



ORIGINAL ARTICLE

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Analysis of modern methods for increasing and managing the financial prosperity of businesses in the context of performance: a case study of the tourism sector in Slovakia

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Keywords: *business performance; modern methods; performance benchmarking; travel agencies; Principal Component Analysis*

Abstract

Research background: In the context of constantly changing business environment, the financial sector is focusing on new trends in financial management systems. Nowadays, there is a need to achieve long-term financial growth, so financial managers try to develop new models for managing and improving the financial performance of businesses in economic practice.

Purpose of the article: This article aims to determine the financial performance of travel agencies by applying modern business performance evaluation methods in order to create a performance portfolio (ranking) for the years 2013–2017, subsequently to reveal the concordance rate of order of the selected business entities by comparing applied financial methods in the context of performance benchmarking. The research question is as follows: Does the multidimensional PCA

method in the form of the performance portfolio of travel agencies provide similar financial results compared to the EVA indicator?

Methods: For measuring the financial performance of businesses, the method of Principal Component Analysis (PCA) and the indicator Economic Value Added (EVA) were chosen. Spearman's rank-order correlation was applied in order to reveal the concordance rate of the analyzed travel agencies.

Findings & Value added: The results indicate that by applying the PCA method, 6 key performance factors can be identified. Moreover, the findings revealed that the assessment of travel agencies using the PCA method and EVA indicator did not lead to the same financial results. Individual financial methods identified a different number of strong-performing and inefficient business entities. In this backdrop, we concluded that the business performance measurement based on the PCA method is not a suitable alternative to measuring performance using the EVA indicator.

Introduction

The ever-increasing and rising level of competitive pressures makes the process of measuring, evaluating, and continually managing the financial performance necessary for any business interested in increasing its financial performance. The main business goal used to be maximizing accounting profit, but at the moment there is a need to maximize the economic added value for shareholders and quantify business performance using key performance indicators (value drivers). However, these increasing competitive pressures make managers believe that measuring financial performance alone will not suffice. Company performance is to be planned with a long-term perspective (Mihalcova *et al.*, 2017).

The service sector has held the dominant position in the economy of the Slovak Republic over the last ten years, in which tourism also occupies a significant position. Therefore, we decided to focus on the analysis of the financial performance of a select sample of Slovak travel agencies (TAs), which significantly contribute not only to the development of domestic and foreign tourism, but also to the development of the whole service sector.

The aim of the article is to analyze the financial performance of this sample of TAs by applying modern business performance assessment methods to create an average performance portfolio (ranking) for the period 2013 to 2017. The intent was to reveal the concordance rate of order in the financial performance of these business entities based on two financial methods in the context of performance.

The article is structured as follows. The first section includes the justification for the topic's importance. The second section presents the literature review. The third section contains the research methodology. This section describes the research sample and question, as well as the selected statistical methods. The next section involves the presentation of the results. The

fifth section focuses on the comparison of the findings with other research studies. The last section offers a summary of the article and recommendations for practice.

Literature review

Theoretical background of business performance

In research business literature, the term “performance” is understood and explained in various regards and contexts, depending on the interest groups concerned with the issue.

At present, there are significant changes not only within the performance measurement approaches, but also changes affecting performance evaluation methods and tools (Sofrankova *et al.*, 2017). Increasing competitive environment forces businesses to respond flexibly to rapidly changing economic conditions and regularly monitor and evaluate performance levels. Thus, managers constantly address the question of how to measure performance (Soltes & Gavurova, 2015). Simple financial indicators cannot capture the multitude of inputs and outputs, thus the multivariate nature of the efficiency phenomenon, thus reducing the usefulness of standard financial ratios (Balcerzak & Pietrzak, 2016). However, Bacik *et al.* (2019) used traditional organization's financial indicators of profitability (ROA, ROE) to determine performance. According to Vochozka *et al.* (2016), it is the most important to identify the performance criteria that will reflect the key factors for business performance growth, because it is not possible to determine it with one performance indicator. Milichovsky (2015) sees the main problem in the different perception and evaluation of business performance by various target groups.

According to Hyranek *et al.* (2018), each model of performance measurement and prediction uses different mathematical tools, works with different indicators. However, these models also have many common characteristics. Authors Kozena and Jelinkova (2014) emphasize that the right choice of performance measurement methods, taking into account company specifics, can highlight in time the key issues and shortcomings that need to be eliminated and where the business does not reach its full potential.

Principal Component Analysis (PCA) and of Economic Value Added (EVA)

The Principal Component Analysis (PCA) is widely used not only in the financial field. It was developed by Pearson (1901), as a technique from statistics for simplifying a data set.

Simionescu and Dumitrescu (2018) used PCA method to assess business performance. They quantified the principal financial factors to examine the relationship between company financial performance (CFP) and corporate social responsibility (CSR). Moreover, using PCA method, authors developed a CSR index and several specific indices for CSR practices. By estimating cross-sectional regression models, their study provided support for a positive link between CSR and CFP.

Kocmanova *et al.* (2017) constructed a composite model that integrated 5 financial (economic) and 14 non-financial performance indicators, which were determined in a stepwise fashion from a basic set of performance indicators using the principal component analysis (PCA) modelling. As authors reported, this is one of the possible ways to create a tool for measuring and assessing corporate in various areas of their performance.

The Economic Value Added (EVA) was devised by management consulting firm Stern Value Management, originally incorporated as Stern Stewart & Co. The EVA indicator, as the benchmark for measuring business performance, is the subject of many scientific studies. The identification of the EVA indicator application was dealt by Terenteva *et al.* (2018). The study showed that the indicator is an appropriate tool for quantifying business performance, as it reflects the objectives of all key shareholders in the business and takes into account current economic conditions. In the research study of Zhukovets *et al.* (2017) it was revealed that chaotically selected key performance indicators (KPIs), including the EVA, are not effective unless they are linked to the set goals of the business. To achieve these goals, the system of indicators should reflect the specifics of the company's activities.

