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Factors affecting financial performance in the waste management industry: A comparative analysis of pre- and post-COVID-19 periods

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Abstract. The linear economic model is unsustainable for a long time, so the transition to a circular economy seems inevitable. By adopting a new Circular Economy Action Plan, the EU is taking concrete steps in this direction and identifying indicators to measure progress. In this context, businesses operating in the waste management industry are among the key actors helping to meet the objectives of circular economy policies. This study aims to identify and compare the determinants of the financial performance of companies in the NACE 38 industry and to quantify their impact on ROA and ROS in 2019 and 2022. Pearson's R was used to select the variables we examined using principal components analysis as one of the methods used in exploratory factor analysis. Linear regression analysis was employed to explain the influence of the extracted factors on changes in ROA and ROS. For 2019, we extracted five factors (capital structure, business policy, current assets' efficiency, operational activity, and working capital management) that explain 79.2% of the variability in profitability.

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For 2022, we extracted six factors (liquidity management, current assets' efficiency, asset structure, volume of available resources, capital structure and operational activity), which explain 84.17% of the variability of the variables. By comparing the findings, we concluded that while in the pre-crisis period, operating ratios appeared to be key to the financial performance of companies, in the post-crisis period, the factors of liquidity and available resources have become more critical.

Keywords: determinants of financial performance, exploratory factor analysis, regression analysis, waste industry, Slovakia

JEL Classification: G39, L69, O14, Q59

1. INTRODUCTION

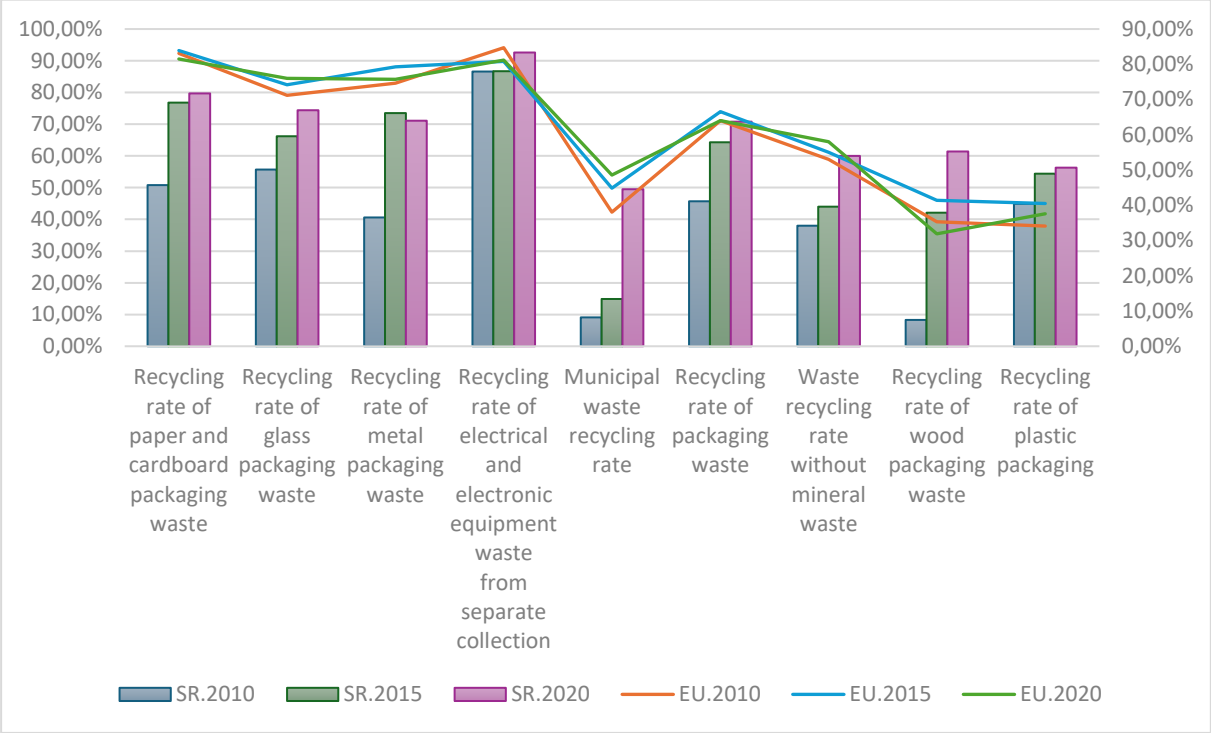
The economic model of contemporary society is primarily linear. This means that the majority of production is based on the consumption of newly extracted natural resources, which are then distributed for processing to countries with low production costs, and the manufactured products are again transported back and sold around the world. It was an open secret that companies, to increase production and profit, applied the so-called defective part or the so-called suicide code in the production process, which ensured that the product broke down after a specific time. Its repair was not possible or practical for technical or economic reasons, so the customer had no choice but to discard the damaged product and buy a new one. The consumerist way of life to which society has gradually adapted and the associated overproduction have contributed to the key problem of our time – the pollution of nature by the amount of waste that accumulates in various landfills is burned in incinerators or remains loose in the wild. Part of the solution was to take measures to recycle some used raw materials (mainly textiles, glass, plastics, paper and cardboard, metals and wood). However, it did not solve the problem at its core. This linear economic model, based on the high consumption of non-renewable resources that the Industrial Revolution started, cannot logically work in the long term. This is both the economic, environmental and social side of the problem.

The opposite, which is currently receiving increased attention, is the circular economy model. The circular economy has been a critical political topic in the EU since 2015 when the United Nations adopted The 2030 Agenda for Sustainable Development. This year, the European Commission published the Action Plan for the Circular Economy (2015), which was revised for 2022. The new monitoring framework aims to provide a comprehensive overview by measuring the direct and indirect benefits of increasing circulation. These indicators make it possible to measure progress towards meeting the goals of circular economy policies. The indicators are grouped into five thematic areas: (1) production and consumption, (2) waste management, (3) secondary raw materials, (4) competitiveness and innovation, and (5) global sustainability and resilience (www.enviroportal.sk).

For this reason, special attention is also paid to the circular economy in Slovakia. Responsibility in this area lies with the Ministry of the Environment of the Slovak Republic, which in November 2020 prepared the Waste Management Program of the Slovak Republic for the years 2021-2025, which in its binding part is based on the provisions of the Waste Act No. 79/2015 Coll. Z. and sets goals, indicators and measures in individual areas of waste management.

The information portal of the Ministry of the Environment of the Slovak Republic (www.enviroportal.sk/envidat) provides an overview of environmental indicators. Circular economy indicators in waste management track the recycling rate of packaging waste (paper and cardboard, glass, metal, wood, plastic) and the recycling rate of municipal waste, non-mineral waste, and waste.

Graph 1 compares recycling rates between the EU and Slovakia in 2010, 2015, and 2020.



Graph 1. Circular economy monitoring framework - waste management
Source: https://www.enviroportal.sk/indicator/381?langversion=sk
Authors' calculations.

From the data, it is possible to observe the gradual increase in the waste recycling rate in Slovakia. The highest growth in the rate of recycling in the Slovak Republic between 2010 and 2020 can be seen in the recycling rate of wood packing waste (640%) and the municipal waste recycling rate (444%). In electronic waste and plastic packaging recycling, Slovakia has a higher recycling rate than the EU average throughout the entire period. During the 10 years, SR recorded an increase in the recycling rate in all evaluated areas.

