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INVESTIGATION OF ACCOUNTING MANIPULATION USING THE BENEISH MODEL: HUNGARIAN CASE

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ABSTRACT. The study examined the manipulation level of Hungarian corporate financial statements using Beneish's M-score model with eight variables between 2017 and 2021. The research also investigated whether the financial statement manipulations depend on the type of sector, company size and age, and region. The research sample was comprised of 32,024 financial statements each year. Statistical tests were used to compare the M-score values of several groups. The proportion of companies with possibly manipulated financial statements varied between 46.43% and 51.67% in the five years. It can be concluded that the manipulation of Hungarian companies' reports is very high. The analysis showed that the ratios of unlikely manipulated (UM) and likely manipulated (LM) reports were improved at size category 1-4, and size category five significantly improved. The comparison by regions revealed that the UM/LM indicator is lower in more developed regions than in less developed ones. The results draw the attention of government decision-makers to pay more attention to checking financial statements. In addition, it shows to the companies' stakeholders that the reliability of the financial statements must also be considered during their decision preparations and risk assessment.

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Introduction

Given that company performance measurement heavily relies on financial statements, instances of accounting manipulations can significantly erode investor confidence and bias business analyses for corporate performance. Manipulation activities related to preparing financial statements gained heightened attention, particularly after the Enron scandal in the USA (Nigrini, 2005). Table 1 shows the ten most severe accounting scandals involving companies manipulating their financial statements.

The Association of Certified Fraud Examiners (ACFE) report in 2020 stated that accounting manipulations caused an unrealised 5% annual sales revenue. The ACFE defines accounting manipulations as fraud and other manipulated acts committed by accountants or manipulations associated with an organisation’s accounting methods and practices. The cumulative losses from 2,504 accounting scandals from 125 countries exceeded $3.6 billion. The consequences of accounting scandals extend far beyond company stakeholders, affecting economies, investor confidence, and the accounting sector. The financial welfare of companies may also depend on preventing accounting manipulations and rapidly detecting and responding effectively (ACFE, 2020). Other widely publicised scandals include cases of Parmalat, Ahold (Rezaee, 2005), Xerox, Sunbeam, Adelphia, Global Crossing (Coates, 2007), and Lehman Brothers (Grove and Basilico, 2011).

Table 1. Top 10 worst accounting scandals

No.	Company name	Year
1	Enron	2001
2	Tyco	2002
3	WorldCom	2002
4	Freddie Mac	2003
5	HealthSouth	2003
6	American Insurance Group	2005
7	Lehman Brothers	2008
8	Bernie Madoff	2009
9	Satyam	2009
10	General Electric Co.	2016

Source: own editing using data from Wallstreetmojo Team: Accounting Scandals

It is crucial to predict potential issues to avert future damages, and several methods are available to make them. The values generated by these methods indicate whether it is worth conducting a more thorough investigation when investors and suppliers engage with a company. Therefore, applying these methods aims to bring attention to potential problems.

Financial statement manipulations can occur across all sectors of the economy. The possibility of financial manipulations may prompt stakeholders to reconsider their behaviour concerning the company. The deceptive financial statements because of accounting manipulation can have significant adverse consequences for information users.

In Hungary, several factors can cause the manipulation of financial reports, for example, the high corruption index and limited controls over financial statements. Controls over financial statements have a low level in Hungary. Businesses must make their financial statements public on a designated website (e.beszamolo.hu). However, strict verification is lacking during the uploading. It is also possible that incorrect data will be uploaded, leading to reporting errors. The reporting errors may not always indicate manipulation; they could also stem from incorrect data entries. The high corruption index also can potentially impact companies’ financial reports.

The authors applied Beneish's M-score model to analyse the potential manipulation of Hungarian financial statements. This model was selected considering its successful applications in various types of research involving companies from different countries.

The research estimated the proportion of likely manipulated reports for Hungarian companies based on a significant sample. The study also revealed how the likely manipulated reports are distributed for sectors, company size, age, and regional location.

At the same time, the research was also inspired to determine to which extent corporate financial reports are manipulated in Hungary, where the corruption index (CPI) is very low. CPI does not always reflect the real situation with informal relations (Mishchuk et al., 2018). In addition, unfounded and impromptu governmental decisions often compel businesses to manipulate their financial statements as a survival strategy.

1. Literature review

1.1. The Hungarian economic background inspiring the research

The Corruption Perceptions Index (CPI) measured by Transparency International for Hungary was very low in 2012, 55 compared to the best of 90 points (Denmark and Finland). Hungary ranked 46th globally by the CPI index and 19th in the EU. By 2022, the CPI score dropped to 42 points, so Hungary ranked 77th in the world and 27th in the EU. This change is very significant but in the wrong direction. Figure 1 shows the CPI scores of the best (Denmark) and worst (Bulgaria) EU member states, the average scores of EU and former socialist EU member states, and four other member states. Figure 1 also shows that the CPI scores fell off significantly only in Hungary. In 2022, even Bulgaria overtook Hungary. No other EU member state fell 31 positions (from 46 to 77) in the global CPI ranking as Hungary.

