“Family businesses and predictability of financial strength: a Hungarian study”

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FAMILY BUSINESSES AND PREDICTABILITY OF FINANCIAL STRENGTH: A HUNGARIAN STUDY

Abstract

The aim of this study is to examine how bankruptcy prediction models forecast financial strength for family businesses. Three predictive tests are used to study financial strength for three consecutive years (2016, 2017 and 2018) for a sample of 462,200 active Hungarian companies using the Amadeus database and expert data. Complex statistical model tests for credit assessment (bankruptcy predictions) are performed by size and ownership of the companies. It is found that the revised Altman model is impeded by a superfluous high weighting on net working capital; therefore, IN05 Quick Test predicted better chances for businesses in generating cash flows in a small emerging economy. By re-formulating the Bankruptcy Index of Karas and Režňáková and refining its coefficients, the modified Bankruptcy Index is more robust for predicting the financial health of family businesses on a cash flow basis. The test results of this modified Bankruptcy Index confirm the relative advance of family businesses in creating added value for owners. Practical implications arise from a management perspective: family businesses work better with predictability of survival in accordance with the model; therefore, their ability to adapt to financial constraints caused by crises is also more promising.

Keywords capital structure, bankruptcy, predictive tests, financial sustainability, revised Altman Z-score

JEL Classification C53, G32

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INTRODUCTION

Family businesses – their entrepreneurial values, personal leadership, and the name of the family with the intent of succession – are more oriented towards financial sustainability than non-family businesses. Those family business owners, who have sufficient management skills and know-how (as entrepreneurs) and also possess high creativity and innovation (as owner-managers), are likely to have a greater chance of survival and success (Chandler & Sági, 2018).

Family businesses struggle to survive in turbulent economic times, and thus bankruptcy prediction becomes increasingly important (Sági & Nikulin, 2017; Shkolnyk, Pisula, Loboda, & Nebaba, 2019). The bankruptcy of a family business does not only mean the end of the company's activity, but also the end of a family legacy, not to mention the knock-on effect for company stakeholders. The far-reaching effects of bankruptcy, if occurring on a large scale, can affect communities and even society as a whole, and can have far reaching constraints on governing bodies as well (Lentner & Kolozsi, 2019). The family business setup in Hungary and its development since the last decade of the previous (socialist) political regime, and mainly from the beginning of the regime change, attach great importance to this study. Family businesses have constantly been highlighted by Hungarian governmental

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policies as seeds of the market economy, promoting growth, not only generating substantial income for families, but also creating workplaces for others (Lentner, 2020). This study examines the financial perspectives and operational riskiness of family businesses by evaluating recent financial data and predicting their survival.

Predictive models have been developed as attempts to minimize losses or prevent bankruptcy as quickly as possible (Wu, Gaunt, & Gray, 2010). In this study, three such models are compared: the revised Altman Z-score; the IN05 Quick Test; and a new Bankruptcy Index. Quantitative data based on past and present financial data of Hungarian companies, alongside qualitative information about their size and ownership, have been compiled in the analysis.

1. LITERATURE REVIEW

Although many small businesses fail in the early years, this does not always apply to small businesses. Amann and Jaussaud (2012) investigated both non-family and family firms and found that, during an economic downturn, family businesses were more resilient both during and after an economic crisis when compared to non-family businesses. Moreover, they resist the downturn better, recover faster, and continue this trend of higher performance afterwards. Many studies on bankruptcies or failure in family businesses tend to focus on this resilience and reasons for survival, rather than question the likelihood of failure or financial health. As such, no empirical studies were found regarding the predicting bankruptcy in family businesses. Therefore, the following sub-section gives an overview of empirical studies that have compared predictive models, but not necessarily for family businesses.

1.1. Empirical studies on predictive modeling

Given an applicable combination of accounting ratios, bankruptcy indices can be built to predict whether a company generates added value to its owners in the long run, losing the invested capital, or stays in an unpredictable grey zone (Beaver, 1966; Edmister, 1972; Blum, 1974; Ohlson, 1980). These models are run with an approximate of 95-99 per cent of certainty (however, these model certainties are changing with time, see Altman, 2000).

The Altman Z-score tests a company's credit-strength, and this in turn indicates the likelihood of bankruptcy. It is based on five financial ratios (using the *F*-test), which are calculated using the data from a company's annual report. These five ratios provide data on profitability, leverage, liquidity, solvency and activity, which in turn can serve as indicators of potential bankruptcy with the use of a discriminate analysis. This study will use the revised model, which will be elaborated further in the Methodology section, along with the formulae for each model. Altman (1968) originally tested 33 bankrupt enterprises and 33 financially healthy enterprises, with a resulting 95% accuracy. The Altman Z-Score model has been tested in many studies (e.g., Wang & Campbell et al., 2010). For this study, however, the model will be tested on an unprecedentedly larger scale (i.e. on the total of registered companies of a country), due to accessibility to a larger database.

The IN05 model was based on data collected from 1,526 industrial companies in the Czech Republic for the year 2004 and is interpreted as a combination of predicting bankruptcy and solvency, through criteria that determine the value that a company creates for its owners. This model will also be tested on the country-wide sample, assuming that the financial strength might have different patterns in accordance with the nature of company owners.

H. Platt and M. Platt (1990) focus on the supplemental testing of any kind of bankruptcy indicators. Karas et al. (2013), after examining the potential use of the Altman Model in the Czech Republic, made a suggestion for an alternative Bankruptcy Index (Karas & Režňáková, 2014). The model was later tested by Karas and Režňáková (2015) on a larger sample (58,244 companies), who found lower accuracy than before. This model was modified in accordance with the experts' database of

family businesses (the details can be found in the Methodology section), by taking into consideration low capitalization of Hungarian companies. The companies within the scope of this investigation have come traditionally from years with weak capital accumulation, high reliance on bank loans (mostly of foreign denominations), and the lack of expertise in financial planning.

Many studies on bankruptcies or failures in family businesses tend to focus on this resilience and reasons for survival, rather than question the likelihood of failure. As such, no empirical studies were found on predicting bankruptcy in family businesses. Baixauli and Módica-Milo (2010) examine how unhealthy SMEs may affect predictive bankruptcy modeling by creating a predictive bias, which eschews predictions. Beaver et al. (2005) also question the accuracy of predictive models but from the point of view of the financial statement data used for predictions. They found that predictive power varied little over a forty-year period, despite changes in financial reporting that could have influenced predictability.