The measures of the Slovak government, focused on the area of waste management, bring positive results, which we can report thanks to enterprises whose main activity is the collection, processing and disposal of waste and recycling of materials. These enterprises operate according to the NACE Rev. 2 classification in the NACE 38 sector – Waste collection, treatment and disposal activities, and materials recovery, and contribute decisively to the achievement of the objectives formulated in the individual programs. The financial prosperity of these enterprises is a key condition for the implementation of the Circular Economy Action Plan. For this reason, the main objective of this study is to identify the financial and economic determinants that decisively affect the financial performance of enterprises operating in waste management.

The rest of this study is divided as follows: Part 2 provides an overview of relevant theoretical starting points and empirical works focused on researching selected financial aspects of the circular economy. Part 3 presents the research methodology and characterizes the researched data and methods used. The fourth part presents data analysis, statistical results, and discussion. The last part summarizes the study's conclusions.

2. LITERATURE REVIEW

Several authors have researched the circular economy (CE) and various aspects of its manifestation and impact. Musová et al. (2021a) and Musová et al. (2021b) have investigated consumer behaviour in this context. However, research into its economic and financial aspects is still in its early stages.

Hondroyiannis et al. (2024) investigated macroeconomic aspects of the circular economy in 28 European countries. Aranda-Usón et al. (2019) investigated the relationships between the volume of investments and the level of CE in businesses and the characteristics of financial resources related to CE. They analyzed different aspects of the financial sources that companies use to finance circular activities.

Studies focused on researching the financial performance of companies primarily focus on various aspects of the impact of more efficient waste use and the application of good environmental practices related to waste sorting and collection, its recycling and subsequent secondary recovery on selected indicators monitoring the financial situation and performance of companies. Such authors include, for example, Scarpellini et al. (2018), Zhidebekkyzy et al. (2023), and Potkány et al. (2024), who examine the association of firms' financial performance with the implementation of the circular economy.

Yin et al. (2023) contributed to this area with the results of their meta-analysis of circular economy and sustainable economic practices. The contribution provides an overview of the research conducted in the area of the influence of circular economic practices on the company´s performance. Some were measured as positive, and other authors found a negative impact.

Gull et al. (2022) and Štreimikienė (2023) investigated the impact of waste management practices on the financial performance of companies. They found a significantly negative (positive) relationship between waste generation (recycling) and economic performance. They also pointed out several factors that influence this relationship. Similarly focused research was carried out by e.g. Bartolacci et al. (2018a), Bartolacci et al. (2018b), Zhang et al. (2018), Sitnikov et al. (2023) or Modi and Mishra (2011).

The relationship between the financial performance of companies and the determinants that influence it has been the subject of research by several authors. Capon et al. (1990) published a meta-analysis of results from 320 published studies relating environmental, strategic and organisational factors to financial performance. They pointed out factors that have been extensively studied (industry concentration, growth in sales and assets, capital investment, size and others) as well as those that have required more attention from researchers (firm control, inventory, variability in return, firm social responsibility and others). Many areas have become the subject of research in the following period.

Mirza and Javed (2013) examined the possible relationship between a firm's financial performance and economic indicators, corporate governance, ownership structure, capital structure, and risk management. Their results consistently support this potential relationship, although the strength of the relationship varies across performance indicators.

Microeconomic determinants of corporate financial performance were examined in a sample of industrial companies by Pantea et al. (2014). They provide a historical overview of variables focused on assessing corporate performance and summarise the key determinants of corporate performance. They test the hypothesis of a positive relationship between firm size, firm growth, capital intensity, human resources, CSR and financial performance, measured by return on assets and return on equity.

Naz et al. (2016) examined the relationship between asset utilisation ratios, profitability ratios, leverage ratios, liquidity ratios, cash conversion cycle and the financial performance of the company, which was measured by the return on investment ratio. Ha et al. (2019) examined the impact of determinants on economic performance. They employed quantile regression and OLS and found that firm size has a positive association. Still, capital structure, short-term liquidity and fixed asset investment have a negative relationship with financial performance, as measured by return on sales, return on assets and return on

equity. Vieira et al. (2019) found that the determinants of business performance differ depending on the variable used by individual stakeholders to measure business performance.

Belas and Rahman (2023) examined the attitudes of business owners and managers towards understanding the most critical aspects of financial management that contribute decisively to managing financial risk and achieving the desired financial performance. This research was conducted on a sample of companies based in the Czech and Slovak Republics. Vartiak (2016) compared the economic performance of Slovak excellent companies. For this purpose, he used the following financial indicators: sales revenue, earnings after taxes, return on assets, gross margin and total indebtedness.

An analysis of the determinants of financial performance on a sample of agricultural enterprises in the Slovak Republic was carried out by Lehenchuk et al. (2022). They performed regression analysis according to four developed models based on the use of four different dependent variables (return on assets, net profit margin, return on equity, return on sales) and 10 independent variables (leverage, long-term debt to assets, short-term debt to assets, debt to equity, capital intensity, asset weight, current ratio, size, dummy variable for ownership type, dummy variable for legal form), which were the same for all four models. Research into the impact of a crisis, which was undoubtedly the COVID-19 pandemic, on the financial performance of companies in Slovakia was also conducted by Valášková et al. (2023).

Our study follows up and complements the above analyses. It applies appropriate statistical methods and identifies financial and economic determinants that decisively affect the financial situation and performance of enterprises. We extract determinants from data available for 2019 and 2022, which represent the situation in the pre-crisis and post-crisis period caused by the COVID-19 pandemic and identify key changes that this crisis period brought to the financial and economic management processes of the studied companies and were reflected in the composition of financial management determinants. The analysis is applied to a set of companies operating in the waste management sector, which have not yet been subjected to a separate analysis. In this way, our study contributes to the expansion of knowledge in the field of management of financial and economic processes of companies, which are among the key ones in fulfilling the objectives of the Action Plan for the Circular Economy.

3. METHODOLOGY

This study aims to identify the determinants of the financial performance of enterprises based in the Slovak Republic in 2019 and 2022, examine changes in the composition of determinants between the monitored periods, and use linear regression analysis to quantify their impact on selected indicators of the financial performance of enterprises (ROA and ROS). Determinants will be identified from a set of financial indicators that are key to monitoring the financial situation and performance of companies. The study will focus on enterprises in the Industry sector, specifically those operating in the NACE E 38 - Waste collection, treatment and disposal activities; materials recovery. This sector includes businesses dealing with waste collection (E38.1 - Waste collection), waste treatment and disposal (E38.2 - Waste treatment and disposal) and material recycling (E38.3 - Materials recovery). About the importance of these business entities in the circular economy in general, but especially in fulfilling the goals of the EU Action Plan for the circular economy, we consider the identification of factors affecting their financial performance to be an essential contribution to the successful management of financial processes and ensuring the long-term prosperity of these businesses.

Financial data at the level of individual enterprises were obtained from the database of financial statements provided by the company CRIF – Slovak Credit Bureau, s. r. o., which operates the CRIBIS.sk Universal Register.

The investigated periods are 2019 and 2022, which represent before and after the crisis period caused by the spread of COVID-19. The database of data from the financial statements for the years 2019 and 2022 of companies operating in the NACE 38 sector before the adjustments contained a total of 2,001 entities, which are represented by individual accounting periods. This data set was subsequently reduced, taking into account the established research objectives and the assumptions underlying the selected research methods. In the first wave of adjustments, accounting periods in which companies reported zero values in the following items were removed from the database: profit and loss, revenue from the sale of goods, products and services, ROA and ROS. After this selection, the database contained 1,635 accounting periods (764 in 2019 and 871 in 2022). These periods served as the input for relevant calculations and statistical analyses. In each accounting period, a total of 28 financial analysis indicators, commonly used by companies to evaluate their economic situation, were calculated (see Table 1). Additionally, another 19 financial indicators, expressed in monetary units (EUR), were selected from the balance sheet and income statement. These indicators were subsequently the subject of our analysis. We list them in Table 1 and the text below the table.

