% reliability:

$$O=-1,32-0,407*\log(TA/GNP)+6,03*TL/TA-1,43*WC/TA+0,0757*CL/CA-1,72*X-2,37*NI/TA-1,83*FFO/TL+0,285*Y-0,521*(NIt-NIt-1)/(abs(NIt)-abs(NIt-1)) \quad (2)$$

$$P = \frac{e^0}{1 - e^0} \quad (3)$$

TA = total assets

GNP = Gross National Product price index level

TL = total liabilities

WC = working capital

CL = current liabilities

CA = current assets

X = 1 if TL > TA, 0 otherwise

NI = net income

FFO = funds from operations (calculated according to Bíró (2015) and law 2000/C)

Y = 1 if a net loss for the last two years, 0 otherwise

The Ohlson-O score has lower popularity in the literature: the Ebsco database accounts for 172 articles which is remarkably lower than the appearance of the Altman-Z score (N=2536). However, it can be converted to an exact default-probability instead of thresholds and the relative size of the company was involved to consider the too-big-to-fail effect as well as the cash-flow. This approach was mostly used to calibrate and backtest other more specific models on big data analyses: US pricing anomalies were studied by Novy-Marx (2013), Stambaugh et al. (2012) or by Charitou et al. (2011).

The combined use of the Altman-Z and Ohlson-O methods was suggested by Dichev (1998) due to their different econometric fundaments (discriminant analysis and logit regression) and different calibration background (samples from the 1960's and the 1970's).

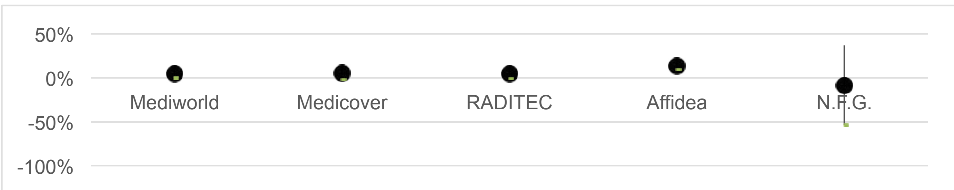
3. DATA AND METHODS

The analysed sample covered all the mayor companies on the Hungarian MRI imaging diagnostics market between 2006 and 2017, based on their publicly available annual financial reports:

- Mediworld Plus Egészségügyi Szolgáltató és Tanácsadó Kft. (3 facilities)
- Medicover Egészségközpont Zrt. (1 location)
- Raditec Kft. (1 location)
- Affidea Diagnosztika Kft. (earlier: Euromedic Diagnostics Magyarország Kft. and Nemzetközi Egészségügyi Központ Kft, 7 facilities)
- N.F.G. Egészségügyi Szolgáltató Bt. (1 location)

Other MRI machines are operated directly by the clinical centres or the companies were to new to fit to the sample period. However, sample companies have a diversified healthcare portfolio: from the different diagnostic services to real-estate management or insurance business. The market is dominated by the Affidea Diagnosztika Kft. with a remarkable 50-70% share in the balance sheet as well as in the revenues. Mediworld and Medicover takes the second and third place, while Raditech and N.F.G had marginal importance.

Picture 1.: Pre-tax margins



Source: corporate annual financial reports, author's edition

Their profitability (pre-tax ratio: pre-tax profit divided by revenues) varied on a narrow scale (except the volatile N.F.G.): Affidea seemed to be most profitable in the sample (14%), whileMediworld, Medicover and Raditec has lower (4-5%) ratio.

This study focuses on the reasons behind the changes of the default ratios, that is why they were regressed on different economic variables. Changes in the total and state healthcare spending to GDP (source: Hungarian Statistical Office – KSH) or log differentials of hospital beds (source: KSH), and the appearance of "MRI" in the Hungarian google searches (source: Google trends) represents the overall conditions in the sector. The macroeconomic and financial conditions were represented by the changes of price index in the service sector (source: KSH), log changes of the total corporate debt (source: Hungarian National Bank – MNB), changes of the short-term corporate debt interest rates (source: MNB), log changes of EUR/HUF rate (source: stooq.com), recession in the Euro-zone (source: CEPR). General technological environment was represented by the log change of mobile internet subscriptions (source: KSH).