Gu (2002) applied a multiple discriminant analysis to examine US restaurants. The method proved to have the 92 percent accuracy in classifying firms into bankrupt and non-bankrupt categories, with an 89 percent cross-validation accuracy rate and 80 percent ex-post classification. Kwansa and Parsa (1990) analyzed the events leading up to bankruptcy as a means of considering the predictive power of models. The study identified certain factors that specific to bankrupt firms: net losses, management turnover, loan default, credit accommodation, royalty default, decline in unit sales, and renegotiation of franchise contract. Thanh Tung and Phung (2019) evaluated other factors – both financial and non-financial – to consider how they would affect bankruptcy risk. The method employed a binary logistic regression; however, this study involved a rather limited dataset. Cho et al. (2010) used a different method to predict bankruptcies: a neural network learning approach. After testing, findings indicated only a slight increase in prediction accuracy compared to other methods.

Grice and Dugan (2001) considered how accuracy may alter based on varying the time periods used for models and found that accuracy declined. Fang-Mei and Yi-Chung (2010) suggest including other methodologies, i.e. logit, quadratic interval logit, neural and fuzzy neural networks for investigations, with the purpose of advising the company's management to introduce actions to prevent a potential bankruptcy. In relation to the latter of these three methodologies, Kozlovskyi, Butyrskyi, Poliakov, Bobkova, Lavrov, and Ivanyuta (2019) employed a fuzzy sets method to predict the likelihood of bankruptcy of Ukrainian enterprises, but for large capital-market oriented companies, which report in accordance with the International Financial Reporting Standards.

In summary, there is a lack of research on the predictive modeling of bankruptcies and financial health in family businesses, especially when the focus is on the type of ownership. Existing studies can be grouped into three areas that relate to the predictive power of models for bankruptcies (Beaver, 1966). Firstly, some studies examine the data used for the modeling, such as the events chosen as criteria for bankruptcy or the financial data for which requirements change over time. The second group examines accuracy issues based on the choice of model, and considers new or better methods for predictive capability. The scope of this study falls within the second group of studies. The third is the statistic method used for estimation, including the applicability tests for small samples (e.g., Kim, 2011; Lukason & Käsper, 2017; Gavurova, Packova, Misankova, & Smrcka, 2017).

2. AIMS

The aim of the paper is to test on a robust sample whether family businesses work better than non-family businesses, when survival prospects (predictions for bankruptcy) are modelled, and to consider the accuracy of these models.

3. DATA AND METHODS

3.1. Operational definitions and assumptions

This study examines the predictive models for bankruptcy, and the precursor to this that financial health is a function of a company's credibility

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and financial added value to shareholders (Korom & Sági, 2005). The study assumes that declining financial health is an indicator of bankruptcy, all other things being equal. It is also assumed that growth and decline are linear processes that can thus be predicting based upon selected financial data used in company reports.

The research question relates to the behavior of family businesses. Their defining characteristics involve three key elements. Firstly, decision-making rights, on the whole, are held by either the founders, a buyer of share capital in the family business, or owned by family relatives that constitute direct heirs. Secondly, at least one family representative is formally involved in the governance of the firm. Thirdly, for limited companies, the founder, or family relatives, own 25 per cent of the decision-making rights.

The variable of company size has also been included in tests. SMEs have been defined by the European Commission as: less than 250 persons employed, a maximum annual turnover of EUR 50 million, or a balance sheet total of no more than EUR 43 million[1]; whereas large companies are in excess of these limits. According to this sample, within SMEs, the small-size enterprises dominate among Hungarian enterprises, by 89.9 per cent out of the total. For family businesses, the ratio of small enterprises stands at 92.1 per cent. These facts underline the importance of measuring the bankruptcy risks for family businesses, considering that the living conditions of families are at stake. These criteria will be used for the sample and will be detailed further in the following section.

3.2. Methodology

Statistical models can be used to derive a selection and weighting of creditworthiness factors, and, thus, optimize accuracy when categorizing companies into solvent or insolvent. In the linear multiple discriminant analysis, the use of a weighted linear combination of indicators ensures that solvency cases are optimally classified, based the discriminant score D:

$$D = a_0 + a_1 \cdot K_1 + a_2 \cdot K_2 + \ldots + a_n \cdot K_n. \quad (1)$$

In the above equation, n refers to the number of financial indicators included in the bankruptcy prediction model, K_i refers to the specific indicator value, and a stands for each indicator's coefficient within the bankruptcy prediction model.

As with discriminant analysis, regression models model the dependence of a binary variable on other independent variables. When this general definition is applied to bankruptcy prediction models, certain creditworthiness characteristics (independent variables) can be used to classify borrowers as solvent or insolvent (a dependent binary variable). The combination of nonlinear model functions and the maximum likelihood method results in the potential for regression models to calculate membership probabilities. In this way, default probabilities can be directly ascertained (OeNB, 2004).

When selecting the bankruptcy risk models, the aim was to consider only those which can be applied to family businesses and do not make restrictions concerning publicly quoted shares or the availability of market capitalization (see, for example, Scott, 1981; and Wu et al., 2010). According to the applicability of bankruptcy models to companies operating in smaller EU countries in latest years of the crisis, the highest relevance was found for the Altman Z-score and the IN05 Quick Test (see Bohdalová & Klempaiová, 2017; Dolejšová, 2015). This section details the method of using the models, or, in some cases, adapted for this study along with further information on the data sample.

3.2.1. Altman Z-score model

Altman pioneered the use of the multifactor discriminant analysis to predict corporate bankruptcy (Altman, 1968). In the revised model (adjusted to companies with all types of ownership; see Altman et al., 1977), the Altman Z-score (multiple discriminant function) is a linear combination of the following five financial ratios:

$$Z = 0.717 \cdot WC/TA + 0.847 \cdot RE/TA + 3.107 \cdot EBIT/TA + 0.42 \cdot E/D + 0.998 \cdot S/TA, \quad (2)$$

1 http://ec.europa.eu/eurostat/web/structural-business-statistics/structural-business-statistics/sme

where WC/TA is the ratio of net working capital to total assets, RE/TA is the ratio of retained earnings to total assets, $EBIT/TA$ is the ratio of earnings before interest and taxes to total assets, E/D is the ratio of the accounting value of equity to total liabilities, and S/TA is the ratio of sales to total assets.

In the model interpretation, companies with the Altman Z-score less than 1.23 are in danger of bankruptcy, while those above 2.9 are assumed to be financially healthy. The interval of 1.23 and 2.9 is considered a grey area concerning the company's financial soundness and survival.

