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MONITORING CHANGES IMPLEMENTATION OF INTERNATIONAL ACCOUNTING STANDARDS BASED ON THE STATISTICAL METHOD OF PRINCIPAL COMPONENTS

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A B S T R A C T

Small and medium-sized enterprises constitute a strong potential in the economy of the entire European Union, but also in the Slovak Republic. The significance of these enterprises is not only at the national level, but also reaches a transnational dimension. Small and medium-sized enterprises resist not only various external influences, but also frequent legislative changes. Individual legislative changes can also result in a change in the financial performance of small and medium-sized enterprises. The aim of the paper is to point out the change in results through the method of principal components, which was performed from the input data of ratio indicators, in the event of a mandatory transformation of national accounting standards into international accounting standards. At present, however, small and medium-sized enterprises are not obliged to present financial statements according to international accounting standards, but the progressing time and the Slovak Republic's part in the European Union may also cause the harmonization of financial statements itself.

1. INTRODUCTION

Nowadays the large amount of legislation changes are put in practice in the Slovak Republic. Small and medium-sized enterprises carrying out business activities on the territory of the Slovak Republic must present national financial statements. However, the ever-advancing period may cause a change in the reporting of financial statements according to the international accounting standards. Currently, only large international and multinational companies have have to mandatory report their financials in the according to the international accounting standards.

The guidance that small and medium-sized enterprises would need in reporting financial statements according to the international accounting standards, they would not be able to find either from competent authorities such as the Financial Directorate of the Slovak Republic, or through consulting with renowned accounting firms that provide various accounting software.

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The contribution of this paper is to point at the difference between the final results prepared through national financial statements and financial statements with the implementation of international accounting standards. The difference in results was investigated using the principal components (PCA) statistical method.

2. LITERATURE REVIEW

The main goal of PCA analysis is to focus on the greatest variability from the input data, which implies that elements that have a larger scale of measurement have the greatest influence on individual components than other elements. (Venables, Ripley, 1999).
The main task of the PCA method is to group similar indicators into main components (Chajdiak et al. 1999), (Anděl, 2007). The beginnings of this method can be traced back to 1933, when it was proposed by a mathematician in England, Karl Pearson. The main goal of this method is to find a linear combination of the original variable indicators while maintaining the greatest amount of original information. (Giudici, 2011).

The simplest explanation of principal component analysis is shown through a formula (1):

$$Y = XP \tag{1}$$

It follows from the previous formula that in the PCA analysis the input data is transformed into other systems. X represents a centered matrix with input data d - dimensional data in n - rows in the matrix. X represents the multiple of d and n (Timm, 2002). P represents the matrix of eigenvectors resulting from the covariance matrix, which determines the linear dependence of two quantities. (Filzmoser, Hron, Reimann, 2009), (Bharathi, Sukanesh, 2012). The article further examines the arrangement of the most advantageous components. When arranging objects, it would be most advantageous to have only one main component (Tinsley, Brown, 2000). However, such a situation rarely occurs. The number of components depends on the number of input variables. Based on that, it applies (2):

$$\sigma_1^2 + \sigma_2^2 + \cdots + \sigma_p^2 = \\ = \sum_{i=1}^{p} Var(X_i) = \lambda_1 + \cdots + \lambda_p = \\ = \sum_{i=1}^{p} Var(Y_i) \tag{2}$$

That implies that the variance from the input data X_1, X_2, ..., X_P is the same as the total variance of the main components (Afifi, 2004). As a rule, the sum of the variables of the first components should represent at least a value of 70 % - 90 %. In such a case, the main components, the sum of which usually represents a value higher than 70 %, can be replaced by the input data (Milewska et al., 2014), (Kirk, 2008) (3).