Table 1

Investigated financial indicators

Description	**Symbol**	**Measurement**
Return on assets	ROA	EBIT/total assets
Return on sales	ROS	EBIT/sales
Gross margin	GM	gross profit/sales
Current liquidity ratio	L3	current assets/current liabilities
Quick liquidity ratio	L2	(current assets-inventory)/current liabilities
Cash ratio	L1	cash and cash equivalents/current liabilities
Insolvency ratio	INSR	trade liabilities/trade receivables
Asset turnover ratio	ATR	sales/total assets
Fixed asset turnover ratio	FATR	sales/fixed assets
Current asset turnover ratio	CATR	sales/current assets
Inventory turnover ratio	ITR	cost of goods sold/inventory
Receivable turnover ratio	RTR	sales/receivables
Liabilities turnover ratio	LTR	cost of goods sold/liabilities
Net working capital turnover ratio	NWCTR	sales/net working capital
Cash conversion cycle	CCC	receivables turnover period + inventory turnover time - turnover period of liabilities
Net working capital	NWC	current assets-current liabilities
Share of fixed assets to total assets	FAAS	fixed assets/total assets
Share of current assets to total assets	CAAS	current assets/total assets
Share of inventory to current assets	ICAS	inventory/current assets
Share of receivables to current assets	RCAS	receivables/current assets
Cash to current assets	CCAS	(cash+cash equivalents)/current assets
Equity to assets ratio	EAR	equity/total assets
Indebtedness	IND	liabilities/total assets
Share of current liabilities to liabilities	CLLS	current liabilities/liabilities
Assets growth rate	AGR	$(assets_1\text{-}assets_0)/assets_0$
Net profit growth rate	NPGR	$(net\ profit_1\text{-}net\ profit_0)/net\ profit_0$
Sales growth rate	SGR	$(sales_1\text{-}sales_0)/sales_0$
Cost of goods sold growth rate	CGSGR	$(assets_1\text{-}assets_0)/assets_0$

Source: Authors.

For analysis, were selected the following items expressed in monetary value from the financial statements: non-current assets (NCA), inventory (I), receivables (RVB), financial accounts (FIA), equity (E), non-current liabilities without loans and provisions (NCL), liabilities to employees (L2E), tax liabilities and

subsidies (TLS), bank loans and short-term financial assistance (BLFA), provisions (P), other current liabilities (OL), revenues (REV), gross profit (GP), cost of merchandise sold (CMS), consumed raw materials, energy consumption, and consumption of other non-inventory supplies (RMEC), services (S), personnel expenses (PE), amortization and value adjustments to non -current assets (AM) and profit/loss from financial activities (FALP).

Several statistical methods in the SPSS program are used to fulfil the aim of the study. We selected the variables that would be the subject of factor analysis for each year using correlation analysis and Pearson's R. Compared to the factor analysis of the data from the entire set of variables mentioned above (except ROA and ROS), we obtained better results this way. For this reason, only those indicators that were statistically significantly correlated with ROA and ROS were included in the factor analysis in the years under review. We verified the hypothesis about the statistical significance of the correlation coefficients (H_0: $\varrho = 0$; H_1: $\varrho \neq 0$) at the significance level $\alpha = 0.05$.

This study presents the determinants of the financial performance of companies identified using exploratory factor analysis and principal component analysis. During the factor analysis, several criteria were taken into account, and relevant statistical tests were used. The suitability of the set for factor analysis was verified using the Kaiser-Meyer-Olkin measure of sampling adequacy (KMO), Bartlett's test of sphericity, and the measure of sampling adequacy (MSA). Any variable whose MSA value was less than 0.5 was excluded from the factor analysis. The data set was also assessed based on the commonality value, which indicates the proportion of the variance of the given variable that is explained by all the extracted factors. We accepted a value greater than 0.4. When removing the factors, we followed Kaiser's recommendation, which we set for the initial eigenvalues in SPSS to a value higher than 1. The interpretability of the factors was increased by the VARIMAX rotation, which maximises the variance of the loadings within the factors. Since we want to ensure that the factor scores are not correlated, we chose the Anderson-Rubin method to calculate them. Factor score values were used to identify the influence of factors on selected financial performance indicators. We modelled the impact of factors using linear regression analysis. The dependent variables are ROA and ROS, while the independent variables are the scores of individual factors. The model is built separately for ROA and ROS in each examined period. We verified the hypothesis about the statistical significance of the regression coefficients (H_0: $\varrho = 0$; H_1: $\varrho \neq 0$) at the significance level $\alpha = 0.05$.

This study identifies changes in the determinants of financial performance between 2019 and 2022, focusing on the composition of individually extracted factors and their respective contributions to explaining total variability. It also compares the results of the regression analysis between the investigated periods and those of relevant research conducted by other authors.

4. EMPIRICAL RESULTS AND DISCUSSION

The analysis's results are presented in three parts: the first part presents the findings for 2019, the second part presents the findings for 2022, and the third part includes a comparative analysis between the years 2019 and 2022 and a comparison with solutions proposed by other authors.

4.1. Identification of determinants of financial performance of enterprises in 2019

Based on the results of the correlation analysis, the following 17 variables entered the factor analysis (explanation of abbreviations is in Table 1 and below): GM, ATR, CATR, LTR, CCC, FAAS, RCAS, EAR, IND, RVB, TLS, BLFA, REV, GP, RMEC, S, FALP. The KMO shows a value of 0.457. Bartlett's test of sphericity indicates the value of Sig. = 0.000. However, we excluded seven indicators from the further analysis (FAAS, TLS, BLFA, REV, GP, RMEC, and S) because they had an MSA value below 0.5. We

repeated the factor analysis on the set of the remaining ten variables. Descriptive statistics of the indicators are presented in Table 2.

Table 2

Descriptive Statistics[a]							
				95% Confidence Interval for Mean		Minimum	Maximum
	Mean	Std. Deviation	Std. Error	Lower Bound	Upper Bound		
ROA	0.02	0.48	0.02	-0.02	0.05	-5.95	3.08
ROS	-0.45	6.33	0.25	-0.94	0.03	-140.05	4.10
GM	0.04	2.12	0.08	-0.13	0.20	-39.54	1.00
ATR	1.86	2.62	0.10	1.66	2.06	0.00	37.74
CATR	3.22	3.69	0.14	2.94	3.51	0.00	37.74
LTR	6.57	121.88	4.79	-2.83	15.97	-2465.11	1596.20
CCC	2117.35	21481.42	843.87	460.29	3774.40	-204.44	519456.57
RCAS	0.52	0.41	0.02	0.49	0.55	-1.81	4.50
EAR	0.22	1.14	0.04	0.13	0.31	-14.18	1.24
IND	0.76	1.15	0.05	0.68	0.85	-0.24	15.18
RVB	1628947.86	33831622.28	1329031.64	-980788.25	4238683.97	-58475.00	861161007.00
FALP	-11487.20	194422.45	7637.64	-26484.75	3510.34	-4096289.00	1401260.00

[a.] Analysis N: 648

Source: *Authors' calculations.*

These variables met the set conditions for data suitability control with the following results: KMO = 0.514, MSA of each variable is at least 0.5, Bartlett's Test of Sphericity Sig. = 0.000, the communality value is at least 0.5. Based on the results, we conclude that the data are suitable for factor analysis and factor extraction. Using the principal component analysis method, we extracted five components that explain 79.2% of the variability (see Table 3).

