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AN UNCONVENTIONAL APPRACH TO EVALUATING THE FINANCIAL PERFORMANCE UNDER CRITICAL MACROECONOMIC DISTURBANCES: THE CASE OF PUBLIC TRANSPORT DURING THE COVID-19 PANDEMIC

Janoskova K., Balcerzak A. P., Kral P.*

Abstract: The period of Covid pandemic was one of the most restrictive times for the passenger transport sector. Due to the impact of anti-pandemic measures, the mobility of the population was limited, which was reflected in the decrease in sales and collapse of long-term financial indicators. Therefore, the period can be considered as the case of critical macroeconomic disturbances. The main purpose of this research is to identify the most relevant financial indicators that affect the transport enterprises performance and define new alternative way of grouping company financial indicators based on their mutual correlation. Therefore, this paper, using the tools of descriptive statistics and factor analysis, identifies the correlations of selected financial indicators that allow a better understanding of their interrelatedness and influence during extraordinary macroeconomic situations on the market. The data source was the financial statements of public passenger transport companies in V4 countries during the period 2018-2021 obtained from the international platform Orbis. Factor analysis made it possible to reduce the number of financial indicators from 17 to 2, 3 or 4 created factors (depending on the country and analysed year). It is a non-traditional multidimensional approach to working with financial information, allowing to identify new related groups of financial indicators based on their mutual relationship, and to name these groups appropriately with the elimination of multicollinearity. The long-term economic sustainability of public transport must be based on the marginal level of demand ensuring the required financial performance, which can also be quantified through defined groups of financial indicators. The applied method can be considered as quasi-universal approach for evaluating financial performance during deep macroeconomic disturbances.

Key words: financial performance, transport companies, factor analysis, Covid-19 pandemic

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* **Katarina Janoskova**, University of Žilina, Slovakia;
✉ email: katarina.janoskova@uniza.sk,
ORCID: 0000-0002-7887-7326
Adam P. Balcerzak, University of Warmia and Mazury in Olsztyn, Poland; Brno University of Technology, Czechia; European Centre for Business Research, Pan-European University, Czechia;
✉ email: a.balcerzak@uwm.edu.pl,
ORCID: 0000-0003-0352-1373
Pavol Kral, University of Žilina, Slovakia;
✉ corresponding author pavol.kral@uniza.sk,
ORCID: 0000-0001-6970-563X

Introduction

Transportation sector plays an important role in a sustainability of country´s economy (Durana et al., 2022). Many previous research highlighted the key importance of transportation companies in European countries. For this reason, it is necessary to deal with the sustainability and resilience of the transport sector as a whole and at the same time pay great attention to the financial management of these enterprises. The long-term sustainability of transportation companies is determined by their ability to ensure performance under its relatively high vulnerability and sensitivity to macroeconomic disturbances. The period of Covid-19 pandemic can be considered as a special case study of this kind (Cui et al., 2021; Ponisciakova, 2022; Valaskova et al., 2023a; 2023b).

The impact of the Covid-19 pandemic on water transport was investigated by Maternova and Materna (2022), or Kleine-Kampmann et al. (2021). Konecny et al. (2021) deal with the impact of Covid-19 pandemic and anti-pandemic measures on the sustainability of demand in suburban bus transport in the Slovakia. The impact of the Covid-19 pandemic on railway transport was investigated by Grechi and Ceron (2022), or Tardivo et al. (2021). Su et al. (2022), Florido-Benitez (2021), or Bernathova et al. (2020) focused on the impact of Covid-19 pandemic on civil aviation passenger transport market.

Transport companies have not yet coped with the effects of the Covid-19 pandemic and already must face other negative impacts, which are fuel price changes (Delsalle, 2022), as well as the current energy crisis (Stanislawska, 2022; Balcerzak et al., 2023). All those latter negative effects are manifested, among other things, on the financial health of the company, and therefore it is necessary for the financial mangement to constantly monitor the financial situation of the company and try to analyse it from different point of view, which helps them in the decision-making process.

For this reason, the paper is focused on the objective of finding an alternative view on financial indicators under significant macroeconomic pressure. The case of transport companies in V4 countries during the period 2018-2021 was applied here. The paper provides a new approach for working with financial information under significant macroeconomic disturbances.

Literature Review

One of the basic tasks of managers is the information task (Kliestik, et al., 2022a; Gallo et al. 2024). In the case of financial managers, it involves working with financial information, which they obtain primarily from the company´s financial statements and use as necessary input, to be able to make appropriate decisions, set plans, monitor, and manage the financial health and performance of the company (Kountur and Aprilia, 2020; Tijani et al., 2021; Durica et al., 2023; Durana et al., 2023; Ključnikov et al., 2022; Kováčová et al., 2022; Fenyves et al., 2023; Letkovsky et al., 2023; Gajdosikova et al., 2024). There are several approaches to working with financial information, which can be divided into two basic groups: *one-dimensional approach*, and *multidimensional approach.*

In the case of one-dimensional approach, the manager simply monitors selected independent financial indicators, which they consider to be key, and based on which they make adequate decisions. The most frequently monitored indicators include e. g. profit, sales, cost, revenues, EBIT, EBITDA or separate ratio indicators such as ROA, ROE, etc.