$$\frac{\lambda_k}{\lambda_1 + \lambda_2 + \cdots \lambda_p} = \frac{\lambda_k}{\mathrm{st}\,(\Sigma)} = \frac{\lambda_k}{st\,(\Lambda)}$$

$$k = 1, 2, \dots p \tag{3}$$

Through the covariance matrix, the correlation coefficients show the relationship between the selected components Yi and the original quantities Xk (markeAitchison, 1983), (Yerznkyan, Gataullin, Gataullin, 2021). Cov(Yi,Xk) express the covariance between the original data quantities (k) and the main selected components (i) (Kráľ et al., 2009). (4)

$$\rho_{Yi,X_k} = \frac{Cov(Y_i, X_k)}{\sqrt{Var(Y_i)}\sqrt{Var(X_k)}} = \frac{\lambda_i \omega_{ik}}{\sqrt{\lambda_i}\sqrt{\sigma_{kk}}} = \\ = \frac{\omega_{ik}}{\sqrt{\sigma_{kk}}}$$

$$i, k = 1, 2, \dots p \tag{4}$$

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3. MATERIALS AND METHODOLOGY

Before applying the PCA analysis itself, it is necessary to adjust the input data so that they provide an accurate and true picture of the investigated results (Izenman, 2008). The main purpose of PCA analysis is to focus on the greatest variability from the input data, which implies that elements with a greater range of measurement have the greatest influence on individual components than other elements (Budíková et al., 2010), (Markechová, Stehlíková, Tirpáková, 2011).

Variability captures principal component data. The components are sorted in descending order according to the proportion of variability (Hendl, 2006).

The research is applied to a sample of small and medium-sized enterprises (Glazkova, 2021) represented in the brewing industry. The number of companies appearing in the sample is 15.

Selected ratios were used to compare the companies: first level liquidity (coefficient) X1, second degree liquidity (coefficient) X2, liquidity of the third degree (coefficient) X3, asset turnov-er time (days) X4, stock turnover time (days) X5, receivables turnover time (days) X6, debt repayment period (days) X7, asset turnover (coefficient) X8, inventory turnover (coefficient) X9, EAT (net profit in €) X10, EBT (profit before tax in €) X11, EBIT (earnings before taxes and interest costs in €) X12, EBITDA (profit before taxes, interest and depreciation in €) X13, profitability of total capital (in %) X14, return on invested capital (in %) X15, return on assets (in %) X16, return on equity (in %) X17, revenue profitability expressed (in %) X18, profitability of sales (in %) X19, cost effectiveness (coefficient) X20, total indebtedness (in %) X21, degree of independence (in %) X22, capital multiplier (coefficient) X23, debt to equity (coefficient) X24, credit debt (in %) X25, interest coverage (coefficient) X26, interest coverage - modification (coefficient) X27, interest burden (in %) X28.

3.1 PCA Method on national accounts

Principal component analysis was created from the indicator data that was applied to national financial statements. Figure 1 shows the variability of the individual elements as well as the cumulative proportion. It is advisable to select the number of components that covers the required cumulative share.

The following Table 1 shows the variability of the individual elements, as well as the cumulative values.

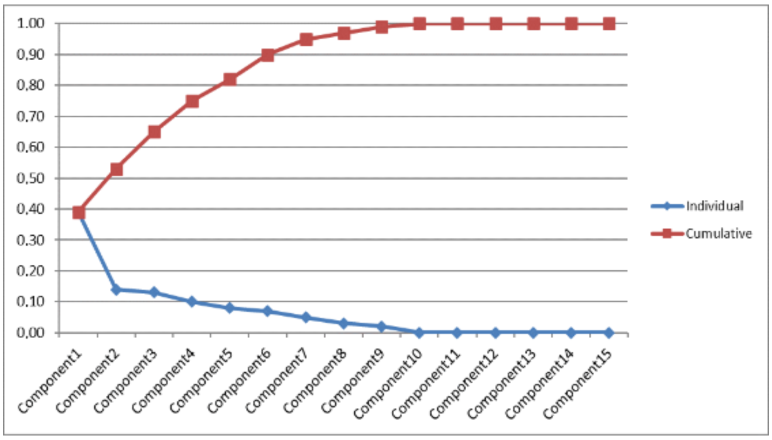

Figure 1. Variability of individual elements and cumulative share of components from national accounts data, Source: Own