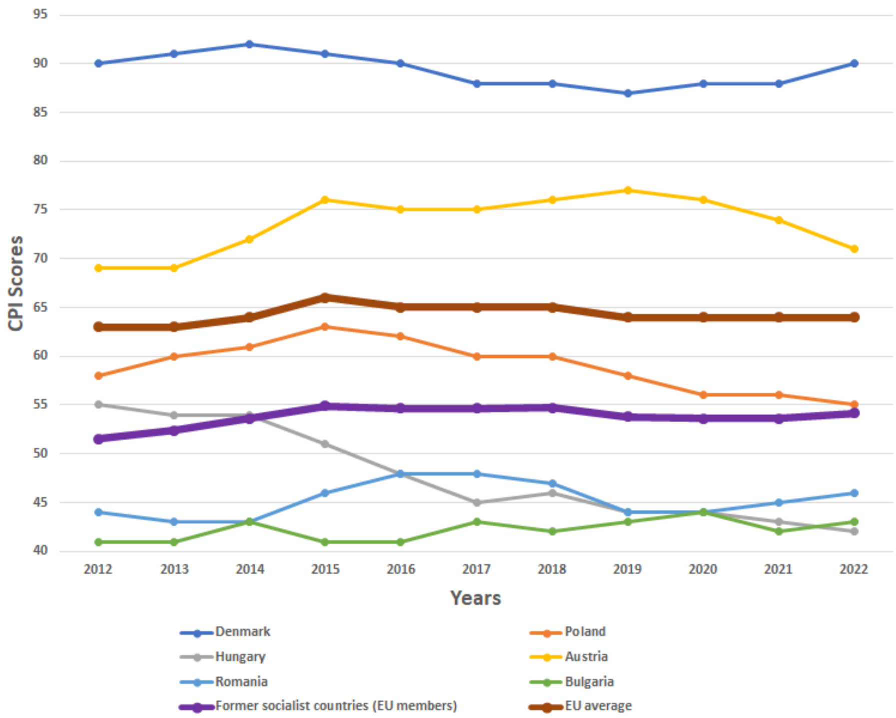

Figure 1. The development of CPI scores in some EU member states between 2012-2022.
Source: own editing using data from Transparency International. Corruption Perceptions Index https://www.transparency.org/en/cpi/2022.

Austria is included in the examination because Hungarian politicians always emphasise getting closer to Austria. However, it can be seen that Hungary is very far from Austria concerning this indicator, and the distance is increasing. Regarding Romania, the earlier opinion was that corruption was high there, as seen in the graph for the first year. The figure also shows that by 2022, the Romanian CPI score improved and reached value 46 (4 better than Hungary). Poland was chosen because Poland and Hungary are the "rebellious" countries of the EU. The figure shows an improvement in the CPI score between 2012 and 2022, but it was only slightly above the starting point by the end of the period. However, it was above the average CPI value of the former socialist countries each year.

1.2. Accounting manipulations

Companies are essential contributors to the long-term sustainable wealth of societies and are vital for social development. Reliable reports disclosures are related to long-term company values and influence the stakeholder value approach (Irwandi and Pamungkas, 2020; Lizińska and Czapiewski, 2019).

Literature on manipulations draws heavily from Sutherland's pioneering work (Sutherland, 1949), which focused on studying manipulations caused by corporate leaders against stockholders. He created the term "white-collar crime" to represent the criminal activities of business people.

Jones (2011) invited researchers from 12 countries (Europe (7), Asia (3), the USA, and Australia) to present manipulations that occurred in their countries as case studies. Thus, 58 accounting manipulations were presented, which attempted to provide a complete picture of the motivations for manipulation and to present the role of creative accounting and accounting manipulation. Halilbegovic et al. (2020) described significant, high-damage corporate accounting scandals of the last 20 years. Since then, more and more authors have been dealing with this topic, and the investigation of accounting report manipulations has brought the focus.

According to Cooper et al. (2013), it is crucial to deal with accounting manipulation because it can significantly affect public trust in various organisations. Manipulations can affect several organisations' legitimacy and impact innovation, entrepreneurship, regulatory compliance, society, and the economy (Belas et al., 2015). Karajan and Ullah (2022) investigated how disclosing the company's accounting manipulations affects the company's profitability. They found that the earnings of these companies were a significant decrease. However, the quick change in managers and auditors after the disclosure positively impacted the longer term.

Zhang et al. (2020) examined the relationship between the firm and its employees and the perpetration likelihood of manipulation. They found that firms with proper relations with their employees had a lower probability of manipulation perpetrating.

Vladu et al. (2017) stated that accounting manipulations are morally reprehensible, prejudicing stakeholders, leading to an unrealistic power exercise, and reducing the belief in accounting regulators. They also concluded that ethical erosion has occurred in the accounting profession because if accounting professionals acted ethically in all cases, manipulations would not happen.

Mohammed et al. (2021) examined the earnings manipulation and corporate governance. According to them, earnings manipulation tries financial statements to put storefront, mainly earnings, because it can impress the stakeholders. It is unacceptable behaviour because the financial statements are tools of the firm governance and are related to value creation.

1.3. Beneish model

The literature has several methods for estimating the probability of accounting manipulation (e.g., ratio analysis, Beneish model, Benford's law, data mining, and others) (Zack, 2013; Kliestik et al., 2022; Mantone, 2013; Tutino and Merlo, 2019; Gruszczyński; 2020; Rad et al., 2021; Isaković-Kaplan et al., 2021).

Two versions of the M-score model exist: the 8-variable and 5-variable models. The difference between the two models is that in the case of the 5-variable model, the last three variables (SGAI, LVGI, TATA) of the 8-variable model are omitted. The processed literature used the variables defined by Beneish in all cases. Even those authors (Svabova et al., 2020; Sabău et al., 2021) used the same variables, trying to create their model using Beneish's variables, and only the model coefficients changed. Some authors used the 8- and 5-variable models together (Durana et al., 2022).