On the other hand, in the case of multidimensional approach, the manager does not monitor individual indicators, but focuses on certain areas, or separate units. There are again several approaches to the creation of these units, which can be divided into *traditional way*, and *alternative way*. Advocates of the traditional approach prefer conventional methods of grouping company financial data that have been widely applied thus far are financial ratios. These financial ratios are divided into four categories: profitability, liquidity, activity, and solvency (Granda, 2020; Vochozka et al., 2016). Proponents of an alternative approach try to introduce an element of innovation into financial analysis. They make an effort to create related groups of the financial indicators based on their mutual relationship and try to reduce the number of analysed financial indicators. For example, Kounture and Aprilia (2020) worked with twenty financial indicators from 2017 financial reports of 120 companies listed in EDX. The result of their research is the reduction of financial indicators from the origin twenty to fourth newly created latent variables. Souza et al. (2017) in their research originally worked with seventeen financial indicators of 118 banking institutions in Brazil, which they first reduced to eight and from which three new latent variables were created. Ocal et al. (2007) worked with sixteen financial indicators collected from Turkish construction companies for a 5-year period. The result of their research is reduction of financial indicators from the original sixteen to five newly created laten variables. All of aforementioned researchers applied alternative instruments in their research, resulting in newly created dimensions of financial indicators.

Ocal et al. (2007) present three main approaches that have been applied to the classification of financial ratios. The first is the pragmatic approach, within which the classification of indicators into some groups is based on the business practices and the personal view of the distinguished analysts. The second is the deductive approach, where the classification is based on the technical relationship between the different ratios, and Du Pont financial control system is an example. The third approach is the inductive approach, within which the classification of indicators is based on statistical techniques like discriminant, logit/probit, recursive partitioning, cluster, and factor analysis. Ocal et al. (2007) simultaneously states that the latest researches have largely focused on the inductive approach. Based on the definition of the mentioned approaches, we can state that the inductive approach belongs to alternative way and the pragmatic, and deductive approaches belong to the traditional way by their nature.

Financial ratios are widely used to analyse the behaviour and the performance (Kliestik et al., 2022b; Valaskova et al., 2018; Gavurova et al. 2022; Karas and Režňáková, 2023) of a firm, because they not only provide information about a firm´s performance, but allow to compare results across the industry to which the firm belongs (Petersen and Plenborg, 2012; Vergara and Serna, 2018). However, the calculation of many financial ratios is not only impractical, but also of little use, in capturing more advanced information about the firms analysed, as they can have interrelationships, which statistically means the presence of multicollinearity (Ali and Charbaji, 1994 in Vergara a Serna, 2018). The use of some statistical methods can reduce this effect by seeking the factors that underlay the entire set of financial ratios.
In our research, the factor analysis was used to reduce the number of financial indicators. Historically, factor analysis was used primarily in the field of psychology (Williams et al., 2010). Charles Spearman is considered to be its founder, who in 1904 in an article on the nature of intelligence proposed the hypothesis of the existence of a common factor of „general intellectual ability", causing correlations between the results of various intelligence tests. In addition to the common factor, Charles Spearman also assumed several specific factors, each of which applies only within the given test and does not correlate with the others. For a long time, factor analysis was used almost exclusively in psychology. In the last fifty years, however, in connection with the growth of computational possibilities, because of the removal of some subjective elements of the method and the narrow psychometric interpretation, as well as the abandonment of the original methods of factor solutions, factor analysis has penetrated other fields - sociology, healthcare, marketing, business, finance, economics and others. This increase is illustrated in published articles indexed in Web of Science database, where articles reporting factor analysis increased over the last 60 years from 39 (1961) to 10090 (2021). The primary function of factor analysis is variable reduction. This can only be done under the conditions of interdependence of variables and the assumption that these dependencies are the result of the action of a certain smaller number of unmeasurable variables standing in the background. These quantities are referred to as factors.

Research Methodology

The main purpose of this research is to identify the most relevant financial indicators that affect the transport enterprises performance and define a new alternative way of grouping company financial indicators into dimensions based on their mutual correlation. This objective is realised for the period of unusual macroeconomic disturbances, which can be considered as additional value of the current research.
The data used in the research were taken from the financial statements of companies, available through the Orbis platform. The companies were selected from the transport sector (passenger rail transport, interurban, urban, and suburban passenger land transport, taxi operation, sea and coastal passenger water transport, passenger

air transport) of V4 countries for the year 2018–2021. The IBM SPSS Statistics 26 was used to the calculations.

The initial database contained 37 financial indicators. Consequently, due to incomplete data, the final data set was created from 17 financial indicators (in thousands EUR): total assets, fixed assets, intangible fixed assets, stock, shareholders' funds, capital, non-current liabilities, current liabilities, cash flow, EBITDA, creditors, operating revenue (turnover), operating P/L [=EBIT], financial revenue, financial expenses, costs of employees, and average cost of employee.

To achieve the purpose of the article, factor analysis is applied. Factor analysis is a statistical method used to describe variability among observed, correlated variables in terms of a potentially lower number of unobserved variables called factors.

Factor analysis is based on a p-dimensional data set $\begin{pmatrix} y_{11} & \cdots & y_{1p} \\ \cdots & \cdots & \cdots \\ y_{n1} & \cdots & y_{np} \end{pmatrix}$.