Table 1. Main components from national accounts data, Source: Own

Component	C1	C2	C3	C4	C5	C6	C7	C8
Individual	0.39	0.14	0.13	0.10	0.08	0.07	0.05	0.03
Cumulative	0.39	0.53	0.65	0.75	0.82	0.90	0.95	0.97
Component	C9	C10	C11	C12	C13	C14	C15	
Individual	0.02	0.00	0.00	0.00	0.00	0.00	0.00	
Cumulative	0.99	1.00	1.00	1.00	1.00	1.00	1.00	

C1 – C15 express individual components.
Based on the strong correlation between some elements, the four elements shown by the PCA analysis are approximated in the analysis. Table 2 shows the four components showing approximately 75 % of the variability of the original data from the indicators. Green color saturation indicates positive saturation of the main components by individual indicators. While the red color saturation records the negative saturation of the main components by individual indicators.

Table 2. Four components from principal component analysis of national accounts data, Source: Own

	Components			
	C1	C2	C3	C4
X1	0.00	-0.20	0.18	-0.20
X2	0.14	-0.33	0.10	0.05
X3	0.14	-0.31	0.18	0.03
X4	0.20	-0.07	0.24	0.29
X5	0.08	0.10	0.14	0.11
X6	0.18	-0.29	-0.11	0.15
X7	0.04	-0.03	0.43	0.31
X8	-0.20	0.07	-0.24	-0.29
X9	-0.08	0.34	0.10	0.34
X10	-0.24	-0.09	-0.05	0.25
X11	-0.22	-0.20	-0.18	0.26
X12	-0.22	-0.19	-0.18	0.26
X13	-0.25	-0.02	0.13	-0.12
X14	-0.29	0.04	0.01	0.08
X15	-0.15	-0.02	0.06	-0.06
X16	-0.20	-0.15	-0.24	0.14
X17	-0.13	-0.40	-0.09	0.00
X18	-0.27	-0.04	0.08	0.07
X19	-0.23	0.14	0.23	0.03
X20	0.23	-0.17	-0.24	-0.11
X21	-0.18	0.03	0.25	0.05
X22	0.10	-0.21	0.04	-0.23
X23	-0.09	-0.25	0.30	-0.17
X24	-0.14	-0.20	0.37	-0.12
X25	-0.24	-0.13	0.02	-0.20
X26	-0.26	-0.05	-0.04	-0.03
X27	-0.27	-0.04	-0.03	-0.03
X28	0.08	-0.20	-0.16	0.36

From the given data, it can be concluded that positive elements contribute the most to component C1, such as cost effectiveness, asset turnover, receivables turnover time, 2nd degree liquidity and 3rd degree liquidity. At the same time, the component is affected by negative elements such as profitability of investments, profitability of revenues, interest coverage, or credit indebtedness. The positive elements of inventory turnover and profitability of sales contribute the most to component C2, while negative values also affect the component, especially in the indicators' profitability of equity capital, 2nd degree liquidity, 3rd degree liquidity, receivables turnover period and capital multiplier. The positive elements of the indicators' debt repayment period, debt to equity, equity multiplier, total indebtedness and asset turnover period contribute the most to the component C3. At the same time, the negative elements of the indicators of asset turnover, asset profitability and cost profitability also affect the component. The fourth and last component C4, which contributed to approximately 75 % of the variability of the original data, is most influenced by the positive values of the inventory turnover, asset turnover period, liability repayment period and the interest burden. At the same time, this component is also affected by negative elements, such as asset turnover, degree of independence, credit indebtedness, and Tier 1 liquidity.

3.2 PCA Method on international financial statements

Subsequently, an analysis of the main components was created from the indicator data, which were modified according to the selected international accounting standards IAS/IFRS. The transformation of national financial statements into international financial statements was carried out through the 5 most used implementations of IAS/IFRS (Silva, Couto, Cordeiro 2007), and that:

- implementation on unused land with buildings, provided for rent (IAS 16 land, buildings and equipment),
- sale of long-term tangible assets that the company does not use for its business activities (IAS4 – depreciation of assets),
- for spare parts included in inventory, which must be included in long-term tangible assets when accounting using IAS/IFRS (IAS2 inventory),
- for long-term receivables (IAS 34 financial reporting),
- for long-term liabilities (IAS 32 financial liabilities and capital instruments). (Fbetkowski, (2018).