Another view was given by Santos *et al.* (2018), who investigated the empirical relationship between EVA and revenue performance of 178 companies for the period 2010–2015. The Authors performed Spearman correlation and estimated a regression model with panel data and random effects. Based on the results, it was possible to observe that firms have shown negative returns and value destruction for shareholders. A weak, positive correlation between EVA and returns was confirmed.

The relationship between the EVA indicator and the selected financial metrics, such as rate of return on invested capital, sales, operating expenses, share of borrowed capital, share of equity, taxes paid and assets, was ana-

lysed also by Fialkowska (2017). The results showed that only the rate of return on invested capital has statistically significant cause-effect relationship with the EVA indicator among all chosen factors. Other determinant factors considered in the paper have no influence on EVA.

Important research in the field was carried out by Salaga *et al.* (2015), who devoted themselves to modifying the method of calculating the EVA indicator under the Slovak accounting legislation. The justification for the application of modern performance evaluation methods, including the EVA, was also emphasized by Malichova *et al.* (2017). The Authors pointed out several variants of the calculation of EVA indicator, defined the possibilities to apply EVA methods to the conditions of enterprises in the Slovak Republic and the need to adjust data providing financial statements. Although, as reported by Daraban (2017), it is quite complicated to quantify the EVA indicator correctly, it has been documented that EVA-rated enterprises have achieved the sustainable performance in the long-term.

Research methodology

Research sample

The research sample consists of 57 TAs operating in the Slovak Republic, which according to the statistical classification of economic activities (SK NACE Review 2) belong to section *N* — *Administrative and support services, namely to subclass 79120: Travel agency activities*. The resulting research sample was compiled by the TAs listed in Table 1.

The sample was selected on the basis of predetermined criteria. All TAs met the following criteria during the analyzed years:

- TAs must have a positive value of equity,
- TAs must achieve profit over the current accounting period,
- TAs must employ more than 9 employees (micro-enterprises),
- TAs must only consist Ltd. or Inc. enterprises.

The input data, in the form of financial statements for the analyzed TAs, were obtained from the internet portal managed by the company DataSpot, Ltd., which manages an overall database of Slovak business entities.

Methods and statistical processing of the data

The performance of the selected sample of TAs was quantified by the *Principal Component Analysis (PCA)* method of. The method is one of the basic data compression methods — the original “*n*” variables can be repre-

sented by a smaller number of “*m*” variables, while retaining a sufficiently large part of the variability of the original data set so as not to lose information. According to Benasseni (2018), the original data extracts characteristic features and at the same time reduces the dimensionality of the set of multivariate observations, while it remains important to preserve as much as possible of their original variability. This method does not require the input variables to have a multidimensional normal distribution (Kral *et al.*, 2009). Hebak *et al.* (2007) emphasize the necessary condition for using the PCA method — there must be a correlation between the original variables.

The search for the principal components is as follows:

1. Create a correlation matrix from the input data (Kaiser-Meyer-Olkin’s test and Bartlett’s test of sphericity);
2. Quantify the eigenvalues:
 - determine the eigenvalues of the correlation matrix,
 - appoint allocated ratios of the variability assigned to the components,
 - identify cumulative ratios of variability to determine how many principal components need to be taken into account;
3. Select the number of principal components based on the predefined rule;
4. Determine the correlation coefficients of the principal components (factor coordinates of variables);
5. Quantify component weight for individual variables;
6. Graphically display the original variables in the coordinate system where the axes are formed from the first two principal components (performance portfolio or ranking of TAs).

The coefficients and weights of the principal components are estimated in the following manner (Hebak *et al.*, 2007):

- the total variability of the principal components will not change — the variance of the new and original variables equals 1, i.e.:

$$\sum a_{ij}^2 = 1 \tag{1}$$

$$a_{i1}^2 + a_{i2}^2 + \dots + a_{ip}^2 = 1, \text{ for each } i = 1; 2; \dots; p$$

- the independence of the new variables, i.e. the principal components, is ensured, i.e.:

$$a_{i1}a_{j1} + a_{i2}a_{j2} + \dots + a_{ip}a_{jp} = 0 \text{ pre } i \neq j \text{ } i, j = 1; 2; \dots; p \tag{2}$$

– all properties of the principal components are respected, i.e.:

$$\begin{aligned}
 E(Y_i) &= 0 \\
 D(Y_i) &= \lambda_i \\
 D(Y_1) \geq D(Y_2) \geq D(Y_3) \dots \geq D(Y_p) &= \lambda_1 \geq \lambda_2 \geq \lambda_3 \dots \geq \lambda_p \\
 cov(Y_i, Y_j) &= 0, \text{ pre } i \neq j
 \end{aligned}
 \tag{3}$$

The second tool to measure the performance of TAs consisted of *EVA* (*Economic Value Added*). The major benefit that the EVA indicator provides compared to traditional instruments of economic measurement is that it also involves capital costs (Daraban, 2017). The indicator, according to Kollar and Kliestik (2014), tries to faithfully reflect the true economic profit of the enterprise. Its considerable advantage over regular methodology is the fact that it represents the combination of economic performance and the degree of risk that is needed to achieve that performance.

The method for calculating the EVA has several modifications: the entity method, the equity method, and the adjusted present value method. In terms of Slovak legislation, the equity method is the most appropriate method since the adjustment of NOPAT is problematic when calculating EVA by the entity method. The formula takes the following form (Stern *et al.*, 2003):

$$EVA = (ROE - r_e) \cdot E
 \tag{4}$$

where:

ROE – *Return on Equity*,

r_e – *Cost of Equity*,

E – *Equity*.

In calculating *r_e*, we applied the Global CAPM model (Damodaran, 2012), which is the only theoretically based and globally well-known valuation practice by the method of calculating the discount rate of market valuation. The final cost of own capital is set as follows:

$$r_e = r_f + \beta \cdot ERP + CRP \quad (5)$$

where:

r_f – Risk Free Rate of Return,

ERP – Equity Risk Premium,

β – Beta Coefficient,

CRP – Country Risk Premium.