Panel data can be analysed mainly through tree approaches: fixed (FE) or random (RE) effect models (4) or dynamic approach if the model has a tendency towards autocorrelation.

$$\text{FE: } \gamma_{it} = (\alpha + u_i) + X_{it}'\beta + \varepsilon_{it}$$

$$\text{RE: } \gamma_{it} = \alpha + X_{it}'\beta + (u_i + \varepsilon_{it}) \quad (4)$$

The fixed effect model assumes that variables are different but stable in time, while random effect models model points on the differences among the variables more. Input variables shall be stationary (Im, Pesaran and Shin test $p<0.05$), residuals can not be autocorrelated (FE: Wooldridge $p>0.05$, RE: Baltagi and Li-test $p>0.05$, or Durbin-Watson-test~2). Choice between FE and RE models depends on the Hausman test: RE is preferred under $p>0.05$, otherwise FE (Wooldridge 2010).

Dynamic panel regression is used when the number of variables are big, but the analysed time frame is relatively short and the dependent variable is autocorrelated, so it can be assumed as a product of an AR(1) process (Blundell – Bond, 1998; Arellano – Bond, 1991):

$$\gamma_{it} = \alpha\gamma_{it-1} + \beta\chi_{it} + \mu_i + \upsilon_{it},\ i=1,\ldots, n,\ t=1,\ldots,T_i. \quad (5)$$

considering:

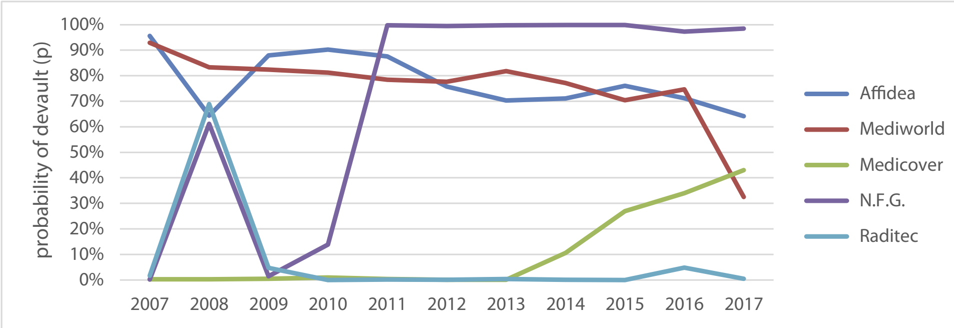
$$\gamma_{it} = \beta\chi_{it} + f_i,\ \xi_{it}\ ahol\ \xi_{it} = \alpha\xi_{it-1} = \upsilon_i\ és\ \mu_i = (1\text{-}\alpha)f_i,\ |\alpha| < 1. \quad (6)$$

The over identification of the model is checked via Sargan-test ($p>0.05$).

4. RESULTS

The biggest advantage of the Ohlson-O score is its better scalability (100%>P>0%), while the relative corporate size and the cash-flow positions are included as well. Later this statistics will be used in the panel regressions, after they were validated by by Altman-Z' score.

Picture 2.: Ohlson-O scores, probability of default

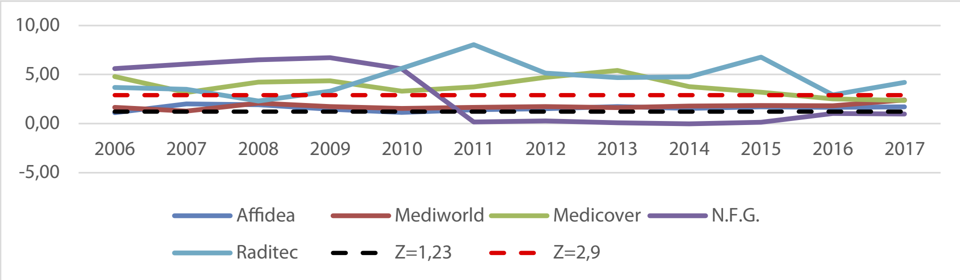


Source: corporate annual financial reports, author's edition

The N.F.G. Bt increased its balance sheet by ten times during the sample-period, creating serous financial distress after 2011. Meanwhile the market-leader Affidea followed an improving-but-risky path as well as the Mediworld through improved cash-flow making and balance-sheet size growth. Medicover was on an opposite path due to their deteriorating operational cash.flow. The Raditec operated completely cautiously with under conservative principles. However, the crisis year of 2008 had a significant impact on the entire sample.