3.2.2. IN05 Quick Test

The IN05 model, on the other hand, can be written in the following form (Neumaier & Neumaierová, 2005):

$$IN05 = 0.13 \cdot TA/TL + 0.04 \cdot EBIT/I + \\ +3.97 \cdot EBIT/TA + 0.21 \cdot OR/TA + \\ +0.09 \cdot CA/CL, \quad (3)$$

where TA/TL is the ratio of total assets to total liabilities, $EBIT/I$ is the ratio of earnings before interest and taxes to interest, $EBIT/TA$ is the ratio of earnings before interest and taxes to total assets, OR/TA is the ratio of operating revenue to total assets, and CA/CL is the ratio of current assets to current liabilities.

For IN05 Quick Test values < 0.9, the company does not create value for its owners or may even destroy value, for IN05 values > 1.6, the company creates new value for its owners, and for values falling within a range of 1.6 > IN05 > 0.9, the results are inconclusive (a grey area).

The IN05 model has been designed for companies operating in one of the Central European countries, which is more relevant in the rather similar context of business environment of Hungarian companies.

3.2.3. Modified Bankruptcy Index

To examine Hungarian companies, the Bankruptcy Index of Karas and Režňáková (2015) was modified by substituting the element of the value of total assets in the formula to an asset-based solvency ratio (as the latter is more applicable according to, for example, Thornhill and Amit, 2003). Also, the coefficients for the indicators were refined through a blend of linear discriminant analysis and Box-Cox transformation of variables (see Zmijewski, 1984). The modified Bankruptcy Index is as follows:

$$BI = 1.1120 \cdot (X_1 + 1)^{-0.35627} + \\ +13.5500 \cdot (X_2 + 1.12)^{-2.97955} + \\ +1.8410 \cdot (X_3)^{0.02941}, \quad (4)$$

where X_1 is the total assets turnover ratio (ratio of sales to total assets), X_2 is the ratio of quick assets (current assets minus inventories) to sales, and X_3 is the invert of the asset-based solvency ratio (total assets to total liabilities).

A company is evaluated as of high risk of bankruptcy if the index is lower than 7, in grey zone from 7 to 9, otherwise it is evaluated as of low risk of bankruptcy.

3.3. Data source

Data from Amadeus (Analyse Major Databases from European Sources) has been utilized in this study. The database allows its users to specify formulas for a given set of variables, and then run tests accordingly. Hungarian companies' data between 2016 and 2018 was examined. Out of the total 462,200 active companies at the end of 2018, there were 339,305 ones with family ownership (in comparison to 122,895 other companies). To select family owned companies, expert additional data from the Hungarian Chamber of Auditors was used. The employed descriptive variables were: company owners (family or non-family), and the category of each company by size.

Following the working definition of family businesses referred to earlier in this paper, the European Commission criteria were examined for each business. Only companies that met these criteria were marked and selected for analysis. The categories of companies by size were:

- Very large (Operating revenue more than or equal to 100 million EUR; Total assets more than 200 million EUR; Employees more than

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or equal to 1,000 listed) and large companies (Operating revenue more than or equal to 10 million EUR; Total assets more than or equal to 20 million EUR; Employees more than or equal to 150);

- Medium-sized companies (Operating revenue more than or equal to 1 million EUR; Total assets more than or equal to 2 million EUR; Employees more than or equal to 15; and they are not very large or large); and
- Small companies (those not included in any other category).

Keasey and Watson (1991) outlined the importance of appropriateness of sample selection methods, therefore, the companies were examined by their ownership and size for all three models.

4. RESULTS

Three models that are tested will be listed here consecutively. For each model, the total data sample is presented first, followed by the scores for family-owned and other companies grouped according to size. Tables 1 and 2 show the bankruptcy test results for Altman Z-scores.

In case of the IN05 model, three out of the five elements of the index refer directly to earnings generating capability of the companies. The overall results are also more positive for family businesses than non-family businesses in case of this test (Tables 3 and 4), especially for small and medium-sized companies.

The last sets of Tables 5 and 6 are based on the third model, the modified Bankruptcy Index. This index was developed to demonstrate the added value (in terms of operating cash flow) relative to the assets invested to the company. According to the tests, the distribution of the overall Hungarian companies by size is quite similar to the ones of the Altman Z and the IN05, except that the middle range (the grey zone) was narrowed to enhance the model predictability. In case of ownership differentiation, family businesses work better than average.

Table 1. Altman Z-scores of the total of active Hungarian companies grouped by size

Source: Own tests based on company data from Amadeus.

Category of companies	Altman Z-score (%)							
	Less than 123.00%		From 123.00% to 290.00%		More than 290.00%		All	
Reference year: 2018								
Very large companies	343	0.1%	212	0.0%	183	0.0%	738	0.2%
Large companies	1 916	0.4%	1 474	0.3%	1 462	0.3%	4 852	1.0%
Medium-sized companies	13 743	3.0%	12 201	2.6%	15 219	3.3%	41 163	8.9%
Small companies	220 975	47.8%	98 492	21.3%	95 980	20.8%	415 447	89.9%
All	236 977	51.3%	112 379	24.3%	112 844	24.4%	462 200	100.0%
Reference year: 2017								
Very large companies	334	0.1%	237	0.1%	167	0.0%	738	0.2%
Large companies	1 938	0.4%	1 523	0.3%	1 391	0.3%	4 852	1.0%
Medium-sized companies	14 684	3.2%	12 454	2.7%	14 025	3.0%	41 163	8.9%
Small companies	227 066	49.1%	97 356	21.1%	91 025	19.7%	415 447	89.9%
All	244 022	52.8%	111 570	24.1%	106 608	23.1%	462 200	100.0%
Reference year: 2016								
Very large companies	334	0.1%	243	0.1%	161	0.0%	738	0.2%
Large companies	2 072	0.4%	1 507	0.3%	1 273	0.3%	4 852	1.0%
Medium sized companies	16 452	3.6%	11 696	2.5%	13 015	2.8%	41 163	8.9%
Small companies	232 467	50.3%	92 219	20.0%	90 761	19.6%	415 447	89.9%
All	251 325	54.4%	105 665	22.9%	105 210	22.8%	462 200	100.0%

Note: Figures refer to the number of companies and their shares in the total.

Table 2. Altman Z-scores of the total of active Hungarian companies grouped by size and differentiated by ownership

Source: Own tests based on company data from Amadeus.