We adjusted the level of r_e to the conditions of the Slovak business environment as much as possible. The level of r_f was quantified on the basis of 10-year Slovak government bonds (NBS, 2019); the level of ERP and CRP for the country was taken from the official website of Damodaran (2019a) and the values of $\beta_{Levered}$ were recalculated from $\beta_{Unlevered}$ after taking into account the capital structure of Slovak TAs (Damodaran, 2019b). From several available datasets, the Authors chose sectoral statistics for the European capital market.

In order to determine the concordance rate of order of the analyzed TAs performance based on the PCA method and the EVA indicator, Spearman's rank-order correlation was applied in the presented research paper.

Due to the constantly changing business environment, the Authors believe that business performance should be analyzed from different financial points of view, so the following research question (RQ) is proposed:

RQ: Does the multidimensional method PCA in the form of the performance portfolio of travel agencies provide similar financial results over the analyzed period compared to the EVA indicator?

All of the statistical analyses were processed using STATISTICA 13.1.

Results

Firstly, the performance of selected TAs was quantified using the PCA method. The initial information concerning the correlation structure of the research sample was obtained from the implementation of a correlation matrix of the selected 29 financial indicators (on average over the analyzed period) subsequently entering the PCA. The correlation matrix confirmed the existence of statistically significant positive and negative dependencies among the indicators. Since the KMO value is greater than 0.6, we were able to continue with the testing. Moreover, Bartlett's test of sphericity, at the selected significance level ($\alpha = 5\%$), achieved a value of $p = 0.0000$, so the PCA method is deemed appropriate.

The next step was to define the number of principal components that can be used to describe the monitored financial indicators. In general, the number of principal components is less than the number of input variables. Table 2 presents the eigenvalues of the correlation matrix and related statistics.

Based on the results, the Authors state that Factor 1 explains 21.85% of variability, Factor 2 explains 14.85%, and Factor 3 explains approximately 11.54% of the variability of the original variables. Every other factor gradually explains the smaller and smaller proportion of variability that is not explained by the previous factors. If the Kaiser rule is taken into account, those principal components whose value of the number is greater than 1 would be considered. In this case, the number of principal components would be 10. If the required rule is used so that the principal components account for at least 70% of the total scatter, the resulting count would number 6.

When determining the number of principal components, a Scree plot may also be applied where the break point is identified, taking into account the principal components in this break (Figure1).

Figure 1 shows that the number of principal components would be 8 and the break point was 4.0173% of total scattering. As mentioned in the methodological section of the paper, there are several ways to determine the number of principal components. In this paper, the rule that the principal components explain at least 70% of variability was applied. Based on this rule, 6 principal components were worked with in the following part of the research, which together account for 70.9066% of total variance.

The next step of the analysis was to determine the factor coordinates of variables based on the correlation of variables with factors after the Varimax method rotation. The high absolute value of the coefficient (the highlighted variables) means that this variable is significantly represented in this factor (Table 3).

Table 3 shows that all Liquidity ratios and EDR indicators are directly related to the first component (factor). The second component directly correlates to the most indicators, namely the TLA, DOC, DUC, LRP, and SI. The third factor achieved positive correlations with the DPO and DRO indicators. The fourth component had shown direct correlations with NCA, DIO, TMP, and RS. The fifth component confirmed a negative dependency for RE and RI. The significant positive direct correlation of the sixth factor was quantified with SI and ER. On the contrary, indirect negative dependence was confirmed for DAR.

Based on the PCA, Component Score figure was created, the so-called performance portfolio of TAs (Figure2). The first two principal factors

were applied in the construction of the figure. The principal Factor 1 included indicators such as QR, CL, TL, and EDR. The principal Factor 2 correlated with TLA, DOC, DUC, LRP, and SI. Based on the Component Score figure, we can monitor the position of the TAs as well as their interdependencies. TAs located further away from the coordinate system may be termed as extremes. The position of TAs was determined by different financial indicators in both positive and negative terms. In this case, it was TA 14, TA 27, TA 43, and TA 53 (for the numerical designation of TAs, see Table 1). On the contrary, TAs located as close as possible to the coordinate system can be considered the most typical for a given industry and group of monitored objects.

For the compilation of the resulting performance portfolio of the TAs, the authors analyzed the individual quadrants of the component score (Figure 2). Quadrant A contains TAs that achieved very good results for Principal Factor 2 and worse results for Principal Factor 1. In this quadrant, 6 TAs were located in total (TA 3, TA 19, TA 25, TA 34, TA 35, and TA 50). In Quadrant B there were 11 TAs (TA 1, TA 4, TA 15, TA 18, TA 21, TA 27, TA 32, TA 38, TA 40, TA 42, and TA 47), which achieved very good results for both principal factors. The Component Score figure confirmed that this quadrant can be considered the best. The third Quadrant C, characterized as the worst due to the worse results for both principal factors, contained up to 30 TAs (TA 2, TA 6, TA 7, TA 8, TA 10, TA 12, TA 16, TA 17, TA 22, TA 23, TA 24, TA 26, TA 28, TA 29, TA 30, TA 31, TA 33, TA 37, TA 39, TA 41, TA 45, TA 46, TA 48, TA 49, TA 51, TA 52, TA 53, TA 54, TA 55, and TA 57). In Quadrant D of the Component Score figure, TAs were placed which achieved very good results for Principal Factor 1, but worse results for Principal Factor 2. In total there were 10 TAs (TA 5, TA 9, TA 11, TA 13, TA 14, TA 20, TA 36, TA 43, TA 44, and TA 56). In the context of these results, it can be stated that in order to increase performance, TAs should focus primarily on improving the Principal Factor 1 and Principal Factor 2 indicators, depending on which factor had worse results. For enterprises located in Quadrant B, where both principal factors have been quantified to a very good level, the level of performance still needs to be maintained.