Default is likely under 1.23 Altman-Z' scores (picture 3), while the company is in the green-zone above 2.9. The N.F.G. Bt went trough a serious expansion, but it had an adverse impact on financial stability – aggressive funding and lagged income growth characterized the sample-period. The Raditec Kft. had similar size, but stayed continuously in the green-zone (except 2008) – due to their remarkable retained earnings and financial assets and limited liabilities. Conservative funding characterized the Medicover until 2016 – they were unique with their generous dividend-policy and the huge short-term funding which is balanced by cash reserves and profitability. Affidea and Mediworld was located in the middle of the grey-zone – the first company can be characterized through aggressive funding, limited financial assets but high profitability. The second company had lower scores due to their higher share in short term liabilities and low stock of financial assets.

Picture 3.: Altman-Z' scores



Source: corporate annual financial reports, author's edition

Both default ratios supported each other: while Raditec followed an extraordinary stable path, Affidea and Mediworld proved to be riskier and the N.F.G. presented serious financial distress. After the robustness-check, the validated default ratios are analysed in three models, how they reacted on major sectorial, economic and technological developments (7-9).

Technological model: $\Delta P = \alpha \Delta IT + \varepsilon$ (7)

Sectorial model: $\Delta P = \alpha \Delta \frac{\Sigma H}{GDP} + \beta \Delta \frac{public\ H}{GDP} + \gamma \Delta NO + \varepsilon$ (8)

Economic model: $\Delta P = ar + \beta \Delta L + \gamma \Delta EURHUF + \delta a \Delta Rec + \delta a \Delta Price$ (9ab)

The developments in the technologic environment (7) can described trough the mobile internet penetration which opens the opportunities for cost cuts (distant diagnostics, internet-of-things, lower component-prices).

Model 1: Fixed-effects, using 40 observations
Included 5 cross-sectional units
Time-series length = 8
Dependent variable: dOhlson
Robust (HAC) standard errors

	coefficient	std. error	t-ratio	p-value
const	−0.0609040	0.0660465	−0.9221	0.4086
dInternet	−0.276243	0.377278	−0.7322	0.5046
dInternet_1	**0.658775**	0.207680	3.172	0.0338 **
dOhlson_1	0.0506658	0.0389944	1.299	0.2637

Mean dependent var	0.015385	S.D. dependent var	0.161773
Sum squared resid	0.828216	S.E. of regression	0.160878
LSDV R-squared	0.188542	Within R-squared	0.026975
Log-likelihood	20.78967	Akaike criterion	−25.57934
Schwarz criterion	−12.06830	Hannan-Quinn	−20.69418
rho	−0.036750	Durbin-Watson	1.909331

However, the regression had to opposite result: overall technological development increased the default ratio (even with the excusion of the N.F.G. Bt – 0.61 coefficient), which request for further analysis in the future.

The healthcare sector (8) in highly affected by the continuous withdrawal of public spending ($\frac{public\ H}{GDP}$), and decrease in hospital capacities (ΔNO). Households shall compensate it from their private savings (directly or through private healthcare insurance plans) to balance the general healthcare spending ($\Delta\frac{\Sigma H}{GDP}$). Sample companies are allowed to sell the excessive machine-hours, so waiting-lists can be bypassed. It can be more profitable for sample companies, because of the increased public healthcare spending increases the probability of default. We had similar results with the bed-number as well.

Model 2a: Random-effects (GLS). using 40 observations
Included 5 cross-sectional units
Time-series length = 8
Dependent variable: dOhlson

	coefficient	std. error	z	p-value	
const	0.0435631	0.0333815	1.305	0.1919	
dpub_H_GDP	−0.0260059	0.481841	−0.05397	0.9570	
dpub_H_GDP_1	**0.433288**	0.185614	2.334	0.0196	**
dOhlson_1	**−0.258329**	0.118608	−2.178	0.0294	**

Mean dependent var	0.000948	S.D. dependent var	0.206508
Sum squared resid	1.224280	S.E. of regression	0.181903
Log-likelihood	12.97299	Akaike criterion	−17.94598
Schwarz criterion	−11.19046	Hannan-Quinn	−15.50339

Breusch-Pagan test -
Null hypothesis: Variance of the unit-specific error = 0
Asymptotic test statistic: Chi-square(1) = 0.120547
with p-value = 0.728442
Hausman test -
Null hypothesis: GLS estimates are consistent
Asymptotic test statistic: Chi-square(1) = 2.34388
with p-value = 0.125776

However, the increase of private and public healthcare spending all together decreased the bankruptcy likelihood (in the case of the exclusion of the N.F.G. Bt).