Table 3

Total Variance Explained									
Component	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	2.216	22.163	22.163	2.216	22.163	22.163	2.019	20.189	20.189
2	1.900	18.999	41.162	1.900	18.999	41.162	1.824	18.244	38.433
3	1.647	16.469	57.630	1.647	16.469	57.630	1.800	17.996	56.429
4	1.094	10.940	68.570	1.094	10.940	68.570	1.167	11.672	68.100
5	1.063	10.630	79.200	1.063	10.630	79.200	1.110	11.100	79.200
6	.879	8.787	87.987						
7	.787	7.868	95.855						
8	.238	2.385	98.240						
9	.175	1.746	99.986						
10	.001	.014	100.000						

Extraction Method: Principal Component Analysis.

Source: *Authors' calculations.*

Through the use of VARIMAX rotation, Component 1 explains the largest share of variability (20.2%), followed by Component 2 with 18.2%, Component 3 with 18%, Component 4 with 11.7%, and Component 5 with 11.1%. Table 4 shows the classification of the variables in each of the extracted five factors. Only values 0.3 and above are shown.

Table 4

Rotated Component Matrix

	Component				
	1	2	3	4	5
GM				-.673	
ATR			.927		
CATR			.921		
LTR					-.807
CCC				.809	
RCAS					.643
EAR	-.990				
IND	.990				
RVB		-.955			
FALP		.953			

Extraction Method: Principal Component Analysis.
Rotation Method: Varimax with Kaiser Normalization.
Suppressed small coefficients: absolute value below 0.3.
[a.] Rotation converged in 5 iterations.
Source: *Authors' calculations.*

Factor 1, which explains the highest share of variability (20.2%), consists of the indicators equity to assets ratio (EAR) and indebtedness (IND). The indicators show inverse relationships to each other; for example, in the rotated matrix of components, EAR exhibits a negative value (-0.990), whereas indebtedness shows a positive value (0.990). The factor points to the high importance of the structure of financing sources in evaluating financial performance, not only of waste management enterprises in Slovakia. A decrease in the proportion of own resources in total assets necessitates an increase in enterprise indebtedness, posing a threat to the financial stability of the enterprise.

Factor 2 comprises company receivables (RVB) and profit/loss from financial activity (FALP). It contributes 18.2% to the explanation of the total variability. These indicators are also inversely related, indicating a situation where an increase in company receivables leads to a shortage of available cash. Companies then need to secure these funds through other means, such as issuing debt securities or taking out bank loans, which are associated with increased financial costs in the form of interest. This subsequently reduces the company's financial activity. The factor points to the importance of appropriately setting the conditions of the company's trade policy.

Factor 3 comprises asset turnover (ATR) and current asset turnover (CATR). The factor contributes to explaining the total variability with a share of 18%. The indicators are directly proportional. The growth in the turnover of current assets creates prerequisites for the growth of the turnover of total assets, which positively affects the company's financial performance. Increasing asset turnover indicates better utilization of the company's short-term assets, which is subsequently reflected in the growth of profit and financial performance.

Factor 4 comprises gross margin (GM) and cash conversion cycle (CCC). The indicators are in an indirect relationship with each other. The growth of the value of one indicator decreases the value of the other. They contribute 11.7 per cent to the explanation of the total variability. A higher factor load is shown in the matrix for the CCC indicator, which expresses the number of days of the company's operating cycle that it needs to finance from sources other than its short-term liabilities, the largest share of which is often made up of trade liabilities. The growth of CCC can be caused by an increase in the turnover time of inventories and receivables and a decrease in the turnover time of liabilities. There is a situation in the company where the volume of liabilities decreases (as a result of their timely payment), but on the other hand, the volume of receivables and inventories, which tie up the company's capital, increases. This creates

prerequisites for the emergence of insolvency and limits the company's ability to carry out operational activities and generate income from the sales and gross profit, which serves to create internal sources of financing for the company's activities. Therefore, the growth of CCC negatively affects the ability to create a gross margin.

Factor 5 consists of the liabilities turnover (LTR) and the ratio of receivables to current assets (RCAS), among the indicators focused on working capital management. LTR and RCAS are inversely proportional to each other. An increase in LTR will cause a decrease in RCAS and vice versa. The growth of the LTR indicator means a reduction in the turnover time of liabilities, which is reflected in the accelerated payment of invoices to suppliers. In the case of the current growth of the share of receivables on current assets, the company is at risk of so-called secondary insolvency, in which the company's claims exceed its liabilities, and the company will no longer be able to pay its obligations until it releases the resources tied up in the claims. From the point of view of working capital management, this is a severe situation that can lead to the company´s demise, so it is essential to pay due attention to the relationship between these items.

By interpreting the extracted factors on the data in the pre-crisis period, we identified five key determinants of the financial performance of companies operating in the circular economy sector. All of them are closely related to the operational activity of enterprises and their ability to ensure its smoothness. We can name the extracted factors as follows:

- factor 1: the structure of funding sources (SFS),
- factor 2: business policy of the company (BP),
- factor 3: the efficiency of the use of the company's current assets (CAE),
- factor 4: operational activity of the company (OA),
- factor 5: working capital management (WCM).

Mathematically, we can describe the individual factors with a linear function using the coefficients displayed in the component score coefficient matrix (see Table 5). In this way, we can construct an equation that describes each factor in terms of the variables that were measured and calculate the factor score for each combination of values of the input variables. The general notation of the factor equation (Y_i) has the form:

$$Y_i = b_1 x_{1i} + b_2 x_{2i} + \cdots + b_n x_{ni} + \varepsilon_i, \quad (1)$$

where: b_1, b_2 ... b_n is the factor loading of individual variables; x_1, x_2 ... x_n are variables; "i" denotes an individual factor; "n" is the number of explanatory variables; ε is the random error.

Table 5

Component Score Coefficient Matrix

	Component				
	1	2	3	4	5
GM	-.037	-.005	.017	-.575	.139
ATR	-.044	-.014	.523	.010	-.023
CATR	-.023	-.010	.515	-.003	.000
LTR	.046	-.013	.119	.140	-.748
CCC	-.119	.031	.047	.716	.116
RCAS	-.003	-.008	.111	.128	.567
EAR	-.500	-.003	.034	.037	.017
IND	.500	.004	-.034	-.037	-.018
RVB	-.010	-.526	.022	-.026	.007
FALP	-.003	.523	-.001	.007	.010

Extraction Method: Principal Component Analysis.
Rotation Method: Varimax with Kaiser Normalization.
Component Scores.
Source: *Authors' calculations.*

The value of the factor score of individual factors can be expressed as follows:

$$SFS = (-.037GM) + (-.044ATR) + (-.023CATR) + (.046LTR) + (-.119CCC) + (-.003RCAS) + (-.500EAR) + (.500IND) + (-.010RVB) + (-.003FALP) + \varepsilon, \quad (2)$$

$$BP = (-.005GM) + (-.014ATR) + (-.010CATR) + (-.013LTR) + (.031CCC) + (-.008RCAS) + (-.003EAR) + (.004IND) + (-.526RVB) + (.523FALP) + \varepsilon, \quad (3)$$

$$CAE = (.017GM) + (.523ATR) + (.515CATR) + (.119LTR) + (.047CCC) + (.111RCAS) + (.034EAR) + (-.034IND) + (.022RVB) + (-.001FALP) + \varepsilon, \quad (4)$$

$$OA = (-.575GM) + (.010ATR) + (-.003CATR) + (.140LTR) + (.716CCC) + (.128RCAS) + (.037EAR) + (-.037IND) + (-.026RVB) + (.007FALP) + \varepsilon, \quad (5)$$

$$WCM = (.139GM) + (-.023ATR) + (.000CATR) + (-.748LTR) + (.116CCC) + (.567RCAS) + (.017EAR) + (-.018IND) + (.007RVB) + (.010FALP) + \varepsilon. \quad (6)$$

Using these equations, the SPSS program calculated the factor score value for each subject and each factor separately. We then used these values in a linear regression analysis and examined the influence of individual factors (independent variables) on ROA and ROS indicators (dependent variables). The regression model that will be the result of our analysis will have the following form:

$$y = b_0 + b_1x_1 + b_2x_2 + \cdots + b_nx_n + \mathrm{e}, \quad (7)$$

where: y = an explained, dependent variable, β = a regression coefficient, x = a selected independent, explanatory variable, ε = a random error, n = a number of explanatory variables.