The second modern tool to evaluate the performance of TAs on average for the years 2013 to 2017 was the EVA indicator. The development of the average value of the EVA for each TA is shown in Figure 3.

Assessing the performance of the analyzed enterprises based on the average EVA indicator during the analyzed period has produced many more positive results than the previous results. The performance of TAs measured by the EVA indicator ranged from €–84,219 to € 1,045,732. Based on

the results, the authors can conclude that only 13 enterprises (out of 57) have reached a negative value for the indicator in the average amount of € –22,567, which means that the business was not more profitable than the other risk-taking methods of capitalizing. The main reason for achieving a negative EVA value was failing the $ROE > r_c$ criteria, so the ROE did not accrue a higher value than r_c . For the abovementioned 13 businesses, this relationship has not been respected and can therefore be labeled ineffective. On the other hand, over the analyzed period, there were on average up to 44 TAs that were able to generate added value for their owners (€ 103,450 on average), which is a sign of a successful and efficient business. During the years 2013–2017, the total average EVA for all TAs was € 78,784. It is also clear from Figure 3 that 3 TAs were identified within the benchmarked sample which, compared to other enterprises, achieved significantly better results for the given indicator and can be described as the most efficient. They are TA 04, TA 42, and TA 43. On the contrary, TAs that can be considered as the least efficient businesses are TA 05, TA 08, and TA 10.

In order to meet the main objective and to find out the answer to the RQ, Spearman's rank-order correlation was used. In Table 4, the authors compare the ranking of individual TAs to their performance in terms of comparing these financial instruments.

Based on the results, it can be stated that the identical concordance rate in performance for TA 1 was quantified. A total of 4 TAs (TA 8, TA 13, TA 24, and TA 54) were identified as having the lowest order difference (only 1 ranking). On the contrary, the highest order difference was identified for TA 46. According to the results, when comparing the PCA method and the EVA indicator, it can be stated that the best performing and the worst performing enterprise was not determined clearly. Spearman's rank-order correlation achieved a value of 0.3816; which indicates a weak concordance rate of order.

Discussion

The performance of the selected sample of TAs was quantified using the multi-dimensional PCA method and the EVA indicator. By comparing the results, we found non-compliance, indicating that the RQ was not confirmed, i.e. that the performance portfolio (ranking) of TAs by applying a multidimensional PCA method does not provide identical results in alignment with the EVA indicator's performance portfolio.

The reasons for non-compliance can be found in several facts. The results can be determined by an insufficient research sample, short assess-

ment period, but also by the fact that each financial method or indicator uses different metrics to assess the performance of the company, which can significantly affect the identified financial results. However, we take the view that very different approaches to performance evaluation can be beneficial to an enterprise as they provide a different view for assessing performance.

By analyzing previous studies, we found that several authors dealt with enterprise performance assessments using the PCA method and the EVA indicator, but both methods were never applied at the same time. The research confirms that no authors dealt with comparing these financial instruments. Tung *et al.* (2009) focused only on PCA in order to evaluate the financial performance of selected companies. The selection of the principal components was used by the authors to create a model that allowed them to monitor changes in financial performance. Li and Zhang (2011) quantified performance through financial indicators, using the PCA method to select key indicators. As reported by Jiang *et al.* (2018), economic performance is an important measure of enterprise input and output. In the paper, the authors selected seven financial indicators and conducted an evaluation of the economic performance of fifteen companies by PCA. Sofrankova *et al.* (2017) also applied the PCA method to identify the key indicators of an enterprise performance. Therefore, we agree with the opinion of those authors who claim that by using this method, it is possible to classify businesses into performance fields and identify their financial threats. The EVA indicator as a benchmarking tool was used in the study presented by Ali (2018), which considered it as the most suitable metric to measure performance. Guermat *et al.* (2019) examined the long-term effects of adopting the EVA indicator and confirmed that EVA adopters, relative to non-EVA adopters, results in an increase of the working capital cycle. The study results highlighted that EVA adoption provides more incentives to reduce the total costs for capital rather than increasing operations and maximizing shareholder wealth.

Panigrahi (2017) also investigated performance measurement tools and the wealth relationships of shareholders. The results conclusively support the claim that EVA is a useful metric for internal and external performance assessment. According to Na and Qian (2017), each enterprise should create a comprehensive financial analysis with a focus on quantifying the EVA, since maximizing this value should be the primary objective of the business's financial strategy. We are inclined to agree with the opinions of the above-mentioned authors and we also considered EVA as key performance indicator.

Conclusions

The presented research analyses the performance of selected TAs based on the multidimensional PCA method and at the same time using the EVA indicator in order to create an average performance portfolio (ranking) of enterprises for the period of 2013–2017. The research was aimed at revealing the concordance rate of order in the context of performance benchmarking for selected enterprises. In summary, the results showed that the best performing TA was TA 42; on the other hand, the worst performing was quantified as TA 08. Spearman's rank-order correlation did not confirm an identical concordance rate of order in the performance rankings, and we can state that by applying a multidimensional PCA method the performance portfolio of TAs did not provide identical results compared to the EVA indicator.

The article has important theoretical implications. The literature review presents actual issues in this area. It provides a brief comparison of several authors' opinions within the field of enterprise performance evaluation and the methodological part of the paper comprehensively describes the chosen financial methods.

The article also offers useful practical implications as well. By applying the PCA method, 29 interdependent variables (financial ratios) were reduced to 6 principal factors (correlation independent components), which together account for up to 70.9066% of total variance; this will definitely help in the process of quantifying business performance. Using factor coordinates, the relevant indicators were assigned to each factor, identifying key performance indicators, which should be prioritized by financial managers in the future. Finally, it is important to emphasize that the application of the PCA method and the EVA indicator has made it possible to build a performance portfolio of TAs and thus to create a performance ranking for the selected research sample. This performance evaluation methodology can be implemented in any business sector and its useful economic value is usable in financial practice.