Model 2b.: Random-effects (GLS), using 32 observations
Using Nerlove's transformation
Included 4 cross-sectional units
Time-series length = 8

Dependent variable: dOhlson
Robust (HAC) standard errors

	coefficient	std. error	z	p-value
const	0.00995748	0.0297382	0.3348	0.7377
dpub_H_GDP	−0.00315067	0.374006	−0.008424	0.9933
dpub_H_GDP_1	0.443835	0.331633	1.338	0.1808
dH_GDP	−0.199156	0.153104	−1.301	0.1933
dH_GDP_1	**−0.189004**	0.0811505	−2.329	0.0199 **
dOhlson_1	**−0.413069**	0.0278364	−14.84	8.18e-050 ***

Mean dependent var	−0.010089	S.D. dependent var	0.132855
Sum squared resid	0.325692	S.E. of regression	0.109830
Log-likelihood	27.99458	Akaike criterion	−43.98916
Schwarz criterion	−35.19475	Hannan-Quinn	−41.07406

Breusch-Pagan test -
Null hypothesis: Variance of the unit-specific error = 0
Asymptotic test statistic: Chi-square(1) = 1.74578
with p-value = **0.186409**
Hausman test -
Null hypothesis: GLS estimates are consistent
Asymptotic test statistic: Chi-square(1) = 2.25095
with p-value = **0.133532**

The general economic environment included price level, funding conditions, exchange rates and external conjuncture (9ab). Central banks were fighting deleveraging with low interest rates, creating volatility on the exchange rates as well. This is why low interest rates can have adverse impacts on default probability – generally they should improve profitability through cheaper funding, however an accommodating monetary policy is a sign of systemically shrinking macro-demand.

Model 3a: 1-step dynamic panel, using 35 observations
Included 5 cross-sectional units
H-matrix as per Ox/DPD
Dependent variable: dOhlson

	coefficient	std. error	z	p-value
dOhlson(-1)	**−0.110161**	0.0616348	−1.787	0.0739 *
dOhlson(-2)	**−0.263189**	0.124511	−2.114	0.0345 **
const	−0.00878895	0.0212695	−0.4132	0.6794
dr_1	**−0.0206261**	0.00765091	−2.696	0.0070 ***
dL_1	0.306372	0.592305	0.5173	0.6050
dEURHUF_1	0.175508	0.569579	0.3081	0.7580
Recession_1	**0.0462163**	0.0124721	3.706	0.0002 ***

Sum squared resid 0.916829 S.E. of regression 0.180953
Number of instruments = 32
Test for AR(1) errors: z = -1.5205 [0.1284]
Test for AR(2) errors: z = 0.890604 [0.3731]
Sargan over-identification test: Chi-square(25) = 36.1907 [**0.0688**]
Wald (joint) test: Chi-square(0) = NA

The importance of the European conjuncture and introduced monetary easing characterized the increase of the default probability. It is remarkable, because most of the sample-companies were focusing mainly on funding through short-term liabilities, instead of "ordinary" long-term loans.

Model 3b: 1-step dynamic panel, using 35 observations
Included 5 cross-sectional units
H-matrix as per Ox/DPD
Dependent variable: dOhlson

	coefficient	std. error	z	p-value
dOhlson(-1)	**−0.0926301**	0.0517468	−1.790	0.0734 *
dOhlson(-2)	**−0.252144**	0.118114	−2.135	0.0328 **
const	−0.0270114	0.0236428	−1.142	0.2533
dr_1	**−0.0184837**	0.00805461	−2.295	0.0217 **
dL_1	−0.787954	0.974828	−0.8083	0.4189
dEURHUF_1	0.761216	0.730065	1.043	0.2971
d_prices_1	**0.0678340**	0.0282505	2.401	0.0163 **

Sum squared resid 0.925011 S.E. of regression 0.181758
Number of instruments = 32
Test for AR(1) errors: z = -1.5054 [0.1322]
Test for AR(2) errors: z = 0.90892 [0.3634]
Sargan over-identification test: Chi-square(25) = 35.6728 [**0.0767**]
Wald (joint) test: Chi-square(0) = NA

The price index in the service sector increased the default probability, underlining the poor market demand.