The basic principle of factor analysis is that each of the observed random variables $Y_j (j = 1, \dots, p)$ can be expressed as the sum of a linear combination of a smaller number of m unobservable (hypothetical) random variables $F_1, \dots, F_m$ – the so-called common factors and another source of variability $E_j (j = 1, \dots p)$ – the so-called specific (residual) components. The variables Y_j are sometimes called manifest variables and the factors $F_1, \dots, F_m$ are called latent variables (Figure 1) (Janoskova and Kral, 2022).

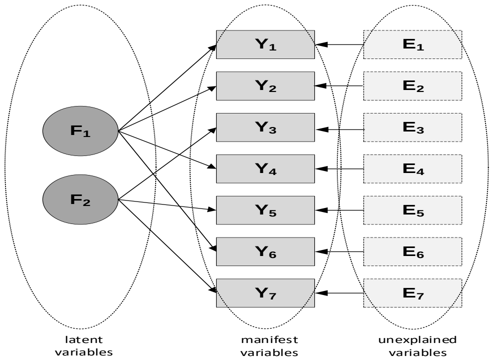

Figure 1: Illustration of factor analysis model
Source: Own elaboration

We assume that the model $Y = \Lambda F + E$ holds for the random vector $Y = (Y_1, \dots, Y_p)'$, where $F = (F_1, \dots F_m)'$, $E = (E_1, \dots E_p)'$ a $\Lambda = (\lambda_{jk})$ is unknow real matrix of type $p \ x \ m$. Matrix Λ is called factor matrix. E_j is random deviation from the exact model corresponding to the jth variable, where $j = 1, \dots, p$. The element λ_{jk} of factor matrix is the factor weight (load) of the kth common factor corresponding to the jth variable, where $k = 1, \dots, m$. The factor analysis model expresses the relationship between latent variables and manifest variables. Coefficient λ_{jk} is the conversion coefficient of F_k to Y_j (Janoskova and Kral, 2022).

The Kaiser-Mayer-Olkin statistics (KMO statistics) is used to assess whether correlations between variables $Y_1, \ldots Y_p$ are explained by means of other variables $F_1, \ldots F_m$. KMO statistics is based on the sample correlation and partial correlation coefficients of variables $Y_1, \ldots Y_p$. KMO statistics reaches takes on values between 0 and 1. To assess whether it makes sense to implement factor analysis, we can use the following values (tab. 1) (Janoskova and Kral, 2022).

Table 1. KMO test – levels of acceptance

KMO value	Level of acceptance
$KMO \geq 0.90$	marvellous / super
$0.80 \leq KMO < 0.90$	meritorious /great
$0.70 \leq KMO < 0.80$	middling /good
$0.60 \leq KMO < 0.70$	mediocre
$0.50 \leq KMO < 0.60$	miserable
$KMO < 0.50$	unacceptable

Source: Own elaboration

Simultaneously with KMO statistics, we can use Bartlett's test of sphericity, where the null hypothesis states that the sample correlation matrix is a unit matrix. The statistics test is given by the relation $\chi^2 \frac{11+2p-6n}{6} \ln|R|$. If the null hypothesis holds, the statistics test asymptotically follows a distribution $\chi^2\left(p\frac{p-1}{2}\right)$. The null hypothesis is rejected at the asymptotic significance level α if $\chi^2 \geq \chi^2_{1-\alpha}\left(p\frac{p-1}{2}\right)$. If the null hypothesis is not rejected, factor analysis is not suitable (Janoskova and Kral, 2022).

Research Results

The research results are organized as follows (Figure 2).

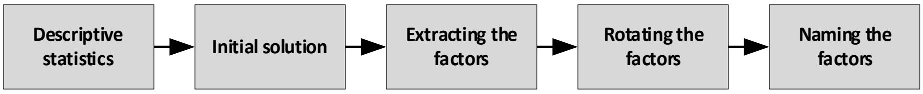

Figure 2: Organization of research results
Source: Own elaboration

Detailed results of the factor analysis will be presented using the example of the Slovak Republic in 2021. Results for other V4 countries and other years will be presented in the final part of the results in the form of summary tables.
The first step consists of summarization and description of characteristics of a data set. *Descriptive statistics* of variables is presented in the Table 2.

Table 2. Descriptive Statistics – financial indicators of transportation enterprises in the Slovak Republic 2021 (in thousands EUR)

Number of variable	Variable	Range	Minimum	Maximum	Mean	Std. Deviation	Variance
1	Total assets	10700842.81	200.19	10701043.00	18073.66	314859.87	99136735275.13
2	Fixed assets	10013357.27	-19.27	10013338.00	15022.72	296219.93	87746244111.92
3	Intangible fixed assets	21744.00	-170.00	21574.00	82.05	1038.49	1078460.29
4	Stock	20436.04	-114.04	20322.00	95.93	763.85	583471.84
5	Shareholders' funds	3914527.64	-11731.64	3902796.00	6980.39	122851.13	15092399143.01
6	Capital	3397968.50	0.50	3397969.00	3994.66	89863.48	8075444901.13
7	Non-current liabilities	6422327.66	-112.66	6422215.00	8431.31	181771.61	33040917671.45
8	Current liabilities	455503.54	-1335.54	454168.00	2278.62	17843.83	318402248.86
9	Cash flow	421345.36	-3376.36	417969.00	985.94	12413.91	154105127.05
10	EBITDA	545449.26	-1101.26	544348.00	1147.19	15513.39	240665409.03
11	Creditors	185701.57	-1343.57	184358.00	775.41	5646.09	31878312.30
12	Operating revenue (Turnover)	622832.00	0.01	622832.00	6381.37	30761.41	946264366.16
13	Operating P/L [=EBIT]	426534.00	-23371.00	403163.00	467.41	10345.00	107018979.51
14	Financial revenue	20409.86	-7.86	20402.00	53.34	671.04	450299.49
15	Financial expenses	30285.00	0.00	30285.00	72.30	858.12	736376.97
16	Costs of employees	294258.99	0.02	294259.00	1341.14	10801.94	116681919.96
17	Average cost of employee	104.57	0.13	104.70	16.67	9.39	88.24