In the regression analysis of ROA, the BP and WCM factors were excluded. The results of this analysis are presented in Table 6.

Table 6

Coefficients [a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
		B	Std. Error	Beta			Tolerance	VIF
1	(Constant)	.015	.019		.831	.406		
	SFS	-.068	.019	-.140	-3.630	.000	1.000	1.000
	CAE	-.058	.019	-.120	-3.095	.002	1.000	1.000
	OA	-.036	.019	-.074	-1.913	.056	1.000	1.000

[a.] Dependent Variable: ROA=EBIT/A
Source: *Authors' calculations.*

The regression equation has the form:

$$ROA_{19} = .015 + (-.068SFS) + (-.058CAE) + (-.036OA) + \varepsilon, \quad (8)$$

F value = 8.803, Sig. = .000, R = .198, R Square = .039, Adjusted R Square = .035, Std. Error of the Estimate = .47, Durbin-Watson = 1.984.

The regression model makes it possible to explain the variability of ROA using three explanatory factors (SFS, CAE and OA), which we extracted from the variables listed in Table 4. All explanatory variables affect ROA inversely, which means that an increase in the value of the factor score will be reflected in a decrease in ROA. The model suggests that the share of equity contributes weakly to the increase of

ROA, while the growth of debt, on the contrary, reduces ROA. A surprise for us is the indirect effect of better utilization of the company's assets (CAE) on ROA, which indicates that when the efficiency of asset utilization increases by 1 unit, ROA decreases by 0.06 units. However, the factor consists of indicators for which we found a weak and moderately strong indirect correlation with ROA in the first round of data selection ($r_{ATR, ROA}$ = -.449, Sig. = .000; $r_{CATR, ROA}$ = -.285, Sig. = .000), and a moderately strong direct correlation ($r_{ATR, CATR}$ = .645, Sig. = .000). The third factor (OA) also affects ROA negatively. The GM and CCC indicators have the highest factor loading in OA. While GM growth contributes to ROA growth, CCC growth contributes to ROA decline.

The regression model created explains only 4% of the variability in ROA, which is insufficient for applying the model in financial management processes. This limitation may be attributed, on one hand, to the quality of the data in the sample set, and on the other hand, to the chosen factor analysis procedure. Since this method does not have a precisely defined procedure, it is possible that choosing a different approach could enable us to construct a model with better explanatory power for describing ROA, which will be the subject of our further research.

In the regression analysis of ROS, only the BP factor was excluded; the other factors (SFS, CAE, OA, WCM) are included in the model as explanatory variables. We present the result of the regression analysis for ROS in Table 7.

Table 7

Coefficients [a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
		B	Std. Error	Beta			Tolerance	VIF
1	(Constant)	-.454	.189		-2.402	.017		
	SFS	-1.092	.189	-.172	-5.770	.000	1.000	1.000
	CAE	.458	.189	.072	2.422	.016	1.000	1.000
	OA	-3.917	.189	-.618	-20.687	.000	1.000	1.000
	WCM	.576	.189	.091	3.043	.002	1.000	1.000

[a.] Dependent Variable: ROS=EBIT/T

Source: *Authors' calculations.*

The regression equation has the form:

$$ROS_{19} = -.454 + (-1.092SFS) + (-.458CAE) + (-3.917OA) + (.576WCM) + \varepsilon, \quad (9)$$

F value = 119.096, Sig. = .000, R = .652, R Square = .426, Adjusted R Square = .422, Std. Error of the Estimate = 4.816, Durbin-Watson = 2.018.

This regression model consists of 4 explanatory factors, among which SFS, CAE and OA inversely affect ROS. This means that an increase in the factor score value will cause a decrease in ROS. Interpretations of the influence of SFS, CAE and OA are similar to the model for ROA. A new variable in this model is WCM, which comprises indicators of the turnover of liabilities and the share of receivables on current assets. The WCM factor and the variables that make it up are directly proportional to ROS. The growth of the WCM factor score contributes to the growth of ROS. While the increase in RCAS, as a result of the increased operational activity of enterprises, is reflected in the increase in ROS, the decrease in the turnover of liabilities contributes to the increase in ROS.

The regression model for ROS exhibits greater explanatory power compared to the model for ROA. It explains about 43% of the ROS variability. This means that 43% of the variability of ROS can be explained by the structure of financing sources, the efficiency of the assets using, the intensity of the company's operational activity and the quality of its working capital management.

4.2. Identification of determinants of financial performance of enterprises in 2022

The years 2020 and 2021 were characterized by the global crisis caused by the government measures taken to prevent the spread of the COVID-19 pandemic. By analyzing the available data in these periods, we could not extract factors that could adequately represent the key areas of managing the financial performance of companies through factor analysis. It is possible to conclude that the non-specific measures taken by governments and companies, in an attempt to ensure their survival, disrupted operational processes and the links between indicators to such an extent that we failed to generate meaningful results on a general level. For this reason, we focused the second stage of the research on the year 2022, during which several governments lifted the state of emergency due to the spread of the COVID-19 pandemic. The war between Russia and Ukraine, which began this year, affected companies by causing a rise in input prices, particularly energy prices. This was due to speculation by traders on commodity markets and as a consequence of EU sanctions against Russia. The operation of enterprises mainly was affected only in cases where, with increased input prices, enterprises could not realize their production on the market with the necessary profit. We are interested in whether there have been any changes in the perception of the determinants of financial performance between the analyzed periods.

In the factor analysis of the data in 2022, we proceeded methodically in the same way as in the analysis of the data in 2019. In the first step, based on the results of the correlation analysis of 47 input financial indicators, we selected these 18 indicators that were statistically significantly correlated with ROA and ROS (explanation of abbreviations is in Table 1): GM, L1, L2, L3, ATR, ITR, LTR, CATR, CCC, FAAS, CAAS, ICAS, EAR, IND, NPGR, NWC, FIA, TLS. The KMO shows a value of 0.590. Bartlett's test of sphericity indicates the value of Sig. = 0.000. Only the NPGR indicator has an MSA value lower than 0.5, which we excluded from further analysis. By performing repeated factor analysis on the remaining 17 indicators, we obtained the results presented below. Table 8 presents the descriptive statistics of the variables that entered the final phase of the factor analysis.