Category of companies	Altman Z-score (%)							
	Less than 123.00%		From 123.00% to 290.00%		More than 290.00%		All	
FAMILY BUSINESSES								
Reference year: 2018								
Very large companies	70	0.0%	22	0.0%	21	0.0%	113	0.0%
Large companies	410	0.1%	443	0.1%	559	0.2%	1 412	0.4%
Medium-sized companies	5 038	1.5%	8 584	2.5%	11 609	3.4%	25 231	7.4%
Small companies	135 669	40.0%	88 133	26.0%	88 747	26.2%	312 549	92.1%
All	141 187	41.6%	97 182	28.6%	100 936	29.7%	339 305	100.0%
Reference year: 2017								
Very large companies	65	0.0%	34	0.0%	14	0.0%	113	0.0%
Large companies	436	0.1%	452	0.1%	524	0.2%	1 412	0.4%
Medium-sized companies	5 778	1.7%	8 802	2.6%	10 651	3.1%	25 231	7.4%
Small companies	141 777	41.8%	87 053	25.7%	83 719	24.7%	312 549	92.1%
All	148 056	43.6%	96 341	28.4%	94 908	28.0%	339 305	100.0%
Reference year: 2016								
Very large companies	62	0.0%	37	0.0%	14	0.0%	113	0.0%
Large companies	480	0.1%	469	0.1%	463	0.1%	1 412	0.4%
Medium-sized companies	6 964	2.1%	8 395	2.5%	9 872	2.9%	25 231	7.4%
Small companies	146 216	43.1%	82 464	24.3%	83 869	24.7%	312 549	92.1%
All	153 722	45.3%	91 365	26.9%	94 218	27.8%	339 305	100.0%
NON-FAMILY BUSINESSES								
Reference year: 2018								
Very large companies	273	0.2%	190	0.2%	162	0.1%	625	0.5%
Large companies	1 506	0.4%	1 031	0.3%	903	0.3%	3 440	1.0%
Medium-sized companies	8 705	2.6%	3 617	1.1%	3 610	1.1%	15 932	4.7%
Small companies	85 306	25.1%	10 359	3.1%	7 233	2.1%	102 898	30.3%
All	95 790	28.2%	15 197	4.5%	11 908	3.5%	122 895	36.2%
Reference year: 2017								
Very large companies	269	0.2%	203	0.2%	153	0.1%	625	0.5%
Large companies	1 502	0.4%	1 071	0.3%	867	0.3%	3 440	1.0%
Medium-sized companies	8 906	2.6%	3 652	1.1%	3 374	1.0%	15 932	4.7%
Small companies	85 289	25.1%	10 303	3.0%	7 306	2.2%	102 898	30.3%
All	95 966	28.3%	15 229	4.5%	11 700	3.4%	122 895	36.2%
Reference year: 2016								
Very large companies	272	0.2%	206	0.2%	147	0.1%	625	0.5%
Large companies	1 592	0.5%	1 038	0.3%	810	0.2%	3 440	1.0%
Medium-sized companies	9 488	2.8%	3 301	1.0%	3 143	0.9%	15 932	4.7%
Small companies	86 251	25.4%	9 755	2.9%	6 892	2.0%	102 898	30.3%
All	97 603	28.8%	14 300	4.2%	10 992	3.2%	122 895	36.2%

Note: Figures refer to the number of companies and their shares in the total.

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Table 3. IN05 values of the total of active Hungarian companies grouped by size

Source: Own tests based on company data from Amadeus.

Category of companies	IN05 (%)							
	Less than 90.00%		From 90.00% to 160.00%		More than 160.00%		All	
Reference year: 2018								
Very large companies	286	0.1%	172	0.0%	280	0.1%	738	0.2%
Large companies	1 475	0.3%	1 065	0.2%	2 312	0.5%	4 852	1.0%
Medium-sized companies	9 974	2.2%	7 227	1.6%	23 962	5.2%	41 163	8.9%
Small companies	182 342	39.5%	42 434	9.2%	190 671	41.3%	415 447	89.9%
All	194 077	42.0%	50 898	11.0%	217 225	47.0%	462 200	100.0%
Reference year: 2017								
Very large companies	269	0.1%	187	0.0%	282	0.1%	738	0.2%
Large companies	1 497	0.3%	1 117	0.2%	2 238	0.5%	4 852	1.0%
Medium-sized companies	10 777	2.3%	7 615	1.6%	22 771	4.9%	41 163	8.9%
Small companies	190 790	41.3%	42 481	9.2%	182 176	39.4%	415 447	89.9%
All	203 333	44.0%	51 400	11.1%	207 467	44.9%	462 200	100.0%
Reference year: 2016								
Very large companies	272	0.1%	190	0.0%	276	0.1%	738	0.2%
Large companies	1 702	0.4%	1 116	0.2%	2 034	0.4%	4 852	1.0%
Medium-sized companies	12 478	2.7%	7 703	1.7%	20 982	4.5%	41 163	8.9%
Small companies	199 409	43.1%	42 130	9.1%	173 908	37.6%	415 447	89.9%
All	213 861	46.3%	51 139	11.1%	197 200	42.7%	462 200	100.0%

Note: Figures refer to the number of companies, and their shares in the total.

Table 4. IN05 values of the total of active Hungarian companies grouped by size and differentiated by ownership

Source: Own tests based on company data from Amadeus.

Category of companies	IN05 (%)							
	Less than 90.00%		From 90.00% to 160.00%		More than 160.00%		All	
FAMILY BUSINESSES								
Reference year: 2018								
Very large companies	51	0.0%	24	0.0%	38	0.0%	113	0.0%
Large companies	277	0.1%	300	0.1%	835	0.2%	1 412	0.4%
Medium-sized companies	4 250	1.3%	4 796	1.4%	16 185	4.8%	25 231	7.4%
Small companies	114 396	33.7%	35 636	10.5%	162 517	47.9%	312 549	92.1%
All	118 974	35.1%	40 756	12.0%	179 575	52.9%	339 305	100.0%
Reference year: 2017								
Very large companies	43	0.0%	26	0.0%	44	0.0%	113	0.0%
Large companies	297	0.1%	309	0.1%	806	0.2%	1 412	0.4%
Medium-sized companies	4 895	1.4%	5 097	1.5%	15 239	4.5%	25 231	7.4%
Small companies	122 573	36.1%	35 621	10.5%	154 355	45.5%	312 549	92.1%
All	127 808	37.7%	41 053	12.1%	170 444	50.2%	339 305	100.0%
Reference year: 2016								
Very large companies	39	0.0%	27	0.0%	47	0.0%	113	0.0%
Large companies	378	0.1%	312	0.1%	722	0.2%	1 412	0.4%
Medium-sized companies	5 980	1.8%	5 198	1.5%	14 053	4.1%	25 231	7.4%
Small companies	129 688	38.2%	35 464	10.5%	147 397	43.4%	312 549	92.1%
All	136 085	40.1%	41 001	12.1%	162 219	47.8%	339 305	100.0%
NON-FAMILY BUSINESSES								
Reference year: 2018								
Very large companies	235	0.2%	148	0.1%	242	0.2%	625	0.5%
Large companies	1 198	1.0%	765	0.6%	1 477	1.2%	3 440	2.8%
Medium-sized companies	5 724	4.7%	2 431	2.0%	7 777	6.3%	15 932	13.0%
Small companies	67 946	55.3%	6 798	5.5%	28 154	22.9%	102 898	83.7%
All	75 103	61.1%	10 142	8.3%	37 650	30.6%	122 895	100.0%