Source: Own elaboration according to the Orbis database

The second step of factor analysis consists of *initial solution.* In this step, an inter-correlation matrix of all the variables is generated. An inter-correlation matrix (Table 3) provides information about the correlation coefficients of the variables with each other ($k \times k$ matrix, where k equals the number of variables).

Table 3. Correlation matrix

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17
1	1.000	.547	.285	.259	.383	.139	.649	.749	.715	.595	.671	.721	.465	.666	.708	.531	.389
2	.547	1.000	.288	.244	.897	.827	.879	.593	.548	.544	.442	.507	.189	.514	.588	.471	.314
3	.285	.288	1.000	.428	.283	.185	.385	.251	.308	.233	.268	.315	.032	.338	.341	.417	.296
4	.259	.244	.428	1.000	.250	.205	.211	.388	.251	.278	.216	.299	-.017	-.002	.063	.580	.133
5	.383	.897	.283	.250	1.000	.916	.680	.350	.434	.495	.353	.432	.158	.300	.375	.458	.311
6	.139	.827	.185	.205	.916	1.000	.548	.199	.155	.272	.096	.154	-.099	.062	.134	.343	.138
7	.649	.879	.385	.211	.680	.548	1.000	.607	.658	.547	.593	.625	.270	.777	.824	.439	.350
8	.749	.593	.251	.388	.350	.199	.607	1.000	.711	.651	.638	.683	.431	.487	.553	.647	.328
9	.715	.548	.308	.251	.434	.155	.658	.711	1.000	.951	.823	.891	.826	.593	.665	.635	.419
10	.595	.544	.233	.278	.495	.272	.547	.651	.951	1.000	.742	.832	.838	.350	.462	.693	.369
11	.671	.442	.268	.216	.353	.096	.593	.638	.823	.742	1.000	.925	.749	.657	.697	.478	.438
12	.721	.507	.315	.299	.432	.154	.625	.683	.891	.832	.925	1.000	.749	.610	.672	.623	.474
13	.465	.189	.032	-.017	.158	-.099	.270	.431	.826	.838	.749	.749	1.000	.369	.430	.352	.320
14	.666	.514	.338	-.002	.300	.062	.777	.487	.593	.350	.657	.610	.369	1.000	.967	.123	.359
15	.708	.588	.341	.063	.375	.134	.824	.553	.665	.462	.697	.672	.430	.967	1.000	.220	.374
16	.531	.471	.417	.580	.458	.343	.439	.647	.635	.693	.478	.623	.352	.123	.220	1.000	.345
17	.389	.314	.296	.133	.311	.138	.350	.328	.419	.369	.438	.474	.320	.359	.374	.345	1.000

Source: Own elaboration using IBM Statistics 26

Note: 1 – total assets, 2 – fixed assets, 3 – intangible fixed assets, 4 – stock, 5 – shareholders funds, 6 – capital, 7 – non-current liabilities, 8 – current liabilities, 9 – cash flow, 10 – EBITDA, 11 – creditors, 12 – operating revenue, 13 – EBIT, 14 – financial revenue, 15 – financial expenses, 16 – costs of employees, and 17 – average cost of employee

Seventeen financial indicators were calculated using the collected financial data of 1549 transport companies operated in the Slovak Republic in 2021, and the correlation matrix was generated. To assess whether it is appropriate to applicate a factor analysis on a given data set, the Kaiser-Mayer-Olkin Measure of Sampling Adequacy and Bartlett´s test of sphericity was used (table 4).

Table 4. KMO and Bartlett´s Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy		.712
Bartlett's Test of Sphericity	Approx. Chi-Square	19804.469
	Degree of freedom	136
	Significance	.000

Source: Own elaboration using IBM Statistics 26

Table 4 shows that KMO and BTS results are satisfactory for the data set of 17 financial indicators. The value of KMO statistics is 0.712, so the implementation of the factor analysis appears to be good. The value of BTS is 19804.469 and the number of degrees of freedom is 136. The P-value is very close to zero, which means that the null hypothesis (the sample correlation matrix by the 17 considered variables is unitary) is rejected at the asymptotic level of significance 0.05.
The third step of factor analysis consists of *extracting the factors*. Table 5 gives the initial solution values (unrotated values).