Several authors have applied the M-score model to reveal whether the investigated companies manipulate their accounting reports. Repousis (2016) applied the eight-variables M-score model to test the financial statement manipulation likely using 25,468 non-financial Greek companies between 2011 and 2012. It was found that 33% of companies had a signal of likely manipulation. The F-test showed that the DSRI, AQI, DEPI, SGAI, TATA, and LVGI ratios significantly affected M-score model values. Anning and Adusei (2022) examined financial statement manipulation with 19 manufacturing and trading companies listed on the Ghana Stock Exchange between 2008 and 2017. They revealed that most firms manipulated their financial statements. Hasan et al. (2017) analysed the financial data of 84,000 listed companies from Asia between 2010 and 2013. They found that 34% of companies selected from seven Asian countries are affected by financial statement manipulations. They stated significant differences among countries on a 5% level. They determined four key variables that impacted the manipulation level: DSRI, DEPI, AQI, and TATA. Durana et al. (2022) analysed Slovak companies using the Beneish and Jones models. They used both 8-parameter and 5-parameter M-score models. They diagnosed the 'Agriculture, fishing, forestry' sector and identified creative accounting practices in the companies examined. They established that the 8-parameter M-score model proved more effective.

Some studies have looked at the strength of the M-score model. Tarjo (2015) examined the ability of the M-score model to detect financial manipulations. The analysis results showed that the M-score model could detect financial manipulations. Shakouri et al. (2021) applied the M-score model to predict and detect financial statement manipulations. They used the financial statements of 161 companies listed on the Tehran Stock Exchange between 2009 and 2018. The applied statistical tests verified the usefulness of the M-score model in separating manipulated and healthy companies, confirming the model's effectiveness. Kamal et al. (2016) stated that the M-score model helps measure likely earnings manipulation in companies' financial statements. The model effectively determined 76% of earnings-manipulated firms detected by the US Securities and Exchange Commission. This model also discovered 71% of the US's greatest financial reporting scandals before the disclosure.

Some researchers have created a model similar to the M-score model to study a specific area. Timofte et al. (2021) determined a discriminant function using the 5-parameter M-score model to separate tax-evading and non-tax-evading firms. They found that about 77% of the firms with accounting manipulations committed tax evasion.

Kaminski et al. (2004) state that manipulated financial statements can cause severe social and economic problems. They aimed to determine whether the financial ratios differ in manipulated versus non-manipulated companies. They investigated 79 firms and used 21 ratios, from which they found 16 significant ratios, but only three were significant for entire periods.

The discriminant analysis used to classify manipulated firms achieved 58% to 98%. Their results showed empirical evidence of the limited useability of financial ratios to reveal fraudulent financial statements.

According to Ibadin and Ehigie (2019), despite the appreciable developments in the prediction methods of financial manipulation, the research results still did not provide adequate evidence or tools to predict manipulation. Therefore, researchers have applied different methods with different successes. The authors reviewed the models used in the various investigations. They stated that there is a crucial changing trend in research because it started to apply computer-aided artificial intelligence tools to predict financial manipulations.

It is difficult to assign an exact value to the financial reports' manipulation ratio based on the analyses performed in different countries. Tarjo (2015) found that the model performed well between 71% and 85%. Those who investigated manipulated financial statements (Repousis, 2016; Hasan et al., 2017; Svaboda et al., 2020; Wadhwa et al., 2020) showed that 32-34% of the companies probably had manipulated financial reports.

2. Methodological approach

2.1. Data

The database was purchased from Opten Kft. and contains data from four years (2016-2021). The companies included in the database were selected by Opten Kft using the conditions given by researchers. First, the companies were classified into five size categories per sector: 0 employees, 1–4 employees, 5-9 employees, 10-49 employees, and 50 or more employees. The database included only operating enterprises. The company with 0 employees had no employees. In Hungary, it often also happens that the company employees work under a commission contract.

Then, the companies were selected from the upper, middle, and lower thirds of the five size categories ranked by sales revenue. The selected firms were proportional to the total number of companies per sector and category. The database only contained companies with financial statements for all four years. Table 2 shows the number of selected companies by sector and size categories. The database contains the same number of companies every year. This type of analysis using such an extensive dataset was unprecedented in Hungary.

Table 2. Distribution of companies by sector and size category

Sectors of the national economy	Size categories					Total
	1	2	3	4	5	
A - Agriculture, forestry, and fishing	177	457	184	187	22	1027
C - Manufacturing	319	1251	667	901	338	3476
F - Construction	427	1629	804	632	54	3546
G - Wholesale and retail trade; repair of motor vehicles and motorcycles	1208	4697	1758	1156	134	8953
H - Transportation and storage	168	611	276	296	66	1417
I - Accommodation and food service activities	141	578	400	419	40	1578
J - Information and communication	349	792	179	180	28	1528
K - Financial and insurance activities	107	226	34	26	7	400
L - Real estate activities	867	901	192	132	12	2104
M - Professional, scientific and technical activities	862	2065	519	334	45	3825
N - Administrative and support service activities	250	631	223	244	88	1436
P - Education	60	173	40	25	0	298
Q - Human health and social work activities	183	1210	147	103	16	1659
R - Arts, entertainment, and recreation	89	204	63	58	16	430

S - Other service activities	44	170	75	51	7	347
Total by size category	5251	15595	5561	4744	873	32024

Source: *own edition*

2.2. Methodology

The description of the M-score model can be found in many literary sources (Özcan, 2018; Sabău et al., 2021). The model correctly identifies potential manipulators for 76% of cases in the first year and 66% in the second year after the profit manipulation. The M-score model applies three ratio groups to estimate the manipulation of financial data: future company performance, cash flows and accruals, and managers' motivations (Ibadin and Ehigie, 2019).