Table 4 (cont.). IN05 values of the total of active Hungarian companies grouped by size and differentiated by ownership

Category of companies	IN05 (%)							
	Less than 90.00%		From 90.00% to 160.00%		More than 160.00%		All	
Reference year: 2017								
Very large companies	226	0.2%	161	0.1%	238	0.2%	625	0.5%
Large companies	1 200	1.0%	808	0.7%	1 432	1.2%	3 440	2.8%
Medium-sized companies	5 882	4.8%	2 518	2.0%	7 532	6.1%	15 932	13.0%
Small companies	68 217	55.5%	6 860	5.6%	27 821	22.6%	102 898	83.7%
All	75 525	61.5%	10 347	8.4%	37 023	30.1%	122 895	100.0%
Reference year: 2016								
Very large companies	233	0.2%	163	0.1%	229	0.2%	625	0.5%
Large companies	1 324	1.1%	804	0.7%	1 312	1.1%	3 440	2.8%
Medium-sized companies	6 498	5.3%	2 505	2.0%	6 929	5.6%	15 932	13.0%
Small companies	69 721	56.7%	6 666	5.4%	26 511	21.6%	102 898	83.7%
All	77 776	63.3%	10 138	8.2%	34 981	28.5%	122 895	100.0%

Note: Figures refer to the number of companies and their shares in the total.

Table 5. Bankruptcy Index values of the total of active Hungarian companies grouped by size

Source: Own tests based on company data from Amadeus.

Category of companies	BI (%)							
	Less than 700.00%		From 700.00% to 900.00%		More than 900.00%		All	
Reference year: 2018								
Very large companies	193	0.0%	180	0.0%	365	0.1%	738	0.2%
Large companies	1 428	0.3%	1 426	0.3%	1 998	0.4%	4 852	1.0%
Medium-sized companies	14 010	3.0%	10 843	2.3%	16 310	3.5%	41 163	8.9%
Small companies	176 721	38.2%	52 419	11.3%	186 307	40.3%	415 447	89.9%
All	192 352	41.6%	64 868	14.0%	204 980	44.3%	462 200	100.0%
Reference year: 2017								
Very large companies	212	0.0%	189	0.0%	337	0.1%	738	0.2%
Large companies	1 465	0.3%	1 434	0.3%	1 953	0.4%	4 852	1.0%
Medium-sized companies	14 187	3.1%	10 188	2.2%	16 788	3.6%	41 163	8.9%
Small companies	172 567	37.3%	50 392	10.9%	192 488	41.6%	415 447	89.9%
All	188 431	40.8%	62 203	13.5%	211 566	45.8%	462 200	100.0%
Reference year: 2016								
Very large companies	209	0.0%	196	0.0%	333	0.1%	738	0.2%
Large companies	1 406	0.3%	1 357	0.3%	2 089	0.5%	4 852	1.0%
Medium-sized companies	13 506	2.9%	9 481	2.1%	18 176	3.9%	41 163	8.9%
Small companies	164 747	35.6%	49 461	10.7%	201 239	43.5%	415 447	89.9%
All	179 868	38.9%	60 495	13.1%	221 837	48.0%	462 200	100.0%

Note: Figures refer to the number of companies and their shares in the total.

Table 6. Bankruptcy Index values of the total of active Hungarian companies grouped by size and differentiated by ownership

Source: Own tests based on company data from Amadeus.

Category of companies	BI (%)							
	Less than 700.00%		From 700.00% to 900.00%		More than 900.00%		All	
FAMILY BUSINESSES								
Reference year: 2018								
Very large companies	16	0.0%	21	0.0%	76	0.0%	113	0.0%
Large companies	320	0.1%	432	0.1%	660	0.2%	1 412	0.4%
Medium-sized companies	8 004	2.4%	7 878	2.3%	9 349	2.8%	25 231	7.4%
Small companies	113 387	33.4%	48 111	14.2%	151 051	44.5%	312 549	92.1%
All	121 727	35.9%	56 442	16.6%	161 136	47.5%	339 305	100.0%

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Table 6 (cont.). Bankruptcy Index values of the total of active Hungarian companies grouped by size and differentiated by ownership

Category of companies	BI (%)							
	Less than 700.00%		From 700.00% to 900.00%		More than 900.00%		All	
Reference year: 2017								
Very large companies	27	0.0%	24	0.0%	62	0.0%	113	0.0%
Large companies	338	0.1%	404	0.1%	670	0.2%	1 412	0.4%
Medium-sized companies	8 291	2.4%	7 246	2.1%	9 694	2.9%	25 231	7.4%
Small companies	109 264	32.2%	46 268	13.6%	157 017	46.3%	312 549	92.1%
All	117 920	34.8%	53 942	15.9%	167 443	49.3%	339 305	100.0%
Reference year: 2016								
Very large companies	28	0.0%	25	0.0%	60	0.0%	113	0.0%
Large companies	334	0.1%	402	0.1%	676	0.2%	1 412	0.4%
Medium-sized companies	8 075	2.4%	6 800	2.0%	10 356	3.1%	25 231	7.4%
Small companies	102 970	30.3%	45 438	13.4%	164 141	48.4%	312 549	92.1%
All	111 407	32.8%	52 665	15.5%	175 233	51.6%	339 305	100.0%
NON-FAMILY BUSINESSES								
Reference year: 2018								
Very large companies	177	0.1%	159	0.1%	289	0.2%	625	0.5%
Large companies	1 108	0.9%	994	0.8%	1 338	1.1%	3 440	2.8%
Medium-sized companies	6 006	4.9%	2 965	2.4%	6 961	5.7%	15 932	13.0%
Small companies	63 334	51.5%	4 308	3.5%	35 256	28.7%	102 898	83.7%
All	70 625	57.5%	8 426	6.9%	43 844	35.7%	122 895	100.0%
Reference year: 2017								
Very large companies	185	0.2%	165	0.1%	275	0.2%	625	0.5%
Large companies	1 127	0.9%	1 030	0.8%	1 283	1.0%	3 440	2.8%
Medium-sized companies	5 896	4.8%	2 942	2.4%	7 094	5.8%	15 932	13.0%
Small companies	63 303	51.5%	4 124	3.4%	35 471	28.9%	102 899	83.7%
All	70 511	57.4%	8 261	6.7%	44 123	35.9%	122 896	100.0%
Reference year: 2016								
Very large companies	181	0.1%	171	0.1%	273	0.2%	625	0.5%
Large companies	1 072	0.9%	955	0.8%	1 413	1.1%	3 440	2.8%
Medium-sized companies	5 431	4.4%	2 681	2.2%	7 820	6.4%	15 932	13.0%
Small companies	61 777	50.3%	4 023	3.3%	37 098	30.2%	102 899	83.7%
All	68 461	55.7%	7 830	6.4%	46 604	37.9%	122 896	100.0%

Note: Figures refer to the number of companies and their shares in the total.