Table 8

Descriptive Statistics [a]

	Mean	Std. Deviation	Std. Error	95% Confidence Interval for Mean		Minimum	Maximum
				Lower Bound	Upper Bound		
GM	.20	.82	.04	.11	.29	-11.74	.85
L1	1.30	3.83	.21	.89	1.71	-1.65	53.06
L2	2.49	6.56	.36	1.79	3.20	.00	83.50
L3	2.97	8.39	.46	2.07	3.87	-.03	121.67
ATR	1.93	2.20	.12	1.69	2.16	.01	21.32
CATR	4.01	5.95	.32	3.37	4.65	.01	86.07
ITR	4.17	13.46	.73	2.73	5.62	-48.80	194.04
LTR	5.15	13.94	.76	3.65	6.64	-53.58	196.04
CCC	695.36	3436.35	187.47	326.59	1064.12	1.03	41134.23
FAAS	.43	.25	.01	.40	.45	.00	.98
CAAS	.57	.26	.01	.54	.59	.02	1.00
ICAS	.13	.58	.03	.07	.20	-1.00	9.00
EAR	.35	.50	.03	.30	.40	-4.65	1.42
IND	.63	.50	.03	.58	.69	-.42	5.65
NWC	669304.57	9715907.69	530046.22	-373333.77	1711942.91	-14589885.00	176811097.00
FIA	712505.81	9186721.87	501176.77	-273344.28	1698355.89	-127124.00	168291770.00
TLS	28355.91	171330.42	9445.75	9774.01	46937.81	-235283.00	2929140.00

[a.] Analysis N: 336

Source: *Authors' calculations.*

The KMO value increased to 0.630, and Bartlett's test of sphericity yielded a significance value of 0.000. From these results, we conclude that the data are suitable for factor analysis and factor extraction. Using principal component analysis and VARIMAX rotation, we extracted six components, which together explain 84.2% of the variability (see Table 9).

Table 9

Total Variance Explained

	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
Component	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	4.582	26.954	26.954	4.582	26.954	26.954	4.204	24.731	24.731
2	2.528	14.873	41.827	2.528	14.873	41.827	2.265	13.322	38.053
3	2.169	12.758	54.585	2.169	12.758	54.585	2.135	12.560	50.613
4	1.933	11.369	65.954	1.933	11.369	65.954	2.095	12.323	62.936
5	1.794	10.550	76.504	1.794	10.550	76.504	1.998	11.752	74.689
6	1.303	7.666	84.170	1.303	7.666	84.170	1.612	9.481	84.170
7	.883	5.193	89.362						
8	.790	4.647	94.009						
9	.395	2.325	96.334						
10	.305	1.792	98.125						
11	.164	.963	99.089						
12	.129	.759	99.847						
13	.009	.055	99.902						
14	.007	.039	99.941						
15	.006	.032	99.974						
16	.003	.016	99.989						
17	.002	.011	100.000						

Extraction Method: Principal Component Analysis.
Source: *Authors' calculations.*

Component 1 explains the highest share of variability at 24.7%, followed by Component 2 at 13.3%, Component 3 at 12.6%, Component 4 at 12.3%, Component 5 at 11.8%, and Component 6 at 9.5%, which contributes the least to the explanation of variability. Table 10 shows the classification of the variables in each of the six extracted factors.

Factor 1 consists of indicators L1, L2, L3, ITR and LTR. The indicators are in direct proportion to each other and explain almost a quarter (24.7%) of the total variability. The growth of the turnover of liabilities and the simultaneous reduction of the period of turnover of liabilities can be shown in the company's balance sheet by reducing the volume of liabilities, contributing to the growth of the company's liquidity. An increase in inventory turnover will provide the company with more resources from the realization of production, thereby contributing to the growth of the company's liquidity. Liquidity management in waste management companies is, therefore, one of the critical factors for ensuring their financial stability and performance.

Factor 2 consists of ATR, CATR and ICAS, contributing 13.3% to the explanation of variability. The indicators are in direct relationship with each other. Their interpretation for ATR and CATR is the same as for Factor 3 in 2019. Between ICAS and the ATR and CATR indicators, we identified a moderately strong positive dependence by correlation analysis. A common feature of the variables is the efficiency of using the company's short-term assets.

Factor 3 contains indicators describing the company's asset structure (FAAS, CAAS). The variables are inversely proportional to each other. An increase in the share of fixed assets reduces the share of current assets in total assets and vice versa.

Table10

Rotated Component Matrix [a]

	Component					
	1	2	3	4	5	6
GM						-.867
L1	.906					
L2	.897					
L3	.938					
ATR		.833	.322			
ITR	.896					
LTR	.889					
CATR		.924				
CCC						.827
FAAS			-.978			
CAAS			.976			
ICAS		.829				
EAR					.979	
IND					-.980	
NWC				.958		
FIA				.960		
TLS				.404		

Extraction Method: Principal Component Analysis.
Rotation Method: Varimax with Kaiser Normalization.
[a.] Rotation converged in 5 iterations.
Suppressed small coefficients: absolute value below 0.3.
Source: *Authors' calculations.*

Factor 4 consists of NWC, FIA and TLS. These items present the amount of money the business has available to finance its operating needs. NWC can also be defined as a specific financial cushion of available resources to bridge unstable periods. We calculate its volume as the difference between the amount of long-term financing sources of the company and the volume of its long-term assets. In the case of a positive difference, the company has NWC, which can be allocated to the company's financial assets as deposits in bank accounts. The source of its coverage of needs in circular economy enterprises is often funds obtained through subsidies and contributions from European funds. The average amount of subsidies in the set of enterprises in the NACE 38 sector nearly doubled between 2019 and 2022. In 2019, a single entity in the initial data set utilized resources in the form of tax liabilities and subsidies amounting to an average of 17,305 euros, but in 2022, this average increased to 30,089 euros. For the entities included in the factor analysis, the average was 24,791 euros in 2019 and 44,770 euros in 2022.

Factor 5 contains the same variables as Factor 1 in 2019. These are the EAR and IND indicators, which provide information about the structure of the company's financing sources. The indicators are inversely related because an increase in the share of own resources in total resources reduces the level of the company´s indebtedness, and vice versa.

Factor 6 contains the same items as Factor 4 in 2019, namely GM and CCC. These indicators provide information about the need to finance the company's operational activities. The indicators are inversely related, with the interpretation provided in Factor 4 of 2019.

The post-crisis period in circular economy enterprises is still characterized by efforts to ensure the continuity of operational process and following the experience of the crisis period to ensure sufficient liquidity and adequate available resources. The extracted factors can be named as follows:

- Factor 1: liquidity management (liquidity management) (LQM),
- Factor 2: the efficiency of the use of the company's current assets (the efficiency of the use of the company's current assets) (CAE),

- Factor 3: asset structure (AS),
- Factor 4: volume of available resources (VAR),
- Factor 5: the structure of funding sources (SFS),
- Factor 6: operational activity of the company (OA).

The mathematical expression of factor scores using a linear function is facilitated by the score values of individual components, as illustrated in Table 11.