The M-score model is a regression model using eight ratios to determine whether a company manipulates its profit (Beneish, 1999). Beneish assumes that the following factors inspire the companies to manipulate their profits: high sales growth, decreasing gross margins, increasing operating expenses, and growing leverages. They will probably manipulate their earnings by quickening sales recognitions, growing cost deferrals, increasing accruals, and decreasing depreciations. The regression function of the M-score model (Halilbegovic *et al.*, 2020):

$$M = -4.84 + 0.92 * DSRI + 0.528 * GMI + 0.404 * AQI + 0.892 * SGI + 0.115 * DEPI - 0.172 * SGAI - 0.327 * LVGI + 4.679 * TATA$$

where

DSRI – Receivables Turnover in Day Index - A significant increase in receivable days can suggest speeding up revenue recognition to raise profits.

GMI – Gross Margin Index - A decreasing gross margin shows a negative signal about the firm's prospects and inspires it to raise profits.

AQI – Asset Quality Index - Increase in long-run assets - except property, plant, and equipment - compared to total assets, a sign that a firm potentially raised deferred costs to increase profits.

SGI – Sales Growth Index - Companies with high growth are more likely to commit financial reporting manipulation because their financial position and capital needs put pressure on the leaders to achieve profit. If growing firms face big share price losses at the first sign of a slowdown, they may have greater inspiration to manipulate their earnings.

DEPI – Depreciation Index - A decreasing depreciation compared to net fixed assets suggests the possibility that a firm has modified the estimated asset applicable upwards or applied a new method to raise its income.

SGAI – Sales, General, and Administrative (SG&A) Expense Index - Analysts can interpret a disproportionate rise in SG&A compared to sales as a negative sign concerning a firm's prospects that motivates it to raise profits.

LVGI – Leverage Index - Leverage is measured as total debt compared to total assets. A rise in leverage inspires the manipulation of earnings to meet debt covenants.

TATA – Total Accruals to Total Assets - Total accruals calculated by working capital - except cash - minus depreciation compared to total assets. Accruals, or their portion, show the extent to which managers make decisions to change earnings. Therefore, a higher level of accruals can be associated with a higher probability of earnings manipulation.

The M-score values were classified into three classes:

1. UM - unlikely manipulated, M-score < -2.22
2. PM - probably manipulated, -1.78 > M-score < -2.22
3. LM - likely manipulated, M-score > -1.78

The variables (indicators) found in the 8-variable Beneish model were used during the analysis since this analysis aimed not to create a new model. The analysis database contained data for the years 2016-2021. The M-score model's six indicators (variables) must be calculated using two years' data, which shows the changing rate compared to the previous year. So, such indicators could be calculated only for 2017-2021.

3. Conducting research and results

Table 3 summarises the distribution by the M-score ratios of companies classified by M-score types and years. The table shows that the financial statements of likely manipulated (LM) companies represent a relatively high proportion, and their value is between 39.19% and 44.55% per year. The rate of probably manipulated (PM) financial statements exceeds 6%, and in 2019-2021 even 7% yearly. There is also a high proportion of financial statements in which the ratios required to determine the M-score could not be calculated due to zero or missing values. If the missing values were omitted, each class would increase, but their relative proportion would not change.

The analysis focused on the UM and LM groups because determining the ratio of manipulated reports within the sample was the primary research objective. The proportion of companies in the LM and UM classes is relatively high compared to the proportions in the literature. One reason for this is unfounded (ad hoc) economic policy decisions; in many cases, legislation is issued in a few days without substantive consultation. Companies have challenges in adapting to the changed circumstances. In addition, the financial statement disclosures are also not sufficiently controlled, which is also a problem.

Table 3. Distribution of the companies by M-score classes and year

Years	**LM**		**PM**		**UM**		**Missing**	
	Firms	**%**	**Firms**	**%**	**Firms**	**%**	**Firms**	**%**
2017	13,618	42.52%	2,045	6.39%	10,699	33.41%	5,662	17.68%
2018	13,318	41.59%	2,223	6.94%	11,753	36.70%	4,730	14.77%
2019	12,551	39.19%	2,241	7.00%	12,210	38.13%	5,022	15.68%
2020	14,169	44.24%	2,324	7.26%	13,736	42.89%	1,795	5.61%
2021	14,267	44.55%	2,299	7.18%	13,248	41.37%	2,210	6.90%

Source: *own compilation*

Economic regulations agreed upon with all interested parties would be necessary to reduce the number of manipulated reports. Since disclosure is already done online today, it would be possible to incorporate stricter control into the uploading software. Table 3 contains the statistical characteristics of the filtered M-score values by years and M-score classes. The standardisation method was used to determine outliers, so the absolute value of the z ratio greater than three was considered outliers (Suri et al., 2019).