This research has several limitations. The limitation of this paper is related to the sample range of the research. Furthermore, the analyzed period is short due to lack of data availability. Therefore, for future research, it would be appropriate to focus on analyzing and applying other economic, mathematic, and statistical methods to measure enterprise performance or efficiency. According to Balcerzak *et al.* (2017), Data Envelopment Analysis and the Malmquist Index are suitable instruments for measuring the efficiency of various business entities. Gallo *et al.* (2019) recommended applying the Total Quality Management tool in enterprises in Slovakia in

achieving business appreciation for its owners and shareholders. In addition, future research could be oriented towards one financial method and towards analyzing all TAs in the tourism sector for the purpose of evaluating certain economic industry. Moreover, it would also be beneficial to compare the financial findings with other sectors.

References

- Ali, S. N. M. (2018). The use of Economic Value Added as a benchmark for evaluating the performance of agricultural companies listed in the IRAQI stock exchange for 2010-2015. *Turkish Online Journal of Design Art and Communication*, 8. doi: 10.7456/1080MSE/120.
- Bacik, R., Fedorko, R., Abbas, E. W., Rigelsky, M., & Ivankova, V. (2019). The impact of selected quality management attributes on the profitability of top hotels in the Visegrad group countries. *Polish Journal of Management Studies*, 19(1). doi: 10.17512/pjms.2019.19.1.04.
- Balcerzak, A. P., Klietnik, T., Streimikiene, D., & Smrcka, L. (2017). Non-parametric approach to measuring the efficiency of banking sectors in European Union countries. *Acta Polytechnica Hungarica*, 14(7). doi: 10.12700/APH.14.7.2017.7.4.
- Balcerzak, A. P. & Pietrzak, M. B. (2016). Quality of institutions for knowledge based economy within new institutional economics framework. Multiple criteria decision analysis for European countries in the years 2000-2013. *Economics & Sociology*, 9(4). doi:10.14254/2071-789X.2016/9-4/4.
- Benasseni, J. (2018). A correction of approximations used in sensitivity study of principal component analysis. *Computational Statistics*, 33(4). doi: 10.1007/s00180-017-0790-7.
- Damodaran, A. (2012). *Investment valuation: tools and techniques for determining the value of any asset*. New York: John Wiley & Sons.
- Damodaran, A. (2019a). Risk premiums for other markets. Retrieved from <http://pages.stern.nyu.edu/~adamodar/> (15.11.2018).
- Damodaran, A. (2019b). Levered and unlevered betas by industry. Retrieved from <http://pages.stern.nyu.edu/~adamodar/> (15.11.2018).
- Daraban, M. C. (2017). Economic Value Added – a general review of the concept. *Ovidius University Annals: Economic Sciences Series*, 17(1).
- Fialkowska, A. (2017). Determinant factors of Economic Value Added: case of Ukrainian wineries. In *Proceedings of the 17th annual conference on finance and accounting*. Springer proceedings in business and economics. Cham: Springer International Publishing AG. doi: 10.1007/978-3-319-49559-0_68.
- Gallo, P., Balogova, B., Tomcikova, L., & Nemecek, J. (2019). The impact of the innovative Total Quality Management tool in small and medium-sized enterprises. *Marketing and Management of Innovations*, 4. doi: 10.21272/mmi.2019.4-02.

- Guermat, C., Misirlioglu, I. U., & Al-Omush, A. M. (2019). The long-term effect of Economic Value Added adoption on the firm's business decision. *Accounting Research Journal*, 32(3). doi: 10.1108/ARJ-01-2018-0018.
- Hebak, P., Hustopecky, J., Jarosova, E., & Pecakova, I. (2007). *Multidimensional statistical methods*. Prague: Inforamtorium.
- Hyranek, E., Grell, M., Nagy, L., & Durinova, I. (2018). The economic-mathematical nature of the HGN model concept as a tool for measuring performance of enterprises. *Journal of Economics*, 66(3).
- Jiang, L., Li, Y., & Cai, L. P. (2018). Evaluation of enterprise economic performance based on principal component analysis. *Journal of Interdisciplinary Mathematics*, 21(5). doi: 10.1080/09720502.2018.1498004
- Kocmanova, A., Docekalova, M. P., & Simanaviciene, Z. (2017). Corporate sustainability measurement and assessment of Czech manufacturing companies using a composite indicator. *Engineering Economics*, 28(1). doi: 10.5755/j01.ee.28.1.15323
- Kollar, B., & Kliestik T. (2014). Simulation approach in credit risk models. In G. Lee (Ed.). *4th international conference on applied social science, Information Engineering Research Institute, advances in education research*, 51. Newark: Information Engineering Research Institution.
- Kozena, M., & Jelinkova, L. (2014). Specifics of performance measurement and management manufacturing company. In *SGEM 2014 conference proceedings on political sciences, law, finance, economics and tourism*, 2(2014). doi:10.5593/SGEMSOCIAL2014/B22/S6.083.
- Kral, P. (2009). *Multidimensional statistical methods focusing on solving problems of economic practice*. Universitas Matthiae Belii in Banska Bystrica.
- Li, Y C., & Zhang, Q. (2011). The application of principal component analysis on financial analysis in real estate listed company. In *Procedia engineering: international conference on advanced in control engineering and information science*, 15. doi: 10.1016/j.proeng.2011.08.845.
- Malichova, E., Durisova, M., & Tokarcikova, E. (2017). Models of application Economic Value Added in automotive company. *Transport Problems*, 12(3). doi: 10.20858/tp.2017.12.3.9.
- Mihalcova, B., Gallo P., & Pruzinsky, M. (2017). Measurement of company performance in a health resort in Slovakia taken as an example. *Quality – Access to Success*, 18(158).
- Milichovsky, F. (2015). Effectiveness of marketing activities in engineering in Czech Republic. *Business: Theory and Practice*, 16(2). doi: 10.3846/btp.2015.436.
- Na, W., & Qian, R. (2017). Enterprise value evaluation: application and improvement based on cash flow model and Economic Value Added model. In Y. Huo & Z. Cheng (Eds.). *Proceedings of the 2017 international conference on humanities science, management and education technology*, 96. Paris: Atlantis Press.