Table 11

Component Score Coefficient Matrix

	Component					
	1	2	3	4	5	6
GM	.004	-.021	.009	.153	-.027	-.583
L1	.224	.006	-.052	.004	.000	-.001
L2	.222	-.007	-.058	-.009	.002	.067
L3	.236	.005	-.067	-.007	-.015	.057
ATR	.013	.370	.162	.014	-.063	-.093
ITR	.225	.017	.001	.009	-.075	-.059
LTR	.221	.009	.000	.009	-.063	-.062
CATR	.024	.410	-.101	.021	-.024	-.003
CCC	-.003	-.015	-.034	.032	.024	.510
FAAS	.046	.008	-.474	.013	-.003	.012
CAAS	-.046	-.010	.473	-.015	.005	-.009
ICAS	-.014	.366	-.040	-.009	.066	.102
EAR	-.040	-.001	.006	.000	.504	.019
IND	.040	.005	.006	-.004	-.505	-.019
NWC	.012	.037	.015	.462	-.018	-.014
FIA	.012	.038	.005	.465	-.027	-.018
TLS	-.013	-.052	-.041	.227	.037	-.180

Extraction Method: Principal Component Analysis.
Rotation Method: Varimax with Kaiser Normalization
Component Scores.
Source: *Authors' calculations.*

The equation for calculating the factor score value for the year 2022, after substituting individual components into equation (1), takes the following general form:

$$Y_i = b_1GM + b_2L1 + b_3L2 + b_4L3 + b_5ATR + b_6ITR + b_7LTR + b_8CATR + b_9CCC + b_{10}FAAS + b_{11}CAAS + b_{12}ICAS + b_{13}EAR + b_{14}IND + b_{15}NWC + b_{16}FIA + b_{17}TLS + \varepsilon, \quad (10)$$

where Y_i is the value of the factor score of the extracted factors (LQM, CAE, AS, VAR, SFS, OA), b_1, b_2 ... b_n is the factor loading of the individual variables listed in Table 11. The reader can independently compile equations based on the pattern from equations (2) to (6) if interested. These equations were used by SPSS to calculate factor score values for each respondent included in the factor analysis in 2022. These values are used to model the influence of factors on the value of the ROA and ROS indicators. A linear regression model is used, the general form of which is presented in relation (7). The dependent variables are ROA and ROS, while the independent variables are Factors 1 to 6 extracted through factor analysis, as presented in Table 10.

CAE and VAR factors were excluded from ROA model through linear regression analysis. The remaining four factors serve as explanatory variables, and their regression coefficients are listed in Table 12.

Table 12

Coefficients [a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
		B	Std. Error	Beta			Tolerance	VIF
1	(Constant)	.062	.011		5.438	.000		
	LQM	.026	.011	.115	2.280	.023	1.000	1.000
	AS	.029	.011	.127	2.510	.013	1.000	1.000
	SFS	.069	.011	.305	6.031	.000	1.000	1.000
	OA	-.038	.011	-.168	-3.316	.001	1.000	1.000

[a.] Dependent Variable: ROA=EBIT/A
Source: *Authors' calculations.*

The regression equation of ROA in 2022 with six factors has the form:

$$ROA_{22(6)} = .062 + .026LQM + .029AS + .069SFS + (-.038OA) + \varepsilon, \quad (11)$$

F value = 14,715, Sig. = .000, R = .389, R Square = .151, Adjusted R Square = .141, Std. Error of the Estimate = .21, Durbin-Watson = 1.884.

This regression model enables interpretation of 15% of the variability in ROA in 2022. Factors LQM, AS and SFS positive influence ROA; as their factor score increases, ROA also increases. Conversely, an increase in factor score of the OA factor contributes to a decrease in ROA.

In the regression analysis of ROS in 2022, factors LQM, AS and CAE were excluded from the analysis. ROS variability is explained by the factors VAR, SFS, and OA. The regression coefficients of the model are presented in Table 13.

Table 13

Coefficients [a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
		B	Std. Error	Beta			Tolerance	VIF
1	(Constant)	-.070	.038		-1.843	.066		
	VAR	.147	.038	.130	3.867	.000	1.000	1.000
	SFS	.111	.038	.098	2.903	.004	1.000	1.000
	OA	-.872	.038	-.772	-22.870	.000	1.000	1.000

[a.] Dependent Variable: ROS=EBIT/T
Source: *Authors' calculations.*

The regression equation has the form:

$$ROS_{22(6)} = -.070 + .147VAR + .111SFS + (-.872OA) + \varepsilon, \quad (12)$$

F value = 182.137, Sig. = .000, R = .789, R Square = .622, Adjusted R Square = .619, Std. Error of the Estimate = .698, Durbin-Watson = 2.036.

The regression model explains 62% of the variability of ROS. The VAR and SFS factors affect the ROS values in direct proportion. An increase in the factor score value of VAR and SFS factors enhances sales profitability. Conversely, an increase in the OA factor score diminishes the ROA value.

Securing an adequate level of liquid available resources, appropriate asset structure and financing sources, and optimizing operational activities are key determinants ensuring financial stability and performance of enterprises in 2022.

Comparison of analysis results, discussion

The progression and outcomes of our analysis highlight several findings. Originally aimed at identifying determinants of financial performance, we aimed to achieve this using the largest possible dataset, encompassing all available data from 2019 to 2022. However, factor analysis did not yield any meaningful results. Therefore, we segmented the analysis into individual annual periods and identified the year 2020 as problematic. Applying the same methodological approach each year, we were unable to extract factors in 2020 that met the control parameters of selected tests. Based on this, we concluded that the crisis period primarily presented by the years 2020 and 2021, may have disrupted operations and economic processes, reflected in the financial analysis indicators to such an extent that that it disrupted the relationships between indicators, thereby precluding analysis across the selected four-year period as a whole. This fact intrigued us, prompting us to focus our analysis on comparing findings between 2019, representing the pre-crisis period, and 2022, which provides the most recent available data and represents the post-crisis period.

The first differences were noted during the initial correlation analysis of variables entering subsequent factor analysis. While the total number of variables was approximately equal in both years, their composition differed. Nine variables (GM, ATR, LTR, CATR, CCC, FAAS, EAR, IND and TLS) significantly correlated with ROA and ROS in both study periods. In 2019, this set was supplemented by RCAS, RVB, BLFA, REV, GP, RMEC, S and FALP. In 2022, these were replaced by the indicators L1, L2, L3, ITR, CAAS, ICAS, NPGR, NWC and FIA. Data adjustments in 2019 led to the exclusion of seven variables, while in 2022 only one was excluded. Consequently, more indicators entered factor analysis in 2022 comparted to 2019, which may have also influenced the number of extracted factors. In 2019, we extracted five factors, whereas in 2022 it was six factors.

Through additional analysis, we adjusted the number of extracted factors to five in 2022 to ensure numerical comparability between periods. We got the following results: Kaiser-Meyer-Olkin Measure of Sampling Adequacy value did not change, KMO = .630, Bartlett's Test of Sphericity Sig. = .000, the MSA value of individual variables is higher than .5.

However, with this modification, we reduced the share of variability explained by the given factors. After adjusting the number of factors, this share decreased from 84.2% to 76.5%, which is still more than 50%, which is the required minimum. After adjustment, Component 1 changed its composition, as well as the share of explained variability, which is now 24.8%. Component 2 exhausts 13.8% of the variability, Component 3 13.3%, Component 4 12.6% and Component 5 11.9%. Table 14 shows the classification of the variables in each of the extracted five factors. Only values 0.3 and above are shown.

The composition of individual factors is essentially very similar. The reduction in the number of factors resulted in the migration of variables that constituted Factor 6 to the group of variables that formed Factor 4. In the modified matrix (see Table 14), all variables are categorized as components of Factor 2, which now encompasses GM, CCC, NWC, FIA and TLS, the latter exhibiting a decreased factor loading of .248. This value is not displayed in Table 14 due to the threshold setting for value presentation. The factors can be designated as follows:

- Factor 1: liquidity management (LQM),
- Factor 2: volume of available resources (VAR),
- Factor 3: the efficiency of the use of the company's current assets (CAE),
- Factor 4: asset structure (AS),
- Factor 5: the structure of funding sources (SFS).