The values of the statistical characteristics were significantly changed, excluding outliers. The following changes occurred in the statistical indicators (Table 4):

1. The minimum value did not change, and the median decreased slightly.
2. The maximum value has been reduced to 1/33 of the original value.
3. The mean has decreased to 41%, and the standard deviation to 11%.
4. The relative standard deviation (CV%) decreased from 2,571.81% to 695.12% (83% decrease).
5. The skewness ratio decreased to 19% of the original value, and the kurtosis ratio to 3.8%.

Table 4. The main statistical characteristics of the LM and UM classes by years.

Statistical indicators	**2017**		**2018**		**2019**		**2020**		**2021**	
	LM	**UM**	**LM**	**UM**	**LM**	**UM**	**LM**	**UM**	**LM**	**UM**
Number of companies	13,618	10,699	13,318	11,753	12,551	12,210	14,169	13,736	14,267	13,248
Outliers	22	14	31	14	27	2	1	1	36	7
Minimum	-1.78	-230.9	-1.78	-193.1	-1.78	-1,667.8	-1.78	-13,786.4	-1.78	-1,606.8
Maximum	2,165.05	-2.22	1,792.7	-2.22	1,572.8	-2.22	395,169.7	-2.22	2,087.1	-2.22
Median	0.03	-3.47	-0.07	-3.46	-0.12	-3.51	0.04	-3.64	-0.01	-3.58
Mean	11.33	-5.19	11.73	-4.85	9.47	-5.51	128.29	-9.76	11.29	-7.52
Standard deviation	80.2	9.2	75.9	7.6	65.9	23.4	4,552.6	149.9	78.9	43.4
CV%	708%	-179%	647%	-157%	696%	-425%	3,548%	-1,536%	699%	-577%
Skewness	15.07	-11.77	12.22	-12.74	14.15	-45.18	63.46	-68.03	15.38	-24.44
Kurtosis	282.89	183.65	182.71	221.02	242.34	2,681.26	4,714.19	5,578.25	299.99	703.57

Source: *own editing*

Table 4 shows that initially, in 2017-2019, the number of LM-class companies decreased slightly yearly, so it can be concluded that the number of non-manipulated financial reports is increasing. However, in 2020-2021, the number of LM-class companies is significantly increasing yearly. Therefore, it can be concluded that in the last three years the number of manipulated financial reports is widely increasing. Growth of UM reports was nearly 28.4% in 5 years. However, the number of LM-class enterprises is still high, but the difference is only 7.69% between LM and UM reports in 2021, while it was 27.28% in 2017.

The Kolmogorov-Smirnov test showed that the LM and UM classes have non-normal distributions each year because the entire distribution was divided into three parts. High skewness and kurtosis values in Table 4 also support the test results. The LM class represents the right side of the distribution (skewed to the right), the UM class is left (skewed to the left), and the PM class has a near-zero skewness ratio. Since the classes have non-normal distributions, the pairwise Wilcoxon test was used to compare their yearly M-score values, and its results are shown in Table 5. The table indicates that the LM class has no significant difference (at the 5% significance level) only in four cases, between 2017 and 2020, 2017 and 2021, 2018 and 2019, 2018 and 2021. For the UM class, there are no significant statistical differences in three cases between 2017 and 2018, 2017 and 2019, 2018 and 2019.

Table 5. Results of pairwise Wilcoxon test

Year	**LM**				**UM**			
	2017	**2018**	**2019**	**2020**	**2017**	**2018**	**2019**	**2020**
2018	0.23 %				55.20 %			
2019	0.00 %	7.21 %			21.20 %	6.10 %		
2020	26.35 %	0.00 %	0.00 %		0.00 %	0.00 %	0.00 %	
2021	12.41 %	11.16 %	0.06 %	1.12 %	0.00 %	0.00 %	0.00 %	4.60 %

Source: *own compilation*

Table 6 contains the annual average values of the ratios in the M-score function, grouped by LM and UM classes. The table shows that the first three ratios of the two classes significantly differ. The last five indicators have also differences, but they are smaller than in the first three. The DSRI ratios of the LM class differ appreciably from the values of the UM class, at least at the 5% significance level.

Table 6. M-score average values per year and ratios of the Beneish model

Ratios in the	LM					UM				
M-score function	**2017**	**2018**	**2019**	**2020**	**2021**	**2017**	**2018**	**2019**	**2020**	**2021**
DSRI	5.74	7.46	6.32	20.23	8.34	0.89	0.96	0.89	0.99	0.75
GMI	3.54	2.54	2.06	-0.81	2.31	-0.84	-0.27	-0.85	-2.58	-1.35
AQI	12.18	12.56	12.71	65.30	11.59	0.70	0.71	0.65	0.65	0.62
SGI	3.86	2.78	1.62	97.82	2.06	1.26	1.08	1.08	-0.76	1.26
DEPI	2.31	2.72	2.35	3.27	1.99	1.15	1.16	1.14	1.06	1.13
SGAI	1.04	1.26	1.15	-1.59	1.29	1.09	1.42	1.87	2.68	2.49
LVGI	1.17	1.10	1.15	1.19	1.19	1.92	1.72	1.96	4.14	3.23
TATA	0.20	0.23	0.24	0.22	0.23	-0.31	-0.28	-0.31	-0.51	-0.57

Source: *own compilation*

The change in the receivable collection policy could cause the high average values of the LM-class DSRI ratios, but it cannot force a difference of 6.5-8 times. The intention to overestimate sales and profits can also produce high value. These remarkable differences between the values of LM and UM classes raise the question of manipulation. The LM-class GMI ratios are higher than one, so the gross margin values have deteriorated, meaning that the LM-class companies' gross margin decreased yearly. On the other hand, growth can be observed in the UM-class companies. The relatively high positive values of the LM class may indicate profit manipulations, too.