Figure 2 shows the variability of individual elements as well as the cumulative proportion. Such a number of components is selected that covers the required cumulative share.
The following Table 3 shows the variability of the individual elements and also shows the cumulative values.

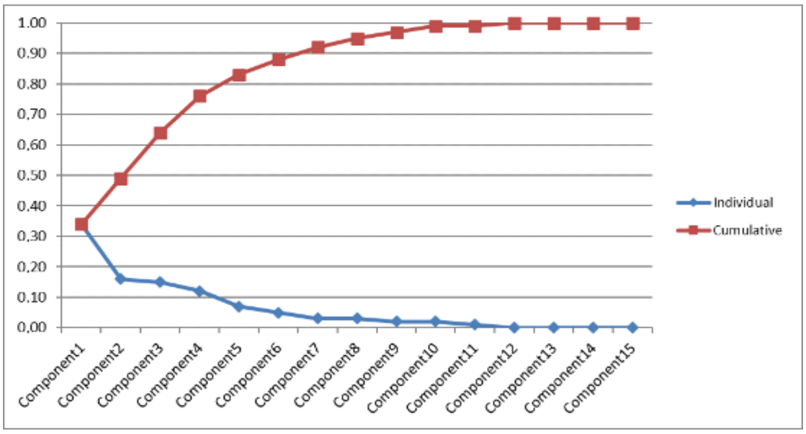

Figure 1. Variability of the individual elements and cumulative share of the components from international financial statements data, Source: Own

Table 3. Main components from national accounts data, Source: Own

Component	C1	C2	C3	C4	C5	C6	C7	C8
Individual	0.34	0.16	0.15	0.12	0.07	0.05	0.03	0.03
Cumulative	0.34	0.49	0.64	0.76	0.83	0.88	0.92	0.95
Component	C9	C10	C11	C12	C13	C14	C15	
Individual	0.02	0.02	0.01	0.00	0.00	0.00	0.00	
Cumulative	0.97	0.99	0.99	1.00	1.00	1.00	1.00	

C1 – C15 express individual components.

Based on the strong correlation between some elements, the four elements shown by the PCA analysis are approximated in the analysis. Table 4 shows the four components showing approximately 76 % of the variability of the original data from the indicators. Green color saturation indicates a positive saturation of the main components by individual indicators, while red color saturation records a negative saturation of the main components by individual indicators.

Table 4. Four components from principal component analysis of data on IAS/IFRS implementation, Source: Own

	Components			
	C1	C2	C3	C4
X1	-0.01	-0.27	-0.18	-0.04
X2	-0.17	-0.18	-0.27	-0.25
X3	-0.22	-0.25	-0.14	-0.13
X4	-0.26	0.23	-0.05	-0.09
X5	-0.13	-0.02	0.11	0.10
X6	-0.14	0.04	-0.27	-0.26
X7	-0.09	0.21	0.07	0.08
X8	0.26	-0.23	0.05	0.09
X9	0.12	0.31	0.04	0.07
X10	0.20	0.01	0.05	-0.41
X11	0.19	-0.03	0.06	-0.39
X12	0.20	-0.02	0.10	-0.32
X13	0.25	-0.16	0.18	0.10
X14	0.10	0.05	0.44	-0.07
X15	0.17	0.05	-0.05	-0.09
X16	0.17	0.10	-0.39	0.02
X17	-0.01	-0.34	-0.21	-0.10
X18	0.21	0.13	-0.30	0.08
X19	0.23	0.09	-0.31	0.01
X20	-0.26	-0.03	0.00	0.21
X21	0.24	-0.02	0.06	0.25
X22	-0.18	-0.24	0.13	-0.19
X23	-0.11	-0.37	0.05	0.13
X24	0.00	-0.37	0.07	0.22
X25	0.25	-0.22	0.07	0.06
X26	0.26	-0.07	-0.16	-0.02
X27	0.27	-0.12	0.06	-0.08
X28	-0.11	0.03	0.31	-0.35