Table 14

Rotated Component Matrix [a]

	Component				
	1	2	3	4	5
GM		-.354			
L1	.907				
L2	.901				
L3	.941				
ATR			.831	.303	
ITR	.893				
LTR	.886				
CATR			.923		
CCC		.647			
FAAS				-.973	
CAAS				.973	
ICAS			.832		
EAR					.955
IND					-.957
NWC		.927			
FIA		.925			
TLS					

Extraction Method: Principal Component Analysis.
Rotation Method: Varimax with Kaiser Normalization.
Suppressed small coefficients: absolute value below 0.3.
[a.] Rotation converged in 5 iterations.
Source: *Authors' calculations.*

Further alterations associated with the reduction in the number of factors were observed when utilizing these factors to elucidate the variability of ROA and ROS through linear regression analysis. The ROA regression equation then has the form:

$$ROA_{22(5)} = .062 + .026LQM + .025AS + .872SFS + \varepsilon, \quad (13)$$

Sig. individual regression coefficients < .026, Std. Errors = .011, F value = 18.119, Sig. = .000, R = .375, R Square = .141, Adjusted R Square = .133, Std. Error of the Estimate = .209. The model (13) explains a slightly lower share of ROA variability (14.1%) than model (11) and does not include the OA factor, which indirectly influenced ROA in model (11). The factors LQM, AS and SFS have a comparable influence as in model (11).

The regression equation of ROS in the extraction of 5 factors has the form:

$$ROS_{22(5)} = -.070 + (-.292)VAR + .325SFS + \varepsilon, \quad (14)$$

Sig. individual regression coefficients = .000, Std. Errors = .057, F value = 29.292, Sig. = .000, R = .387, R Square = .150, Adjusted R Square = .144, Std. Error of the Estimate = 1.045. The model explains a significantly lower share of ROA variability (15%) than model (12) and does not include the OA factor, which in model (12) affected ROS inversely proportionally. The factors VAR and SFS influence ROS to a greater extent than in model (12). In our attempt to adjust the number of factors to 5, we perceive the diminished explanatory power of the ROS model as a sufficient justification for retaining six factors.

We can compare the results of our analysis from several angles, taking into account the applied research methods. Several authors examine the relationships between variables using correlation analysis, which was also the starting point in our study. Shin and Soenen (1998), for instance, investigated the relationships between multiple financial indicators and profitability as measured by ROA and ROS. They found a strong

negative correlation between profitability and cash conversion cycle (CCC). Our findings indicate a weak, statistically insignificant indirect relationship between CCC and profitability. The authors also identified an indirect relationship between profitability, current ratio and indebtedness. In our research, we found an inverse relationship only between profitability and indebtedness, and a direct relationship between profitability and liquidity.

The relationships between variables have also been investigated with varying results by other authors, such as Lazaridis and Tryfonidis (2006), Karaduman et al. (2011), Mohamad and Saad (2010), Gasenan (2007), Vintila and Nenu (2015), Capon et al. (1990), Matar and Eneizan (2018), Mirza and Javed (2013) or Parmar et al. (2013) and Kim et al. (2021).

Their findings are influenced by the focus of the analysis, the scope of the dataset, the industry of the companies studied, and the period under investigation. Despite effort to generalize findings and establish norms for variable manifestations, research indicates that reality may diverge from theory in certain cases.

For example, Ching and Gerab (2012) also applied factor analysis to identify the determinants of financial performance, using this method for 16 companies from 2005 to 2009. The input to the factor analysis was 18 variables, which they divided into four groups: (1) Efficiency (cash conversion efficiency, asset turnover, days receivables, days in inventory, days of working capital, current asset/profit, gross margin, (2) Liquidity (current ratio, quick ratio, general ratio), (3) Leverage (Liability ratio, financial leverage, leverage ratio), (4) Size (inventory, accounts receivable, fixed asset, suppliers, long term debt, equity and gross sale.

The result of their analysis, similar to ours, was the extraction of five factors: firm size (composed of inventory, receivable, fixed asset, suppliers, equity and gross sales), working capital management (composed of asset turnover, days receivable, cash conversion efficiency, days of working capital), solvency (composed by general ratio, current ratio, quick ratio, liability ratio, current asset/profit), margin (composed by days in inventory, gross margin), and financial debt (composed by long term debt, financial leverage and financial ratio). The results of these authors can be partially compared with the findings of our analysis. Like Ching and Gerab, we also extracted indicators L1, L2 and L3 as essential variables for factor identification. Also these variables were assigned to the same factor and were positively correlated with each other. We also obtained similar values for the gross margin indicator, which had a comparable negative value of the factor load in both studies. The classification of their "financial debt" factor and our SFS factor is also similar. The similarity in results is also evident in the "asset turnover" item, which exhibits a positive factor loading and was grouped with activity indicators, represented by turnover time or asset turnover indicators. Similarly we can also evaluate the results regarding the classification of inventories, receivables and fixed assets and their share in assets. We identify differences, for example, in the variables of sales, trade liabilities, and long-term debts, which we have continuously excluded from our analysis.

CONCLUSION

The linear economic model of contemporary society is not sustainable from a long-term perspective. Its opposite is the circular economy model, which is receiving increased attention thanks to the New Action Plan for the Circular Economy and the 2030 Agenda for Sustainable Development. The material provides a set of indicators for measuring progress towards meeting the goals of individual policies in the area of the circular economy. Essential actors in this process are companies operating in the waste management sector, which help in the collection, sorting and processing of waste, and thus, with their activity, inevitably contribute to the fulfilment of the essence of the circular economy model. From the perspective of long-term sustainability of this model, it is essential that these enterprises have suitable conditions for their operations established, including from financial and economic standpoints. Financial stability and

performance are therefore prerequisites for their continued viability. Identifying of determinants affecting the financial situation of the company and its financial performance is valuable information in financial management processes.

Using Principal Component Analysis, we identified the following determinants of the financial performance of waste management enterprises in 2019 and 2022: the structure of sources of financing (SFS), the efficiency of the use of short-term assets of the company (CAE), the operating activity of the enterprise (OA). In 2019, financial performance was further influenced by business conditions (BP) and working capital management (WCM). In 2022, additional influential factors were liquidity management (LQM), asset structure (AS), and the volume of available resources. Through linear regression analysis, we identified the influence of the extracted factors on ROA and ROS indicators, which represent the financial performance of companies. According to the results of regression analysis, ROA is influenced by the structure of financing sources and the company's operational activities. Before the crisis, ROA also affected the efficiency of using current assets (CAE). In 2022, however, the influence of liquidity management (LQM) and asset structure (AS) was more significant. By modelling the explanatory variables of the ROS indicator in both investigated years, we considered the influence of the structure of financing sources (SFS) and the operational activity of the enterprise (OA). In 2019, CAE and WCM continued to influence ROS, while 2022 they were replaced by the indicator volume of available resources (VAR). By comparing the findings, we also concluded that while operating indicators were key to achieving corporate financial performance in the pre-crisis period, the factor of liquidity and available resources gained importance in the post-crisis period.

A limitation of this study, as previously noted, manifested at multiple stages of our research. Our objective was to identify generalizable factors of financial performance within the waste management industry. The analytical process was significantly influenced by the selected analyzed period, which was constrained by the availability, quality, and scope of enterprise-level information. Notwithstanding these limitations, we posit that our analysis contributes to the existing body of knowledge and may inform financial management practices within the industry. We anticipate that our findings will engage readers and stimulate further exploration of pertinent research questions in this field.

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