5. CONCLUSION

Healthcare sector has strategic importance in each economies due to their importance in the maintenance of the human capital. However, the establishment and maintenance of an up to date infrastructure requires huge and long term investments. The medical imaging is a good example for that: an MRI machine can serve an entire city and the neighbouring region, while the equipment can expire within a decade from technological point of view.

The Ohlson and Altman scores provided similar results for the sample companies. However, even a continuously poor value did not resulted default automatically, but it was useful to monitor the financial distress of the underlying companies. This kind of application was supported by our panel findings, were default probabilities responded on the changes in the business environment.

This research was supported by the EU-funded Hungarian grant EFOP-3.6.1-16-2016-00008

REFERENCES

1. Agarwal, V. – Taffler, R. (2008): Comparing the performance of market-based and accounting-based bankruptcy prediction models. Journal of Banking and Finance, 32, 1541–1551. o.
2. Almamy, J. – Aston, J. – Ngwa, L. N. (2016): An evaluation of Altman's Z-score using cash flow ratio to predict corporate failure amid the recent financial crisis: Evidence from the UK. Journal of Corporate Finance, 36, 278-285. o.
3. Altman, E. I. – Haldeman, R. G. – Narayanan, P. (1977): ZETA Analysis: A New Model to Identify Bankruptcy Risk of Corporations. Journal of Banking and Finance, 1, 29-54. o.
4. Altman, E. I. – Iwanicz-Drozdowska, M. – Laitinen, E. K. – Suvas, A. (2017): Financial Distress Prediction in an International Context: A Review and Empirical Analysis of Altman's Z-Score Model. Journal of International Financial Management & Accounting, 28, 131-171. o.
5. Altman, E. I. (1968): Financial Ratios, Discriminant Analysis and the Prediction of Corporate Bankruptcy. Journal of Finance, 23, 589-609. o.
6. Altman, E. I. (1983): Corporate Financial Distress: A Complete Guide to Predicting, Avoiding, and Dealing With Bankruptcy. Wiley-Interscience, John Wiley & Sons, Hoboken.
7. Altman, E. I. (2000): Predicting Financial Distress of Companies: Revisiting the Z-Score and Zeta models. Journal of Banking and Finance, 1, 1-51. o.
8. Altman, E. I. (2002): Corporate Distress Prediction Models in a Turbulent Economic and Basel II Environment. In Ong, M. (ed.): Credit Rating: Methodologies, Rationale and Default Risk, Risk Books, London, 1-29. o.
9. Altman, E. I. (2006): Corporate Financial Distress and Bankruptcy: Predict and Avoid Bankruptcy, Analyze and Invest in Distressed Debt. John Wiley & Sons, Hoboken.
10. Arellano, M. – Bond, S. (1991): Some tests of specification for panel data: Monte carlo evidence and an application to employment equations. The Review of Economic Studies. 58, 277-297. o.
11. Berzkalne, I. – Zelgalve, E. (2013): Bankruptcy Prediction Models: A Comparative Study of the Baltic Listed Companies. Journal of Business Management, 6, 72-82. o.
12. Betts, J. – Belhoul, D. (1987): The Effectiveness of Incorporating Stability Measures in Company Failure Models. Journal of Business Finance & Accounting, 16, 361-383. o.
13. Bíró T. – Kresalek P. – Pucsek J. – Sztanó I. (2015): A vállalkozások tevékenységének komplex elemzése. Perfekt kiadó, Budapest.
14. Blundell, R. – Bond, S. (1998): Initial conditions and moment restrictions in dynamic panel data models. Journal of Econometrics. 87, 115-143. o.
15. Brou, F. B. – Krueger, T. M. (2016): Continental and National Differences in the Financial Ratios of Investment Banking Companies: An Application of the Altman Z Model. Journal of Accounting and Finance, 16, 37-49. o.
16. Charitou, A. – Lambertides, N. – Trigeorgis, L. (2011): Distress Risk, Growth and Earnings Quality. Abacus, 47, 158-181. o.
17. Dichev, I. D. (1998): Is the risk of bankruptcy a systematic risk? Journal of Finance, 53, 1131-1147. o.
18. Grice, J. S. – Ingram, R. W. (2001): Tests of the Generalizability of Altman's Bankruptcy Prediction Model. Journal of Business Research, 54, 53-61. o.