Table 5. Total variance explanation percentages of components – unrotated values

Component (factor)	Initial Eigenvalues			Rotation Sums of Squared Loadings		
	Eigenvalue total (a)	% of Variance (a/17 x 100)	Cumulative variance %	Total	% of Variance	Cumulative %
1	8.783	51.663	51.663	5.119	30.110	30.110
2	2.414	14.201	65.864	3.684	21.670	51.780
3	1.723	10.133	75.997	3.253	19.137	70.917
4	1.284	7.552	83.549	2.148	12.633	83.549
5	.836	4.916	88.465			
6	.635	3.737	92.202			
7	.407	2.392	94.593			
8	.254	1.493	96.086			
9	.230	1.350	97.436			
10	.204	1.203	98.639			
11	.079	.467	99.106			
12	.063	.370	99.476			
13	.037	.215	99.691			
14	.027	.159	99.851			
15	.015	.089	99.939			
16	.010	.058	99.997			
17	.001	.003	100.000			

Source: Own elaboration using IBM Statistics 26

The first component explains 51.663% of the variability contained in the seventeen observed financial indicators, the second component explains 14.201% of the variability, the third component explains 10.133% of the variability and the fourth component explains 7.552% of the variability, etc. before the rotation.
The comparison of the unrotated and rotated values in Table 5 shows that high correlations turned into maximum values, while low correlations turned into minimum values. However, this did not affect the cumulative percentage (85.549%) of the variances and the ranking of the factors. The ranking has showed that while factor 1 had the strongest effect in explaining the financial state of a company, factor 4 had the weakest.

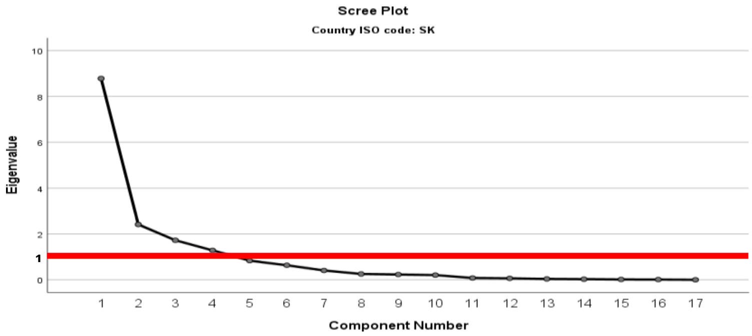

Figure 3: Eigenvalues – Scree Plot
Source: Own elaboration using IBM Statistics 26

An appropriate number of components is extracted from the correlation matrix based on the initial solutions. Based on the scree plot (Figure 3) and the eigenvalues, components 1-4 would be extracted. Four factors were extracted considering as a reference those with a value (eigenvalue) higher than 1 (red line in the scree plot). The cumulative percentage of variability explained by the first four components is 83.549%. It means that a considerable amount of the common variance shared by the 17 variables could be accounted for by these four components. Factor extraction was realized by application of the Principal Component Analysis.
The fourth step of factor analysis is *rotating the factors*. Factors are rotated in order to clarify the relationship between the variables and the components. Factors were rotated using the rotation method called Varimax method with Kaiser Normalization. Table 6 shows the changes in each factor before and after the rotation.

Table 6. Matrix of changes before and after the varimax rotation

	Component Matrix				Rotated Component Matrix			
	Component				Component			
	1	2	3	4	1	2	3	4
1	.813	-.143	-.082	.155	.533	.579	.154	.264
2	.769	.566	-.187	-.162	.248	.402	.853	.147
3	.428	.208	.123	.644	-.021	.379	.079	.711
4	.350	.267	.592	.477	.137	-.079	.122	.856
5	.643	.666	-.041	-.276	.213	.167	.918	.140
6	.397	.851	-.018	-.304	-.025	-.018	.981	.109
7	.842	.289	-.351	.061	.282	.690	.581	.162
8	.789	-.060	.153	.105	.583	.363	.212	.379
9	.911	-.273	.132	-.142	.862	.371	.184	.170
10	.842	-.171	.327	-.319	.908	.105	.292	.162
11	.847	-.345	-.005	-.050	.765	.484	.075	.119
12	.902	-.273	.115	-.053	.813	.416	.147	.222
13	.634	-.572	.158	-.394	.928	.140	-.077	-.153
14	.712	-.180	-.606	.251	.250	.948	.090	-.010
15	.786	-.145	-.528	.195	.335	.903	.164	.026
16	.678	.152	.598	.091	.574	-.052	.309	.648
17	.516	-.058	.009	.125	.334	.330	.109	.231

Source: Own elaboration using IBM Statistics 26

The results after sorting rotated variables by size and considering the minimum value at the level of 0.3 are presented in Table 7. All rotated variables have values higher than 0.5, only variable number 17 has a lower value, due to which the minimum value was reduced to 0.3. While classifying factors into components, it is appropriate to take into consideration not only the correlation valued, but also the fact that the denomination of the factor is meaningful from the financial point of view. Table 7 contains a variable´s communality, which means the total amount of variance a variable share with all factors.