5. DISCUSSION

Regarding the general database of all Hungarian companies, the revised Altman Z-score indicates high bankruptcy probabilities: about half of the companies are on the verge of bankruptcy, and only about 20 per cent of them are projected to survive with stable financials. (Tests for previous years concluded very similar results.) As expected, middle-sized companies perform better than average, unlike small companies (Crutzen, 2009). The tests confirmed better bankruptcy predictions for family owned companies, and better results for medium to large (very large) companies.

According to Altman Z-score, family businesses perform better with predictability of survival. Accordingly, their ability to adapt to crisis financial constraints (the retreat of bank credits giving ground for the accounts suppliers' funds) is more promising. However, the results for this model indicate high bankruptcy predictions in case of Hungarian (in part, family-owned) companies. These results are supported by Cimpoeru (2014) who emphasized that the crisis had more substantial regressive effects for emerging economies in Central and Eastern Europe than elsewhere. This phenomenon is coupled with the restructuring of external financing, whereas the traditional bank credit resources have been mostly substituted by account suppliers' funds. The Altman Z-score is therefore impeded by a superfluous high weighting on net working capital (i.e., accounts suppliers).

When family businesses reached medium size (in terms of employment, asset value and operating revenue), they are predicted to be more financially stable than non-family businesses. In today's business environment, the cash-flow based indices have proved to be more reliable for measuring financial stability and added values. In this respect, IN05 predicted better chances for medium-sized family businesses in generating cash flows.

Finally, the proposed Bankruptcy Index is more focused on the companies' cash flow generating capability (added value) relative to the asset values invested. According to this measurement of relative efficiency, the advance of family businesses is even more substantial.

5.1. Practical implications

By analyzing and comparing the financial strength predictions of family businesses, the informative values of these models have been discovered for family business owners in general and family business owners and stakeholders in particular in Hungary. It is concluded that the strong reliance of family businesses on the entrepreneurial values, personal leadership and the name of the family implies a strong supporting element in the survival of these firms. Also, the meaningful intent of succession in family businesses drives these firms towards financial sustainability over longer periods of time.

The comparison of models in the Hungarian context complements existing studies on the creditworthiness and bankruptcy models and highlights the importance of the model choice and its associated impact on projected outcomes; as can be seen, the weightings and focuses of the indices produce very different outcomes, some of which are much more positive than others, or project a more positive outlook on certain sizes of family businesses. The findings suggest that, based on their stage in the growth cycle, they may have better predictions, e.g., greater cash flows during the growth stage rather than introduction stage means automatic strong financial health. The results may suggest this statement, however, there is space for further research in this matter.

The study has also led to a reconsideration of the concept of failure and financial health. McMillan and Overall (2017) argue that the concept of growth and decline of organizations may be less linear, which gives us an argument in favor of greater complexity in linear modeling. Figure 1 shows the three types of failures in relation to the organization's 'health'.

Figure 1 shows that predictability based on purely a linear temporal process may only apply to one classical type of failure. If, for example, complex failures are caused by structural rigidities

Source: McMillan and Overall (2017).

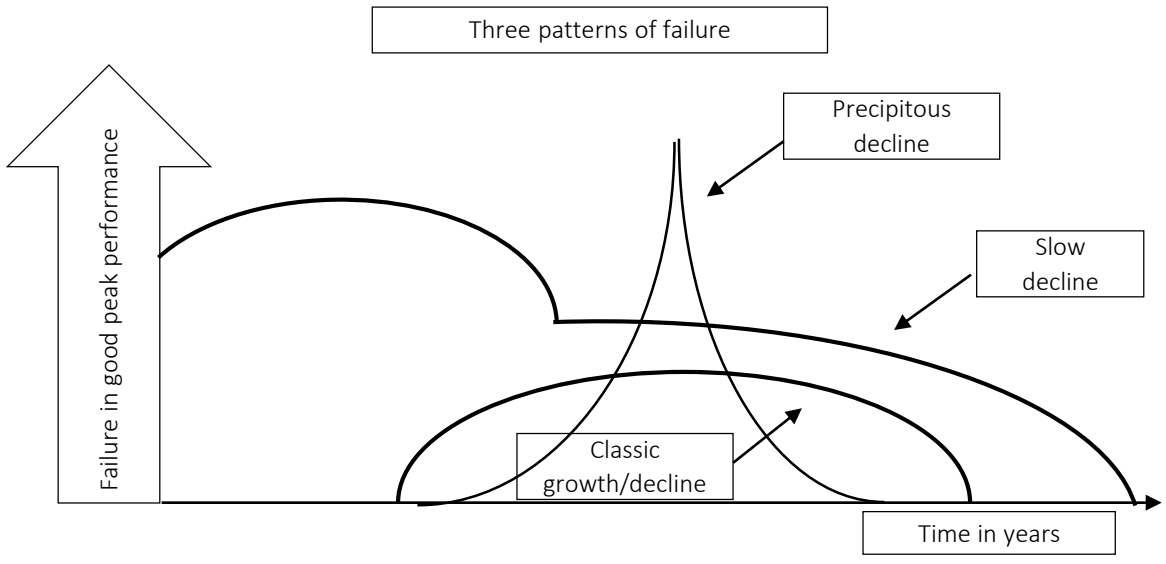

Figure 1. The three patterns of failure

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and intelligence pathologies, there is no reason to assume that this type of failure can also occur in family businesses. Likewise, the peak performance achieved in a born global family business, followed by a subsequent slow decline, cannot be factored into predictive models, and therefore bankruptcy is predicted much earlier than it actually happens.