19. Jackson, R. H. G. – Wood, A. (2013): The Performance of Insolvency Prediction and Credit Risk Models in the UK: A Comparative Study. British Accounting Review, 45, 183-202. o.
20. Karasa, M. – Režňáková, M. (2015): Predicting bankruptcy under alternative conditions: the effect of a change in industry and time period on the accuracy of the model. Procedia - Social and Behavioral Sciences, 213, 397-403. o.
21. Kotormán A. (2009): A mezőgazdasági vállalkozások felszámolásához vezető okok elemzése. Doktori értekezés, Debreceni Egyetem, Debrecen.
22. Machek, O. (2014): Long-term Predictive Ability of Bankruptcy Models in the Czech Republic: Evidence from 2007-2012. Central European Business Review, 3, 14-17. o.
23. Marcinkevicius, R. – Kanapickiene, R. (2014): Bankruptcy prediction in the sector of construction in Lithuania. Procedia - Social and Behavioral Sciences, 156, 553-557. o.
24. Novy-Marx, R. (2013): The other side of value: The gross profitability premium. Journal of Financial Economics, 108, 1-28. o.
25. Ohlson, J. A. (1980): Financial ratios and the probabilistic prediction of bankruptcy. Journal of Accounting Research, 18, 109-131. o.
26. Qi, M. – Zhang, X. – Zhao, X. (2014): Unobserved systematic risk factor and default prediction. Journal of Banking & Finance, 49, 216-227. o.
27. Rybárová, D. – Braunová, M. – Jantošová L. (2016): Analysis of the Construction Industry in the Slovak Republic by Bankruptcy Model. Procedia - Social and Behavioral Sciences, 230, 298 – 306. o.
28. Salimi, A. Y. (2015): Validity of Altmans Z-Score Model in Predicting Bankruptcy in Recent Years. Academy of Accounting and Financial Studies Journal, 19, 233-238. o.
29. Stambaugh, R. F. – Yu, J. – Yuan, Y. (2012): The short of it: Investor sentiment and anomalies. Journal of Financial Economics, 104, 288-302. o.
30. Taffler, R. J. (1984): Empirical Models for the Monitoring of UK Corporations. Journal of Banking and Finance, 8, 199–227. o.
31. Tian, S. – Yu, Y. (2017): Financial ratios and bankruptcy predictions: An international evidence. International Review of Economics and Finance, 51, 510-526. o.
32. Wooldridge, Jeffrey M. (2010): Econometric Analysis of Cross Section and Panel Data. The MIT Press Cambridge, Massachusetts
33. Wu, Y. – Gaunt, C. – Gray, S. (2010): A comparison of alternative bankruptcy prediction models. Journal of Contemporary Accounting & Economics, 6, 34-45. o.
34. Zmijewski, M. E. (1984): Methodological Issues Related to the Estimation of Financial Distress Prediction Models. Journal of Accounting Research, 22, 59–82. o.

ZADANA VJEROJATNOST SLIKE PRUŽATELJA MEDICINSKIH USLUGA U MAĐARSKOJ

SAŽETAK RADA:

Medicinska slika, usluga magnetske rezonance (MRI) ima poseban oligopolistički udio na tržištu. Većina uređaja za magnetsku rezonancu imaju privatnici u sklopu javno-privatnog partnerstva i posluju u glavnim medicinskim centrima. Radni sati uređaja su definirani za javno pružanje medicinskih usluga, a ostatak kapaciteta može se prodavati na tržištu. Ovaj rad analizira zadanu vjerojatnost ovih tvrtki pomoću omjera Ohlson-O i Altman-Z na temelju njihovih godišnjih izvješća. Zatim se zadani omjeri uspoređuju s dijelom tržišta i makro specifičnim varijablama pomoću panel regresijske analize kako bi se identificirali ključni čimbenici ovog tehnološki jakog sektora. Na kraju se rezultati uspoređuju s javnim datotekama definiranih stopa.

***Ključne riječi** MRI, omjer bankrota, Altman-Z', Ohlson-O*