In Table 6, the LM-class AQI values are very high and positive, indicating that companies have increased their cost deferrals, which may also allude to earnings manipulation. The higher the SGI value is than one, the greater the probability of earnings manipulation. In all years, the LM-class SGI values appreciably exceed one. The UM-class SGI values also exceed one (but they are already very close to it), except for 2020, when the SGI value dropped to -0.76. Therefore, the financial statement manipulations of the LM-class companies are likely considering the SGI indicator. Since the LM-class DEPI ratios are greater than one, it indicates that the depreciation expenses have been slowed down, which may also show earnings manipulation. The values of the SGAI and LVGI ratios are also greater than one to a small extent, so they do not indicate the financial statement manipulations. The UM-class ratios for these two indicators are higher than those of the LM class, so that the manipulations may occur more in the UM class concerning these two indicators. The average values of the LM-class TATA indicators are relatively small positive values, and they can sign manipulation. Considering all the indicators, it can be concluded that the M-score function also confirms the classification in the given class.

Companies would have to use the indicators used by the M-score model and disclose them in their business reports. The stakeholders could make better decisions based on the accurate picture of the company.

Table 7 shows the development of the M-score values by the national economy sectors. The fewest companies are in the national economic sector P, about 290 per year, and the most are in the G sector, which exceeds 3,500 in the LM class and 2,400 in the UM class yearly. Table 7 shows that the highest LM class M-score values are found in sector L, followed by K, which has a high value. The average value of the M-score ratio for the L sector was approximately halved by 2019. Similarly, the K sector values decreased in 2017-2019 but increased in 2020 to a very high level of 384.5 (like in the L sector 384.5). Generally, in 2020 (COVID-19 pandemic time), it can be seen that financial statement manipulation occurred in almost all sectors of the national economy. The greatest financial statement manipulations are likely in the L sector in 2020. The smallest earnings manipulations are in sector G, where the average M-score values are 5.7 (in 2017), 6.9 (in 2018), 5.5 (in 2019), 149.2 (in 2020) and 7.2 (in 2021). It is worth noticing that in 2020, sector G obtained the third highest result for M-score values in the LM class. This proves that during the spreading COVID-19 pandemic, this sector also experienced high financial statement manipulations. The M-scores by sectors in Table 7 can draw the attention of inspection bodies to which sectors should focus more attention. In addition, they can also help corporate stakeholders assess the given industry.

Table 7. M-score average values per year and sectors of the national economy

Sectors of the national economy	LM					UM				
	2017	2018	2019	2020	2021	2017	2018	2019	2020	2021
A - Agriculture, forestry, and fishing	10.6	12.9	11.9	10.4	7.9	-6.2	-4.8	-4.9	-8.7	-5.8
C - Manufacturing	8.8	11.4	7.9	58.6	7.8	-4.2	-4.2	-5.0	-7.3	-6.6
F - Construction	11.1	8.2	7.6	58.8	11.3	-6.7	-4.7	-4.5	-11.7	-6.9
G - Wholesale and retail trade; repair of motor vehicles and motorcycles	5.7	6.9	5.5	149.2	7.2	-4.8	-4.9	-5.2	-7.1	-8.0
H - Transportation and storage	7.5	20.0	9.6	90.8	12.7	-4.3	-3.9	-4.4	-6.8	-6.69
I - Accommodation and food service activities	7.5	17.5	11.8	63.5	18.6	-7.3	-6.8	-6.4	-10.3	-9.8
J - Information and communication	16.5	13.2	10.8	34.6	12.7	-5.3	-4.9	-9.1	-6.6	-10.6
K - Financial and insurance activities	32.9	23.6	3.7	146.1	12.7	-6.2	-5.2	-4.8	-4.9	-6.9
L - Real estate activities	34.8	24.6	17.4	384.5	21.8	-5.3	-5.1	-5.8	-13.3	-5.7
M - Professional, scientific and technical activities	12.5	15.6	11.2	256.1	15.4	-5.5	-4.9	-6.7	-18.3	-7.3
N - Administrative and support service activities	14.8	11.9	19.2	53.5	13.7	-5.2	-4.8	-4.8	-15.8	-7.8
P - Education	8.2	10.9	12.9	26.9	11.2	-4.3	-3.7	-4.3	-5.4	-6.5
Q - Human health and social work activities	15.9	10.1	13.9	23.8	15.2	-4.1	-4.6	-4.5	-5.2	-6.1
R - Arts, entertainment, and recreation	18.4	20.4	16.2	79.7	17.8	-4.9	-4.9	-8.9	-9.7	-8.8
S - Other service activities	5.9	3.8	21.0	56.2	8.2	-4.9	-4.7	-5.5	-6.6	-14.1

Source: *own compilation*

Table 8 shows the average M-score values of the LM and UM classes per year and size category. It can be seen from the table that the values are deteriorating for both classes with the size increasing. In 2020, the LM class M-score average value was much higher than in the other four years. Similarly, the UM class had relatively large negative values this year.