CONCLUSION

Given the complexity of factors leading to bankruptcy found in the literature review, there is an apparent need to apply at least two or three different bankruptcy models to properly assess the financial performance of the eligible companies. Since these models indicate probable financial stress to companies, as well as the signaling effect to lenders and the shareholders (to providers of external funds), they are crucial for predictions for family businesses.

In the context of family businesses, it is argued that factors need to be included regarding the companies' cash flow generating capability (value added) relative to the asset values invested, as reflected in their adapted Bankruptcy Index, as this measure has a strong signaling affect for external providers of funds. In case of the Index deterioration, creditors and shareholders receive a signal that warns them to take preventive steps to recover the cash flow generating capability of family businesses. These signals are crucial in connection with the current crisis of 2020, as a sudden decline in purchasing power of households alongside with their climbing indebtedness threatens the outlook for businesses. Unfortunately, the financial awareness of Hungarian private agents is rather low (Sági and Lentner, 2019), which may require policy measures to promote the sound operation of enterprises. The proposed Bankruptcy Index is more understandable in relation to signaling, as the "grey zone" is narrower than in previous models.

Finally, this study highlights the specific nature of financial health and failure of family businesses and necessitates the adaptation of existing predictive models, as done in the third model. Besides, it is concluded that at least two or three different bankruptcy models should be used and adapted to suit family businesses. All of three models' test results gave warning signals about the likelihood of failures, in case of the Bankruptcy Index for 41.6 per cent of the total number of Hungarian companies and for 35.9 per cent of Hungarian family businesses, based on financial indicators for 2018. Given that that family businesses compose the backbone of the Hungarian economy, these results are also associated with macroeconomic risks. Due to the Hungarian enterprises' reliance on external funding, the current crisis that has emerged with the pandemic will probably damage the liquidity positions of most small enterprises. (In previous years, foreign currency loan exposures have caused financial vulnerability to family businesses, which was then partially mitigated by policy interventions, see Matolcsy, 2016.) The results show that social tensions can arise from the mass insolvency of Hungarian family businesses, so that policy actions will be needed in the coming years.

RESEARCH LIMITATIONS AND FUTURE DIRECTIONS

This study provides insight into the predictive financial health of family businesses using three different models. However, since there are more predictive models to be tested, this can be seen as a potential extension of this study. Recent developments regarding how failure is seen as a less linear process may also prompt researchers to consider more complexities when developing predictive models. Furthermore, in the case of family businesses, as found in the literature, they are more resistant to failure than non-family firms (especially from a financial perspective), and this should be taken into account in predictive models as a 'familiness factor'.

AUTHOR CONTRIBUTIONS

Conceptualization: Judit Sági.
Data curation: Judit Sági.
Formal analysis: Judit Sági.
Investigation: Nick Chandler.
Methodology: Judit Sági.
Resources: Nick Chandler.
Supervision: Csaba Lentner.
Validation: Csaba Lentner.
Visualization: Nick Chandler.
Writing – original draft: Judit Sági, Nick Chandler.
Writing – review & editing: Csaba Lentner.

REFERENCES

1. Altman, E. (1968). Financial ratios, discriminant analysis and the prediction of corporate bankruptcy. *The Journal of Finance, 23*(4), 589-609. https://doi.org/10.1111/j.1540-6261.1968.tb00843.x
2. Altman, E. (2000). Predicting financial distress of companies: Revisiting the Z-score and Zeta® models. *Handbook of Research Methods and Applications in Empirical Finance,* 428-456. https://doi.org/10.4337/9780857936097.00027
3. Altman, E., Haldeman, R., & Narayanan, P. (1977). Zeta™ analysis a new model to identify bankruptcy risk of corporations. *Journal of Banking and Finance, 1*(1), 29-54. https://doi.org/10.1016/0378-4266(77)90017-6
4. Amann, B., & Jaussaud, J. (2012). Family and non-family business resilience in an economic downturn. *Asia Pacific Business Review, 18*(2), 203-223. https://doi.org/10.1080/13602381.2010.537057
5. Baixauli, S., & Módica-Milo, A. (2010). The bias of unhealthy SMEs in bankruptcy prediction models. *Journal of Small Business and Enterprise Development, 17*(1), 60-77. https://doi.org/10.1108/14626001011019134
6. Beaver, W. (1966). Financial ratios as predictors of failure. *Journal of Accounting Research, 4*(3), 71-111. https://doi.org/10.2307/2490171
7. Beaver, W., McNichols, M., & Rhie, J. (2005). Have financial statements become less informative? Evidence from the ability of financial ratios to predict bankruptcy. *Review of Accounting Studies, 10,* 93-122. https://doi.org/10.2139/ssrn.634921
8. Blum, M. (1974). Failing company discriminant analysis. *Journal of Accounting Research, 12*(1), 1-25. https://doi.org/10.2307/2490525
9. Bohdalová, M., & Klempaiová, N. (2017). Comparison of bankruptcy models for prediction of the financial health of the Slovak civil engineering companies. *Perspectives of Business and Entrepreneurship Development in Digital Age* (16th International Conference, September 20-22, 2017 Brno, Czech Republic, conference paper: 1-9). Retrieved from https://conference.fbm.vutbr.cz/ic/index.php/ic/article/view/57
10. Chandler, N., & Sági, J. (2018). The secret sauce: a review of the characteristics that define entrepreneurs and owner-managers. *Economics, Management, Innovation,* 209-215.
11. Cho, S., Hong, H., & Ha, B-C. (2010). A hybrid approach based on the combination of variable selection using decision trees and case-based reasoning using the Mahalanobis distance: For bankruptcy prediction. *Expert Systems with Applications, 37*(4). 3482-3488. https://doi.org/10.1016/j.eswa.2009.10.040
12. Cimpoeru, S. (2014). Scoring Functions and Bankruptcy Prediction Models – Case Study for Romanian Companies. *Procedia Economics and Finance, 10,* 217-226. https://doi.org/10.1016/s2212-5671(14)00296-2
13. Crutzen, N. (2009) *Essays on the prevention of small business failure: Taxonomy and validation of five explanatory business failure patterns (EBFPs)* (594 p.). Liege: University of Liege.
14. Dolejšová, M. (2015). Is it Worth Comparing Different Bankruptcy Models? *Acta Universitatis Agriculturae et Silviculturae Mendelianae Brunensis, 63*(2), 525-531. https://doi.org/10.11118/actaun201563020525
15. Edmister, R. (1972). An empirical test of financial ratio analysis for small business failure prediction. *Journal of Financial and Quantitative Analysis, 7*(2), 1477-1493. https://doi.org/10.2307/2329929
16. Fang-Mei, T., & Yi-Chung, H. (2010). Comparing four bankruptcy prediction models: Logit, quadratic interval logit, neural and fuzzy neural networks. *Expert Systems with Applications, 37*(3), 1846-1853. https://doi.org/10.1016/j.eswa.2009.07.081
17. Gavurova, B., Packova, M., Misankova, M., & Smrcka, L. (2017). Predictive potential and risks of selected bankruptcy prediction models in the Slovak business environment. *Journal of Business Economics and Management, 18*(6), 1156-1173. https://doi.org/10.3846/16111699.2017.1400461

http://dx.doi.org/10.21511/ppm.18(2).2020.39

18. Grice, J., & Dugan, M. (2001). The limitations of bankruptcy prediction models: Some cautions for the researchers. *Review of Quantitative Finance and Accounting, 17,* 151-166. https://doi.org/10.1023/a:1017973604789