- NBS (2019). *Long-term interest rates statistics*. Retrieved from <https://www.nbs.sk/statisticke-udaje/financne-trhy/urokove-sadzby/dlhodobé-urokove-sadzby> (10.12.2018).
- Panigrahi, S. K. (2017). Economic Value Added and traditional accounting measures for shareholder's wealth creation. *Asian Journal of Accounting and Governance*, 8(1). doi: 10.17576/AJAG-2017-08-11.
- Pearson, K. (1901). On lines and planes of closest fit to systems of points in space. *Philosophical Magazine*, 2(11).
- Salaga, J., Bartosova, V., & Kicova, E. (2015). Economic Value Added as a measurement tool of financial performance. *Procedia Economics and Finance*, 26(2015). doi: 10.1016/S2212-5671(15)00877-1.
- Santos, J. V., Tavares, A. D., Azevedo, Y. G., & Neto, R. M. (2018). Relationship between stock return and Economic Value Added (EVA): empirical evidences in Brazilian public companies. *Revista Evidenciacao Contabil & Financas*, 6(1). doi: 10.18405/recfin201801077.
- Simionescu, L., N., & Dumitrescu, D. (2018). Empirical study towards business social responsibility practices and company financial performance. Evidence for company listed on the Bucharest stock Exchange. *Sustainability*, 10(9). doi: 10.3390/su10093141.
- Sofrankova, B., Horvathova, J., Kiselakova, D., & Matkova, S. (2017). Identification of key performance indicators with the application of mathematical and statistical methods. *Journal of Financial Studies & Research*, 2017. doi: 10.5171/2017.403204.
- Sofrankova, B., Kiselakova, D., Horvathova, J. (2017). Actual questions of risk management in models affecting enterprise performance. *Journal of Economics*, 65(7).
- Soltes, V., & Gavurova, B. (2015). Modification of performance measurement system in the intentions of globalization trends. *Polish Journal of Management Studies*. 11(2).
- Stern, J. M., Shiely, J. S., & Ross, I. (2003). *The EVA challenge: implementing Value-Added change in an organization*. New York: John Wiley & Sons.
- Terenteva, T., Shashlo, N., Kuzubov, A., & Shnaider, V. (2018). Economic Added Value as a tool of cost-oriented management by business structures of industry. *National Academy of Managerial Staff of Culture and Arts Herald*, 2.
- Tung, C. T., Lee, Y. J., & Wang, K. H. (2009). Combining grey theory and Principal Component Analysis to evaluate financial performance of the airline companies in Taiwan. *Journal of Grey System*, 21(4).
- Vochozka, M., Rowland, Z., & Vrbka, J. (2016). Financial analysis of an average transport company in the Czech Republic. *Our Sea*, 63(3). doi.org/10.17818/NM/2016/SI28.
- Zhukovets, T., Strelnik, E., & Usanova, D. (2017). Regression analysis of key efficiency indicators in the context of corporate financial management based on the indicator of the Economic Value Added (EVA). *National Academy of Managerial Staff of Culture and Arts Herald*, 4.

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Annex

Table 1. Overview and numeric designation of the analyzed companies

Abbr.	Business name of travel agency	Abbr.	Business name of travel agency
TA 01	Aeolus, Ltd.	TA 30	Jazz Welt, Ltd.
TA 02	AGRITOURS Slovakia, Ltd.	TA 31	JG SPORT AGENCY, Ltd.
TA 03	BOMBOVO, travel agency, Ltd.	TA 32	KARTAGO TOURS, Inc.
TA 04	BUBO travel agency, Ltd.	TA 33	Koala Tours, Inc.
TA 05	CASSOFIN, Ltd.	TA 34	LG TRADE, Ltd.
TA 06	Travel agency ECOMM, Ltd.	TA 35	MAGIC Travel, Ltd.
TA 07	Travel agency FIFO, Ltd.	TA 36	Maximum Travel, Ltd.
TA 08	CK AZAD, Ltd.	TA 37	MILLENNIUM TRAVEL, Ltd.
TA 09	CK EUROTOUR, Ltd. Stropkov	TA 38	NA DOSAH, Ltd.
TA 10	CK FANY, Ltd.	TA 39	ONE WORLD Travel, Ltd.
TA 11	CK Slniečko, Ltd..	TA 40	Orex Travel, Ltd.
TA 12	CK TRGOTURS, Ltd.	TA 41	PEGAS TOUR, Ltd.
TA 13	CKM 2000 Travel, Ltd.	TA 42	Pelicantravel.com, Ltd.
TA 14	CORADO, Ltd.	TA 43	PHARMAEDUCA, Ltd.
TA 15	DERTOUR Slovakia, Ltd.	TA 44	Premier Sport Tour, Ltd.
TA 16	Desirea, Ltd.	TA 45	Relaxos, Ltd.
TA 17	DUBTOUR, Ltd.	TA 46	SATUR TRAVEL, Inc.
TA 18	ETI Slovensko, Ltd.	TA 47	SENECA TOURS, Ltd.
TA 19	EZOTOUR, Ltd.	TA 48	SETTOUR SLOVAKIA, Ltd.
TA 20	Fantázia dp, Ltd.	TA 49	SKI TRAVEL-PROEVENTS, Ltd.
TA 21	FERROTOUR, Inc.	TA 50	SOLVEX, Ltd.
TA 22	FIRO-tour, Ltd.	TA 51	SUNFLOWERS agency, Ltd.
TA 23	GLOBTOUR GROUP, Inc.	TA 52	TIP travel, Inc.
TA 24	GO Travel Slovakia, Ltd.	TA 53	Travelco, Ltd.
TA 25	Happy Travel.sk, Ltd.	TA 54	TUI Reise Center Slovensko, Ltd.
TA 26	HEPEX – Slovakia, Ltd.	TA 55	VIP Travel, Ltd.
TA 27	HYDROTOUR, travel agency, Inc.	TA 56	VIP Travel, Ltd.
TA 28	INCOFF AEROSPACE, Ltd.	TA 57	VULPES-NR, Ltd.
TA 29	INTERBUS, Ltd.		