Table 8. M-score average values per year and size category

Size category code	LM						UM					
	2017	2018	2019	2020	2021	5-year average	2017	2018	2019	2020	2021	5-year average
1	18.7	17.9	14.6	232.9	17.5	60.3	-6.9	-6.2	-6.7	-13.5	-8.7	-8.4
2	12.4	11.1	10.3	84.3	11.6	25.9	-5.3	-4.9	-5.8	-8.7	-8.4	-6.6
3	9.2	9.9	6.2	170.6	10.7	41.3	-4.6	-4.5	-4.5	-6.9	-6.5	-5.4
4	6.1	6.0	7.9	104.9	6.5	26.3	-4.3	-3.9	-5.1	-12.2	-4.7	-6.1
5	5.0	41.0	1.6	206.4	6.4	52.1	-3.7	-3.4	-3.5	-13.0	-4.9	-5.7
Average	10.5	16.3	8.3	154.6	10.7		-4.9	-4.6	-5.2	-10.7	-6.8	

Source: *own compilation*

Table 8 shows that the companies of all categories had above-average M-score values in 2020.

For companies suspected of manipulating their financial reports (LM class), the average M-score values for smaller companies are further from the critical value. Table 9 shows that more than 60% of the companies belonging to the LM class are in the first two categories. The question may arise about whether smaller companies tend to manipulate their reports. Considering the state of the Hungarian economy, the probability of this can be high enough. The Hungarian government's economic policy decisions are made in a very ad hoc manner. The rules for companies have been changed many times (e.g. tax laws several times within a year). It is much more difficult for smaller businesses to adapt to these changes than larger ones. Small companies have a narrower scope of activities and fewer resources, so it is more difficult for them to manage changes.

Table 9. The distribution of companies between size categories by year in the LM and UM classes

Size category code	LM					UM				
	2017	2018	2019	2020	2021	2017	2018	2019	2020	2021
1	13.07%	13.16%	12.81%	14.27%	13.89%	15.51%	14.71%	13.92%	15.3%	15.19%
2	47.82%	47.39%	49.15%	48.69%	48.82%	47.91%	49.61%	48.92%	50.96%	50.53%
3	18.73%	19.36%	18.39%	18.77%	18.33%	17.87%	17.26%	18.55%	17.04%	17.31%
4	17.39%	17.42%	16.86%	15.49%	16.33%	15.45%	14.87%	15.42%	14.35%	14.05%
5	2.99%	2.67%	2.8%	2.79%	2.63%	3.27%	3.54%	3.19%	2.34%	2.92%

Source: *own compilation*

In many cases, the detected manipulations are not intentional but may also result from small businesses having fewer well-prepared managers or accounting specialists who can properly follow the changes. Smaller enterprises that probably do not manipulate their reports (UM) are also further from the critical value (Table 8). Table 9 shows that even in the case of the UM class, more than 50% of the enterprises are found in the first two categories. It can be concluded that businesses with appropriately trained professionals can also handle occasional extreme situations without financial statement manipulations. So, by training company professionals and providing expert advice to small businesses, the proportion of manipulated financial statements could probably be significantly reduced.

Figure 2 shows that the ratio of the number of companies, comparing the two classes (UM / LM), decreased until category 4th, and a significant increase occurred in the fifth category every year. Thus, the proportion of companies manipulating financial statements decreased from 2017 to 2021. Except for the first and fifth categories, the number of LM-class companies was larger than in the other categories. The figure also shows that, except for the last category, the proportion of UM-class companies increased yearly in 2017-2019 and even in 2020. In 2020-2021, a decrease in the proportion of UM-class companies was observed. There was a drop of over 20 percentage points between categories 1 and 4, followed by an increase of almost 20 percentage points between categories 4 and 5, considering the average number of companies.

Looking at Table 10, we can see an astonishing result. Generally, in each region, the UM/LM ratio indicator values increased in 2017-2019 (in some regions, they also increased in 2020 and 2021). Considering the five-year average, the lowest UM/LM ratio indicator is found in the Central Hungary region. The Central Hungary region comprises two parts, Budapest and Pest counties. In this region, the GDP per capita calculated at purchasing power parity was 108% in 2018, compared to the EU average. However, in Budapest, the previous value was 145%, while in Pest County, it was only 56%. Only the Central Transdanubia and Western Transdanubia regions have higher values than the 56% in Pest County (66% and 72%). The highest values are in the Southern Transdanubia and Northern Hungary regions, where the value of the previous indicator is only 49% in both counties, which makes the Northern Great Plain region have a lower value (46%).