19. Gu, Z. (2002). Analyzing bankruptcy in the restaurant industry: A multiple discriminant model. *International Journal of Hospitality Management, 21*(1), 25-42. https://doi.org/10.1016/s0278-4319(01)00013-5

20. Karas, M., & Režňáková, M. (2014). Bankruptcy Prediction Models: Can the Prediction Power of the Models be Improved by Using Dynamic Indicators?" *Procedia Economics and Finance, 12,* 565-574. https://doi.org/10.1016/s2212-5671(14)00380-3

21. Karas, 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.

22. Karas, M., Režňáková, M., Bartos, V., & Zinecker, M. (2013). Possibilities for the Application of the Altman Model within the Czech Republic, Recent Research in Law Science and Finances. *Proceedings of the 4th International conference on Finance, Accounting and Law* (ICFA 13): 203-208.

23. Keasey, K., & Watson, R. (1991). The State of the Art of Small Firm Failure Prediction: Achievements and Prognosis. *International Small Business Journal, 9,* 11-28. https://doi.org/10.1177/026624269100900401

24. Kim, S. Y. (2011). Prediction of hotel bankruptcy using support vector machine, artificial neural network, logistic regression, and multivariate discriminant analysis. *The Service Industries Journal, 31*(3), 441-468. https://doi.org/10.1080/02642060802712848

25. Korom, E., & Sági, J. (2005). Measures on competitiveness in agriculture. *Journal of Central European Agriculture, 6*(3), 375-380. Retrieved from https://www.researchgate.net/publication/27201414_MEASURES_OF_COMPETITIVENESS_IN_AGRICULTURE

26. Kozlovskyi, S., Butyrskyi, A., Poliakov, B., Bobkova, A., Lavrov, R., & Ivanyuta, N. (2019). Management and comprehensive assessment of the probability of bankruptcy of Ukrainian enterprises based on the methods of fuzzy sets theory. *Problems and Perspectives in Management, 17*(3), 370-381. https://doi.org/10.21511/ppm.17(3).2019.30

27. Lentner, Cs., & Kolozsi, P. P. (2019). Innovative ways of thinking concerning economic governance after the global financial crisis. *Problems and Perspectives in Management,* 17(3), pp. 122-131. https://doi.org/10.21511/ppm.17(3).2019.10

28. Lentner, Cs. (2020). *East of Europe, West of Asia* (300 p.). Paris: L'Harmattan Publishing.

29. Lukason, O., & Käsper, K. (2017). Failure prediction of government funded start-up firms. *Investment Management and Financial Innovations, 14,* 296-306. https://doi.org/10.21511/imfi.14(2-2).2017.01

30. Matolcsy, Gy. (2016). *Economic balance and growth.* Budapest: Kairosz Publishing.

31. Mcmillan, C., & Overall, J. (2017). Crossing the Chasm and Over the Abyss: Perspectives on Organizational Failure. *Academy of Management Perspectives, 31*(4), 271-287. https://doi.org/10.5465/amp.2017.0018

32. Neumaier, I., & Neumaierová, I. (2005). Index IN 05. *Proceedings of the Evropské finanční systémy,* 143-148.

33. OeNB. (2004). *OeNB Guidelines on Credit Risk Management: Rating models and validation.* Vienna: Oesterreichische Nationalbank.

34. Ohlson, J. (1980). Financial Ratios and the Probabilistic Prediction of Bankruptcy. *Journal of Accounting Research, 18*(1), 109-131. https://doi.org/10.2307/2490395

35. Platt, H. & Platt, M. (1990). Development of a Class of Stable Predictive Variables: The Case of Bankruptcy Prediction. *Journal of Business Finance & Accounting, 17*(1), 31-51. https://doi.org/10.1111/j.1468-5957.1990.tb00548.x

36. Sági J., & Lentner, Cs. (2019) Post-crisis trends in household credit market behavior: evidence from Hungary (Literature review). *Banks and Bank Systems, 14*(3), 162-174. https://doi.org/10.21511/bbs.14(3).2019.14

37. Sági, J., & Nikulin, E. E. (2017). The economic effect of Russia imposing a food embargo on the European Union with Hungary as an example. *Studies in Agricultural Economics, 119*(2), 85-90. https://doi.org/10.7896/j.1708

38. Scott, J. (1981). The probability of bankruptcy: a comparison of empirical predictions and theoretical models. *Journal of Banking & Finance, 5,* 317-344. https://doi.org/10.1016/0378-4266(81)90029-7

39. Shkolnyk, I., Pisula, T., Loboda, L., & Nebaba, N. (2019). Financial crisis of real sector enterprises: an integral assessment. *Problems and Financial Innovations, 16*(4), 366-381. https://doi.org/10.21511/imfi.16(4).2019.31

40. Thanh Tung, D., & Phung, V. (2019). An application of Altman Z-score model to analyze the bankruptcy risk: cases of multidisciplinary enterprises in Vietnam. *Investment Management and Financial Innovations, 16*(4), 181-191. https://doi.org/10.21511/imfi.16(4).2019.16

41. Thornhill, S., & Amit, R. (2003). Learning about Failure: Bankruptcy, Firm Age and the Resource-Based View. *Organization Science, 15,* 497-509. https://doi.org/10.1287/orsc.14.5.497.16761

42. Wu, S., Gaunt, C., & Gray, S. (2010). A comparison of alternative bankruptcy prediction models. *Journal of Contemporary Accounting & Economics, 6,* 34-45. https://doi.org/10.1016/j.jcae.2010.04.002

43. Zmijewski, M. (1984). Methodological issues related to the estimation of financial distress prediction models. *Journal of Accounting Research, 22,* 59-82. https://doi.org/10.2307/2490859