Table 7. Rotated Component Matrix

Variable	Number of variable	Component			
		1	2	3	4
Operating P/L [=EBIT]	13	.928			
EBITDA	10	.908			
Cash flow	9	.862	.371		
Operating revenue (Turnover)	12	.813	.416		
Creditors	11	.765	.484		
Current liabilities	8	.583	.363		.379
Average costs of employee	17	.334	.330		
Financial revenue	14		.948		
Financial expenses	15	.335	.903		
Non-current liabilities	7		.690	.581	
Total assets	1	.533	.579		
Capital	6			.981	
Shareholders’ funds	5			.918	
Fixed assets	2		.402	.853	
Stock	4				.856
Intangible fixed assets	3		.379		.711
Costs of employees	16	.574		.309	.648

Extraction Method: Principal Component Analysis. Rotation Method: Varimax with Kaiser Normalization. Rotation converged in 6 iterations. Source: own processing using IBM Statistics 26

The last step of factor analysis is the *naming of factors*. This subjective and inductive process depends on researcher and his experience. It is the most challenging part of the process, as sometimes the correlation between the included variables in components is not clear at the first sight. The Factors were named as follows:

– The first factor includes seven variables. Four of them have strong factor loads (higher than 0.8). All the four variables provided information on profit. The other two variables with factor load higher than 0.5 provided information on liabilities. The last indicator, with factor load being only 0.334, represents costs. The factor load of 0.334 shows that the average cost of employee was not as influential for transport companies as the rest of variables included in this factor. The factor contains profit indicators on the one hand, and liabilities and cost indicators on the other. Thus, the first factor was named „efficiency”.

- The second factor includes four variables. Two of them with strong factor load (higher than 0.9) provide information on financial revenues and financial expenses. The next variables are non-current liabilities and total assets. Thus, the second factor was named „financial efficiency and capital structure”.
- The third factor was named „shareholders values”. It contains three variables: capital, shareholders’ funds and fixed assets. It represents the correlation between assets and sources of financing the property.
- The fourth factor contains stock, intangible fixed assets, and the costs of employee. The first two variables of this factor can be named as „asset structure and employee costs”.

Graphic representation of the creation of four factors, i.e. of the four latent variables, is shown in the Figure 4.

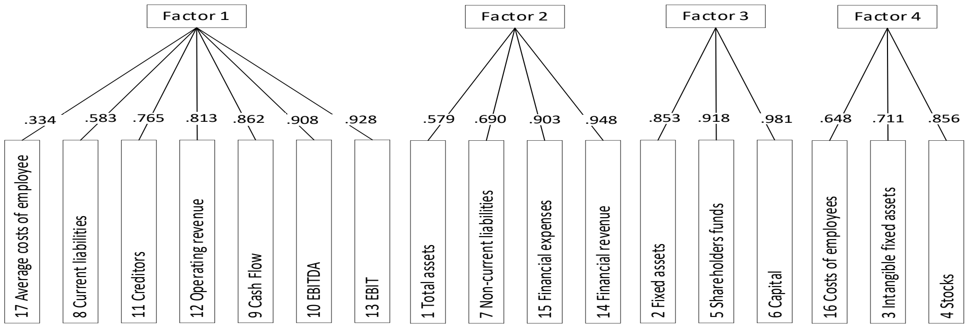

Figure 4: Factor analysis map
Source: Own elaboration

After carrying out the factor analysis in the conditions of the Slovak Republic in 2021, the same procedure was applied to the other V4 countries (the Czech Republic, Hungary, Poland) in all analysed years 2018-2021 (2 years before the covid pandemic crisis and 2 years during the covid pandemic crisis). In the next part of the article, the comparison of the obtained results is presented (Tables 8 – 9).

Table 8. Summary of results

Country	Year	Number of companies	Kaiser-Meyer-Olkin Measure of Sampling Adequacy	Bartlett's Test of Sphericity			Number of extracted factors	Cumulative % of variances
				Approx. Chi-Square	df	Sig.		
Czech Republic	2021	557	0.821	9326.188	136	.000	4	90.732
	2020		0.775	14954.090	136	.000	3	91.425
	2019		0.654	11742.513	136	.000	4	84.321
	2018		0.772	14381.366	136	.000	4	88.368
Hungary	2021	2350	0.791	63604.339	136	.000	3	87.744
	2020		0.673	58006.157	136	.000	4	88.016

	2019		0.694	59781.881	136	.000	3	83.742
	2018		0.638	59259.838	136	.000	4	89.593
Poland	2021	1257	0.728	17133.034	136	.000	4	81.991
	2020		0.762	19925.094	136	.000	4	83.788
	2019		0.804	18170.632	136	.000	3	79.904
	2018		0.837	20340.786	136	.000	2	76.472
Slovak Republic	2021	1549	0.712	19804.469	136	.000	4	83.549
	2020		0.784	45299.608	136	.000	3	88.788
	2019		0.795	42395.880	136	.000	3	88.144
	2018		0.781	34915.145	136	.000	3	84.032

Source: Own elaboration using IBM Statistics 26

Table 9 contains information about the years of analysis, the number of analysed enterprises, results of KMO and BTS statistics, number of extracted factors and cumulative % of variances.

The highest value of the KMO statistics is found for Poland in 2018 (0.837) and the lowest value of the KMO statistics can be seen for Hungary in 2018 (0.638). The values of KMO statistics higher than 0.8 expresses that the implementation of the factor analysis appears to be great. In three cases (the Czech Republic – 2019; Hungary – 2018, 2019, 2020), the value of KMO statistics was lower than 0.6. It means that the implementation of the factor analysis appears to be mediocre. The remaining values of the KMO statistics are higher than 0.7 which means that the implementation of the factor analysis appears to be good. The lowest number of factors was extracted in Poland in 2018 (only 2 factors). In other countries and other years, three of four factors were extracted. The highest cumulative % of variances was achieved for the Czech Republic in 2020 (91.425%) and the lowest cumulative % of variances was achieved in the case of Poland in 2019 (76.472%). In all cases, the p-value is very close to zero, which means that the null hypothesis (the sample correlation matrix by the 17 considered variables is unitary) is rejected at the asymptotic level of significance 0.05.