Table 2. Eigenvalues of correlation matrix

Component	Principal Component Analysis => 29 indicators			
	<i>Eigenvalues</i>	<i>% of Variance</i>	<i>Eigenvalues cumulative</i>	<i>Eigenvalues cumulative (%)</i>
01	6.3360	21.848	6.3361	21.8484
02	4.3053	14.846	10.6414	36.6943
03	3.3458	11.537	13.9872	48.2316
04	2.4925	8.5950	16.4797	56.8266
05	2.2615	7.7983	18.7413	64.6250
06	1.8217	6.2816	20.5629	70.9066
07	1.5343	5.2906	22.0972	76.1972
08	1.1650	4.0173	23.2622	80.2145
09	1.0701	3.6900	24.3323	83.9045
10	1.0053	3.4667	25.3376	87.3712
11	0.8958	3.0891	26.2335	90.4603

Table 2. Continued

Component	Principal Component Analysis => 29 indicators			
	<i>Eigenvalues</i>	<i>% of Variance</i>	<i>Eigenvalues cumulative</i>	<i>Eigenvalues cumulative (%)</i>
12	0.7493	2.5839	26.9828	93.0442
13	0.5890	2.0311	27.5718	95.0752
14	0.3475	1.1984	27.91937	96.2736
15	0.2924	1.0084	28.2118	97.2820
16	0.2491	0.8590	28.4609	98.1410
17	0.1532	0.5284	28.6141	98.6694
18	0.1410	0.4863	28.7552	99.1558
19	0.0909	0.3133	28.8460	99.4691
20	0.0570	0.1965	28.9030	99.6655
21	0.0462	0.1592	28.9492	99.8248
22	0.0329	0.1136	28.9821	99.9383
23	0.0152	0.0525	28.9973	99.9908
24	0.0021	0.0072	28.9994	99.9980
25	0.0005	0.0018	28.9999	99.9998
26	0.0004	0.0002	29.0000	100.0000
27	0.0001	0.0001	29.0000	100.0000
28	0.0000	0.0000	29.0000	100.0000

Source: own processing in STATISTICA software.

Table 3. Factor loadings table

Indicators	Factor Loadings (factor scores); Extraction: Principal components; Method Varimax raw; Marked loadings are >.700000					
	<i>Factor 1</i>	<i>Factor 2</i>	<i>Factor 3</i>	<i>Factor 4</i>	<i>Factor 5</i>	<i>Factor 6</i>
Quick Ratio (QR)	0.9799	0.0257	-0.0249	-0.0823	0.0109	0.1045
Current Liquidity (CL)	0.9752	0.0654	-0.0181	-0.0760	0.0139	0.1296
Total Liquidity (TL)	0.9371	0.0329	0.0192	0.2677	0.0286	0.1232
Net Cash (NC)	0.2026	-0.0444	-0.0272	0.2156	-0.0350	-0.1429
Cash Assets (CA)	0.1355	0.6771	0.0083	0.2857	-0.0212	-0.0129
Net Cash Assets (NCA)	0.1350	0.4302	0.07567	0.8221	0.0116	-0.0017
Security Indicator (SI)	0.2626	0.2279	0.0409	0.1767	-0.0121	0.8012
Days Rec. Outstanding (DRO)	-0.0755	0.0182	0.9248	0.0066	0.0028	0.0299
Days Inv. Outstanding (DIO)	0.0609	-0.0830	0.2410	0.9277	0.0442	0.0015
Days Pay. Outstanding (DPO)	0.0285	-0.0892	0.8612	-0.0009	-0.0206	-0.3318
Turnover Money Period (TMP)	-0.0166	0.0365	-0.2904	0.7545	0.0590	0.3691
Assets Turnover Ratio (ATR)	-0.2550	0.1325	-0.5227	-0.1071	0.0865	-0.0910
Turnover of LT Assets (TLA)	-0.1121	0.7699	-0.1711	-0.0253	0.0105	-0.0308
Debt-to-Assets Ratio (DAR)	-0.1728	-0.0246	0.0783	-0.1292	-0.0682	-0.9383
Equity Ratio (ER)	0.1728	0.0246	-0.0783	0.1292	0.0682	0.9383

Table 3. Continued

Indicators	Factor Loadings (factor scores); Extraction: Principal components; Method Varimax raw; Marked loadings are >.700000					
	Factor 1	Factor 2	Factor 3	Factor 4	Factor 5	Factor 6
Debt-to-Equity Ratio (DER)	-0.0829	-0.0818	0.0936	-0.0676	-0.5571	0.0273
Equity to Debt Ratio (EDR)	0.8880	-0.0174	0.0154	0.3382	0.0473	0.1302
Degree of Over-Capital. (DOC)	0.0861	0.8994	0.0082	0.0054	0.0152	0.1194
Degree of Under-Capit. (DUC)	-0.0267	0.9443	0.0315	0.0199	0.0066	0.0246
Interest Coverage Ratio (ICR)	0.0380	0.0260	-0.4900	0.1422	-0.3490	-0.0254
Interest Load (IL)	-0.0197	0.1416	0.0724	-0.0416	-0.0310	0.1570
Loan Indebtedness (LI)	-0.2056	0.4193	0.0569	-0.0008	0.1435	-0.0042
Loan Repayment Period (LRP)	-0.1635	0.7219	-0.1626	-0.0131	0.0704	0.0003
Stability Indicator (SI)	0.2031	0.8820	0.0079	0.0652	0.0219	0.1330
Return on Assets (RA)	-0.0854	0.0215	-0.4897	0.0707	-0.0678	0.6388
Return on Equity (RE)	-0.0372	-0.0213	0.0159	-0.0364	-0.9524	0.0067
Return on Sales (RS)	0.2123	-0.0271	-0.2153	0.8198	-0.0153	0.3786
Return on Costs (RC)	0.1189	-0.0379	-0.4343	0.5187	-0.1317	0.2436
Return on Investment (RI)	-0.0346	-0.0221	-0.0559	-0.0037	-0.8937	-0.1318
Exploration Variance	4.0682	4.5383	2.82710	3.4880	2.2153	3.4263
Prp. Total	0.1403	0.156493	0.0975	0.1203	0.0764	0.1182