Based on Table 4, it can be concluded that positive elements such as the asset turnover, interest coverage, credit indebtedness, total indebtedness and profitability of sales contribute the most to the component C1. Negative elements such as thev asset turnover time, cost efficiency, 2nd degree liquidity and degree of independence also contribute to the C1 component. Component C2 is mostly represented by positive elements such as the inventory turnover, asset turnover time, while elements with negative values such as debt to equity, equity multiplier, Tier 1 liquidity and Tier 3 liquidity also contribute to the component. Elements with positive values such as the return on investment, interest burden, contribute the most to the component C3. The component C3 is also represented by negative elements such as the profitability of assets, profitability of sales, profitability of revenues, 2nd degree liquidity and receivables turnover time. The fourth and last component C4, which contributed to approximately 76 % of the variability of the original data, is most influenced by the positive values of elements such as total indebtedness, cost effectiveness, debt to equity. At the same time, the component is also affected by negative elements such as the net profit, profit before tax, receivables turnover period, interest burden and Tier 2 liquidity.

4. RESULTS

When implementing the PCA method, it can be concluded that when comparing the C1 component during the use of national financial statements and financial statements during the implementation of international accounting standards, there is no agreement in the values of positive or negative elements that have the greatest impact on the C1 component. In the case of component C2, during the comparison of national financial statements and IAS/IFRS implementations, we noticed an impact on the same positive but also negative elements on the component. Positive elements such as inventory turnover and negative elements such as equity multiplier and Tier 3 liquidity affect the C2 component during the use of national financial statements, but also in the event that individual enterprises decide to report financial statements according to international accounting standards. Component C3 points out that when using national financial statements and financial statements created according to the international standards, in both cases, the C3 component would be affected by a negative element, namely the profitability of assets, in both cases. In the case of the fourth component C4, no common positive or negative element will influence as it did in the case of the C1 component.

Table 5 shows a comparison of the PCA method when using data from national accounting standards and data after the implementation of IAS/IFRS and the subsequent changes in components.

Table 5 Comparison of components when using national financial statements and financial statements according to IAS/IFRS, Source: Own

Component	Positive elements	Negative elements
C1	----	----
C2	inventory turnover	capital multiplier, 3rd degree liquidity
C3	----	profitability of assets
C4	----	----

According to Table 5, it is clear that in both cases: using data from national financial statements and from international financial statements to which selected IAS/IFRS were applied, the same positive element will affect only in the component C2. The C2 component will be affected by negative elements, namely by the capital and liquidity multiplier of the 3rd degree. Negative elements will also affect the component C3, through the profitability of assets, which has an inherent impact on this component even when using national financial statements, but also when using the international accounting standards.

5. CONCLUSION

The subject of the contribution was to point out not only at the theoretical basis of the international accounting standards and the statistical method of the main components, but also to demonstrate the statistical method on a practical example. The practical example in this paper points at thechange in the variability of the input data.

Before the actual application of the principal component method (PCA) on a sample of selected enterprises operating in the brewing industry, 5 international accounting standards were implemented on the national financial statements, which caused the deterioration of the financial situation of the selected enterprises.

The study of the statistical method itself showed us a change in the variability of the original data in 4 main components. When monitoring the results from the national financial statements, we achieved a variability of the original data in the value of 75 %. However, when monitoring the results from the international financial statements, we achieved a variability of the original data in the value of 76 %. We have also noticed a difference in the positive and negative elements themselves, which directly affect the components. We have noticed the biggest change in both positive and negative elements, especially in the C2 component.

Another following study could show whether there would be a change in the amount of variability of input data when using, for example, modern methods of financial analysis. At the same time, it would be appropriate to monitor the change of individual components over a longer period of time, for example over a longer monitored period, namely the year 2022, and then compare the changes in the annual periods.

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