Table 9. Summary of results

Country	**Year**	**Factors**	**1 Total assets**	**2 Fixed assets**	**3 Intangible fixed assets**	**4 Stock**	**5 Shareholders' funds**	**6 Capital**	**7 Non-current liabilities**	**8 Current liabilities**	**9 Cash Flow**	**10 EBITDA**	**11 Creditors**	**12 Operating revenue**	**13 EBIT**	**14 Financial revenues**	**15 Financial expenses**	**16 Cost of employees**	**17 Average cost of employee**
Czech Republic	**2021**	1	.975	.922	.918	.992	.983	.960		.991	.965	.990	.989	.991	.989			.515	
		2														.870	.654		
		3							.985										
		4																	.947
	2020	1	.947	.981	.945		.969	.930	.901							.863	.931	.958	
		2				.807				.760	.688	.707	.701	.888	.867				
		3																	.840

	2019	1	.923	.852			.940	.884	.724		.833	.826						.883	
		2				.886				.770			.778	.792			.470		
		3			.833														.823
		4													.900	.602			
	2018	1	.759	.803			.774	.934	.767		.606	.609						.887	
		2				.886				.822			.777	.915					
		3													.658	.884	.818		
		4			.834														.845
Hungary	**2021**	1	.947	.952	.854	.951	.819		.961	.791	.972	.971	.910	.814	.655			.935	
		2														.831	.722		.474
		3						.887											
	2020	1	.789	.795		.755	.839	.914		.968			.930	.717				.782	
		2							.599		.771	.755			.854				
		3			.981												.960		
		4														.576			.851
	2019	1	.906	.902		.916	.874	.715	.703	.900	.817	.737	.952	.836				.903	
		2			.931										.922	.456	.897		
		3																	.721
	2018	1	.782	.773		.877			.858		.851	.778		.774				.842	
		2					.736	.961		.856			.808						
		3			.963										.867		.944		
		4														.520			.878
Poland	**2021**	1	.959	.967			.928	.805	.913	.851	.896	.893	.724	.825				.946	
		2			.916	.860													
		3													.964				.210
		4														.889	.629		
	2020	1	.930	.938			.873	.810	.930	.782	.880	.935	.624	.837				.957	
		2			.940	.797													.117
		3													.954				
		4														.882	.675		
	2019	1	.906	.946			.920	.837	.912	.692	.956	.950		.792	.618		.855	.895	
		2			.881	.803							.689						
		3														.507			.759
	2018	1	.883	.901			.886	.831	.928	.645	.964	.980		.808	.857	.650	.845	.896	
		2			.906	.744							.702						.129
Slovak Republic	**2021**	1								.583	.862	.908	.765	.813	.928				.334
		2	.579						.690							.948	.903		
		3		.853			.918	.981											
		4			.711	.856												.648	
	2020	1	.826	.823			.872		.778		.960	.971		.669	.982		.927		
		2			.902	.767		.836		.756			.838					.960	
		3														.767			.646
	2019	1	.968	.976	.827	.821	.964	.942	.936	.692	.731	.720	.667	.703				.880	
		2													.683	.844	.913		
		3																	.949
	2018	1	.831	.828		.900			.943		.923	.913		.673	.895				
		2			.697		.878	.876		.632			.634					.722	
		3														.951	.858		.442

Source: Own elaboration using IBM Statistics 26

After a thorough analysis of the results, we can state that slight changes in the composition of factors occurred during the entire analysed period in all V4 countries. In no case did the situation occur that the results of the analysis (number and structure of factors) were identical. Any significant differences between pre-pandemic and post-pandemic results could not be identified. However, we can identify certain connections which are of special interests, for example:

- In all cases, cash flow and EBITDA are part of one common factor.
- In 93.75% of cases, total assets and fixed assets are part of one common factor.
- In 82.35% of cases, shareholders´ fund and capital are part of one common factor.
- In 64.71% of cases, financial revenues and financial expenses are part of one common factor.
- In 64.71% of cases, creditors and operating revenue are part of one common factor.
- In 52.94% of cases, intangible fixed assets and stock are part of one common factor.

Discussion

Even though factor analysis was initially intended for application in research in the field of psychology and education, it is currently also used in other spheres, including economics, management, finance and others. Just like us, factor analysis was applied in the analysis of financial indicators by several authors (Ocal et al., 2007; Kountur and Aprilia, 2020; Vergara and Serna, 2018; Souza et al., 2017, etc.). The main aim of research was to determine the financial indicators that could be used to analyse the financial state of the transport sector in V4 countries under significant macroeconomic pressure. To achieve this, factor analysis was applied to financial data collected from Slovak, Czech, Polish and Hungarian transport companies, which represented the transport sector for the period 2018-2021.