Source: own processing in STATISTICA software

Table 4. Travel agencies performance ranking

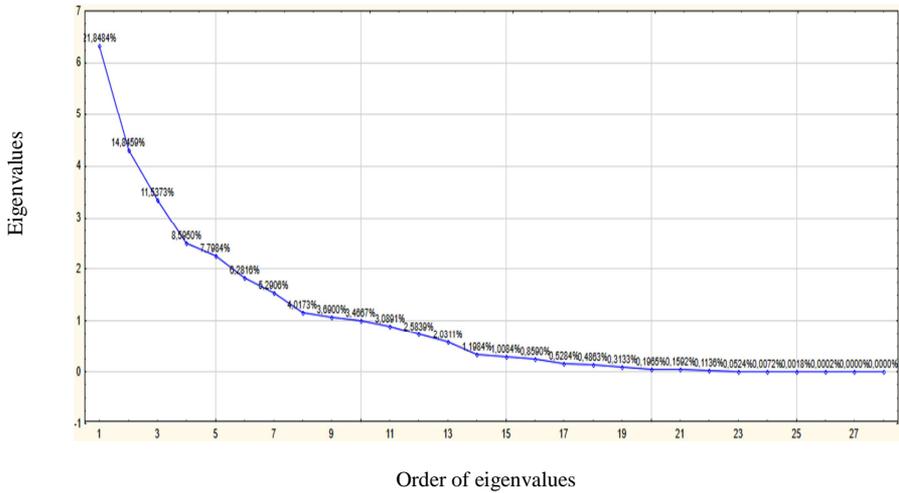
Order of TA	EVA	PCA	Order of TA	EVA	PCA
01.	TA 43	TA 27	30.	TA 44	TA 30
02.	TA 42	TA 21	31.	TA 39	TA 23
03.	TA 04	TA 40	32.	TA 38	TA 16
04.	TA 52	TA 18	33.	TA 20	TA 37
05.	TA 56	TA 04	34.	TA 06	TA 48
06.	TA 33	TA 32	35.	TA 37	TA 51
07.	TA 46	TA 15	36.	TA 57	TA 53
08.	TA 07	TA 42	37.	TA 26	TA 49
09.	TA 27	TA 47	38.	TA 35	TA 41
10.	TA 01	TA 01	39.	TA 40	TA 17
11.	TA 51	TA 38	40.	TA 53	TA 02
12.	TA 32	TA 43	41.	TA 14	TA 31
13.	TA 11	TA 14	42.	TA 03	TA 06
14.	TA 15	TA 09	43.	TA 34	TA 26
15.	TA 13	TA 56	44.	TA 16	TA 33
16.	TA 36	TA 13	45.	TA 29	TA 52
17.	TA 47	TA11	46.	TA 30	TA 12
18.	TA 22	TA 05	47.	TA 48	TA 22

Table 4. Continued

Order of TA	EVA	PCA	Order of TA	EVA	PCA
19.	TA 55	TA 20	48.	TA 19	TA 10
20.	TA 17	TA 36	49.	TA 24	TA 55
21.	TA 41	TA 44	50.	TA 12	TA 24
22.	TA 18	TA 03	51.	TA 49	TA 45
23.	TA 21	TA 25	52.	TA 09	TA 57
24.	TA 45	TA 34	53.	TA 28	TA 54
25.	TA 23	TA 35	54.	TA 54	TA 46
26.	TA 31	TA 50	55.	TA 10	TA 29
27.	TA 02	TA 19	56.	TA 08	TA 28
28.	TA 25	TA 07	57.	TA 05	TA 08
29.	TA 50	TA 39			

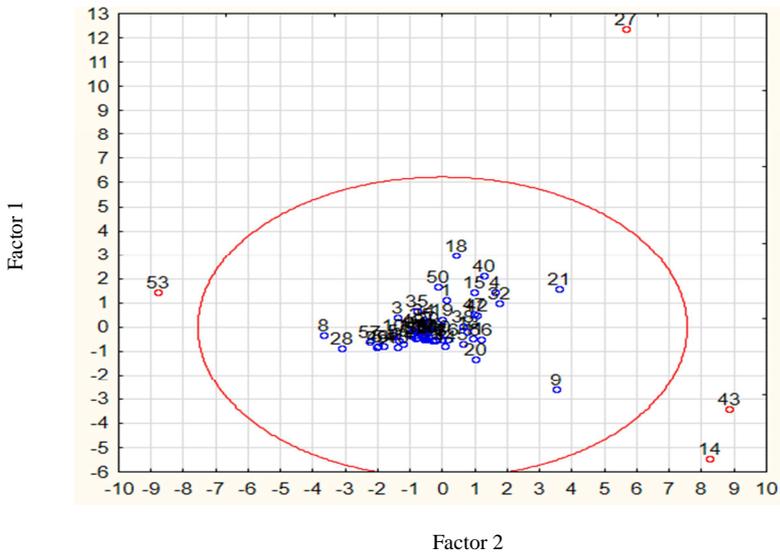
Note: *TA – travel agency

Figure 1. Scree plot



Source: own processing in STATISTICA software.

Figure 2. Component Score Figure



Source: own processing in STATISTICA software.

Figure 3. Average performance of travel agencies based on the EVA indicator