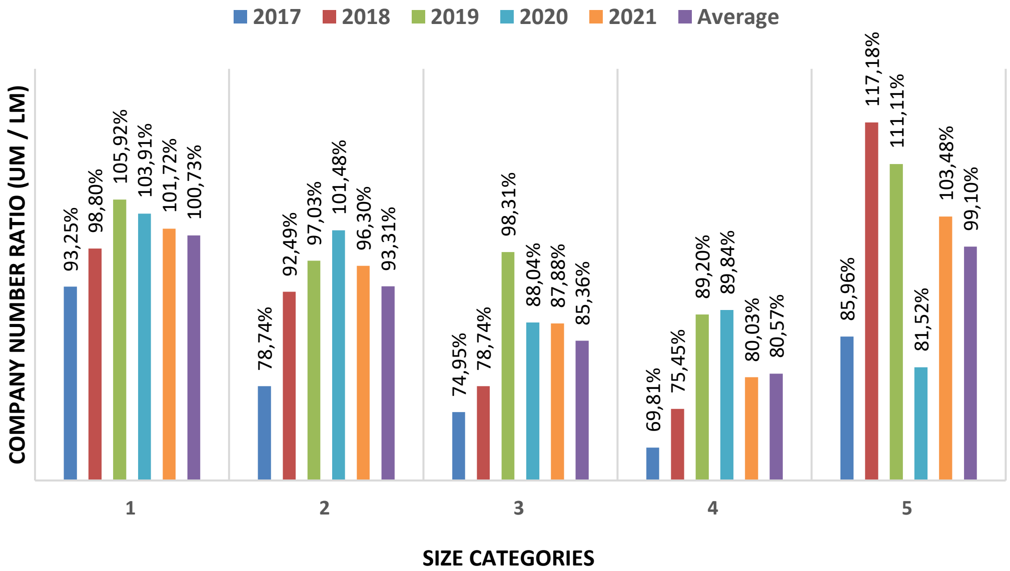

Figure 2. The changes in the ratio of the company numbers in UM/LM ratios by year and size category
Source: *own data*

Table 10. The changes in the ratio of the company numbers in the UM/LM ratios by year and region

Region	UM/LM ratio						GDP per capita
	2017	2018	2019	2020	2021	Average	100% = EU average*
Central Hungary	73.07%	82.07%	92.48%	91.59%	87.73%	85.39%	108
Southern Transdanubia	73.04%	84.38%	93.22%	95.4%	87.14%	86.64%	49
Southern Great Plain	89.58%	100.12%	111.56%	103.24%	101.24%	101.15%	52
Northern Hungary	78.88%	93.03%	96.45%	97.26%	93.32%	91.79%	49
Central Transdanubia	87.92%	98.06%	101.85%	109.33%	100.84%	99.60%	66
Western Transdanubia	86.15%	95.38%	106.9%	104.14%	104.97%	99.51%	72
Northern Great Plain	82.22%	90.42%	104.31%	99.92%	104.05%	96.18%	46

Source: own compilation based on own data and and szazadveg.hu* (https://szazadveg.hu/hu/2021/03/29/budapesti-es-a-videki-teruletek-fejlettsegenek-osszehasonlitasa~n1768).

Based on Table 11, it can be concluded that the companies' ages do not have a determining role in the UM/LM ratio. Although the indicators of companies older than five years are close to each other, only 1-5 years old indicators are lower.

Table 11. The company numbers' ratio changes in the UM/LM ratios by year and company age

Company age	**UM / LM**					
	2017	**2018**	**2019**	**2020**	**2021**	**Average**
1-5 years	69.72%	81.79%	93.46%	95.17%	90.64%	86.16%
6-10 years	81.45%	88.11%	96.87%	94.76%	90.88%	90.41%
11-15 years	80.58%	92.55%	102.25%	95.92%	89.24%	92.11%
16-20 years	81.45%	85.52%	94.79%	98.38%	91.19%	90.26%
20-25 years	81.81%	92.51%	98.65%	102.11%	99.05%	94.82%
26- years	73.62%	94.59%	96.89%	96.88%	100,00%	92.39%

Source: *own compilation*

Conclusion

Several factors can cause the likely high manipulation of financial statements in Hungary. These factors can be frauds, real manipulations and entirely accidental data distortions. High levels of corruption can also cause the manipulation of accounting data. Other factors can include ad hoc changes in the tax system, high personal and corporate taxes and contributions, and a complicated public procurement system encouraging and sometimes forcing business leaders to manipulate their reports.

Regarding the data, it was also a problem that some essential data were missing or zero in the statements. For this reason, 19,419 companies (12%) had to be excluded from the analysis during five years. The missing and false data are in the reports because there are only two controls when uploading the financial statements. First, the profit after tax in the income statement must equal the profit after tax in the equity. The second is that the total assets' value must equal the equity plus total liabilities. Therefore, they should thoroughly check when uploaded to make well-founded analyses from company reports. In this way, most deviations due to data entry errors could be avoided.

The high probably manipulated (LM) financial statement ratio (UM/LM) (46.43%-51.67%) raises many problems. Several institutions and researchers use companies' financial statements to prepare analyses and forecasts. Therefore, financial statements would be essential to provide a reliable, accurate picture of the companies. This lack can lead to incorrect analysis results, and insufficiently founded or possibly incorrect conclusions can be drawn. Therefore, the various competent organisations should ensure the highest possible reliability and realism of corporate financial statements.

Standard control procedures do not always filter out manipulated financial statements, so different organisations also need unique analytical methods to reveal accounting fraud exactly and early on. The study would like to draw the attention of the governmental decision-makers to the urgent need to take the necessary measures to draw a more accurate picture of the situation of Hungarian businesses.

Ethical issues should be emphasised in accounting courses, which do not exist in the Hungarian education system. Economic ethics should be introduced in economics majors, particularly finance and accounting. It is generally believed that education is the most effective weapon against corruption. Scandinavian societies are "cleaner" not because the deterrent power of sanctions is high there but because most citizens consider this behaviour anti-social and, therefore, shameful and reject this form of behaviour (Papanek, 2005).

An essential thing in Hungary would be to make the internal economic environment more predictable and to improve communication between the legislators and the actors of the economy, increasing mutual trust. Such an economic atmosphere that significantly reduces corruption by using the power of the public must develop.

In the future, the financial statements after 2021 will be purchased under the previous criteria. Examining these would be necessary because the impact of the COVID epidemic would already appear in it. There is a plan to consider other analysis methods and apply multivariate statistical tests and regression analyses in further investigation.

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