The results of the research for the Slovak Republic in 2021 were presented in detail in the article, so we can compare our results with the similar pieces of research published by several scholars. The main result of our research is reduction of financial indicators from the original seventeen to four newly created latent factors. The newly created latent factors were named as efficiency, financial efficiency and capital structure, shareholder´s values, and assets structure and employee costs. For example, Kounture and Aprilia (2020) starting with seventeen financial indicators, created four new dimensions of financial-economic indicators using factor analysis: Asset-Income Performance; Leverage performance; Operational Performance; and Owner Return. Souza et al. (2017) reduced financial indicators from the original seventeen to four new groups of financial indicators and named them as: Cost Effectiveness and Profitability, Capital and Liquidity, and Fitting and Interest Sensitivity. By applying factor analysis, Ocal et al. (2007) created five separate groups of financial indicators (from origin sixteen financial variables), which they named: Liquidity factor, capital structure and profitability factor, activity efficiency factor, profit margin and growth factor, and assets structure factor.

In our research, we assumed that companies belonging to the transport sector show certain common features, which means that the factor analysis was carried out on a group of companies. On the other hand, however, it is necessary to realize that financial factors are influenced by the internal environment of the company in addition to industry characteristics. Therefore, it would be appropriate to carry out the analysis also on the conditions of specific companies. The same conclusion from the research carried out on a similar topic is also reached by Ocal et al. (2007).

Despite the most crucial importance of factor analysis consisting in the reduction of the number of variables, it is also necessary to state that certain limitations of the application of this method must be pointed. In many cases, there are situations where factors containing variables are created, which at first glance are not easy to understand as a single whole, which also represents a barrier when determining the names of these factors. In some cases, it is unambiguous and based on the composition of the factor, the researchers can clearly name the factor. In some cases, however, it is complicated. Traditionally, at least two or three variables must load on a factor, so it can be given a meaningful interpretation (Henson and Roberts, 2006 in Williams et al., 2010).

Conclusion

Encouraging transport activities, especially public transport activities are significantly necessary for the proper functioning of the countries. In order to control state and development of the transport industry, a realistic and continuous review of the industry is a necessity. Analysis of financial and economic indicators is a way how to realize continuous status monitoring. However, there are a huge number of indicators and groups of indicators, as well as many approaches to this issue. Thus, the main purpose of this research was to identify the most relevant financial indicators that affect the transport enterprises performance and define new alternative way of grouping company financial indicators into dimensions based on their mutual correlation. To achieve the set aim, factor analysis was applied to financial data collected from transport industry of V4 countries. Factor analysis was carried out on the database of 17 financial indicators of transport companies operated in V4 countries during the period 2018-2021. KMO statistics and Bartlett's Test confirmed the appropriateness of applying factor analysis to the dataset in all cases.

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NIEKONWENCJONALNE PODEJŚCIE DO OCENY WYNIKÓW FINANSOWYCH W WARUNKACH KRYTYCZNYCH ZABURZEŃ MAKROEKONOMICZNYCH: PRZYPADEK TRANSPORTU PUBLICZNEGO PODCZAS PANDEMII COVID-19

Streszczenie: Okres pandemii Covid-19 był jednym z najbardziej restrykcyjnych dla sektora transportu pasażerskiego. Ze względu na wpływ środków antypandemicznych mobilność ludności została ograniczona, co znalazło odzwierciedlenie w spadku sprzedaży i załamaniu długoterminowych wskaźników finansowych. W związku z tym okres ten można uznać za przypadek krytycznych zaburzeń makroekonomicznych. Głównym celem niniejszego badania jest identyfikacja najistotniejszych wskaźników finansowych, które wpływają na wyniki przedsiębiorstw transportowych oraz określenie nowego alternatywnego sposobu grupowania wskaźników finansowych firmy w oparciu o ich wzajemną korelację. W związku z tym w niniejszym artykule, przy użyciu narzędzi statystyki opisowej i analizy czynnikowej, zidentyfikowano korelacje wybranych wskaźników finansowych, które pozwalają na lepsze zrozumienie ich wzajemnych powiązań i wpływu podczas nadzwyczajnych sytuacji makroekonomicznych na rynku. Źródłem danych były sprawozdania finansowe publicznych przedsiębiorstw transportu pasażerskiego w krajach V4 w latach 2018-2021, pozyskane z międzynarodowej platformy Orbis. Analiza czynnikowa umożliwiła zmniejszenie liczby wskaźników finansowych z 17 do 2, 3 lub 4 utworzonych czynników (w zależności od kraju i analizowanego roku). Jest to nietradycyjne wielowymiarowe podejście do pracy z informacjami finansowymi, pozwalające na identyfikację nowych powiązanych grup wskaźników finansowych w oparciu o ich wzajemne relacje oraz odpowiednie nazwanie tych grup z wyeliminowaniem wieloliniowości. Długoterminowa stabilność ekonomiczna transportu publicznego musi opierać się na krańcowym poziomie popytu zapewniającym wymagane wyniki finansowe, które można również określić ilościowo za pomocą zdefiniowanych grup wskaźników finansowych. Zastosowaną metodę można uznać za quasi-uniwersalne podejście do oceny wyników finansowych podczas głębokich zakłóceń makroekonomicznych.

Słowa kluczowe: wyniki finansowe, firmy transportowe, analiza czynnikowa, pandemia Covid-19