“Business performance assessment of small and medium-sized enterprises: Evidence from the Czech Republic”

AUTHORS
Vojtech Stehel
Jakub Horak
Tomas Krulicky

ARTICLE INFO
Vojtech Stehel, Jakub Horak and Tomas Krulicky (2021). Business performance assessment of small and medium-sized enterprises: Evidence from the Czech Republic. Problems and Perspectives in Management, 19(3), 430-439. doi:10.21511/ppm.19(3).2021.35

DOI
http://dx.doi.org/10.21511/ppm.19(3).2021.35

RELEASED ON
Wednesday, 22 September 2021

RECEIVED ON
Thursday, 28 January 2021

ACCEPTED ON
Monday, 13 September 2021

LICENSE
This work is licensed under a Creative Commons Attribution 4.0 International License

JOURNAL
“Problems and Perspectives in Management”

ISSN PRINT
1727-7051

ISSN ONLINE
1810-5467

PUBLISHER
LLC “Consulting Publishing Company “Business Perspectives”

FOUNDER
LLC “Consulting Publishing Company “Business Perspectives”

NUMBER OF REFERENCES
25

NUMBER OF FIGURES
8

NUMBER OF TABLES
2

© The author(s) 2021. This publication is an open access article.
Abstract

Business performance assessment is one of the basic tasks of management. Business performance can be assessed using a number of methods. The basic ones include financial analysis, Balanced Scorecard or Economic Value Added (EVA). The paper is focused on SME business performance assessment based on Economic Value Added, calculated using the INFA build-up model. According to this method, companies were divided into four categories. The first category included companies with a positive EVA value. The second category included companies with a positive EVA result above the risk-free rate. The third category included companies with a positive economic result above the risk-free rate. The fourth category included companies with a negative economic result. The model did not include companies with negative equity. The input represented 15 predictors based on their financial statements. The data were normalized and all extreme values, likely caused by a data rewriting error, were removed. Company performance is visualized by comparing Principal Component Analysis and Kohonen neural networks. Compared to similar research, the methods are compared using the data that analyzes the performance of companies. Both methods made it possible to visualize the given task. With regard to the purpose of facilitating the interpretation of the results, for the given case, the use of PC seems to be more appropriate.

Vojtech Stehel (Czech Republic), Jakub Horak (Czech Republic), Tomas Krulicky (Czech Republic)

INTRODUCTION

When running a business, it is often necessary to make decisions in very complex processes (Synek, 2011). Assessing the influence of individual predictors is often difficult and time-consuming, especially in the case of a dimensional decision problem when individual predictors influence the result (Oo & Thein, 2019). For business managers, mathematical models are often difficult to understand and interpret. Here, the visualization of data can be very useful for the interpretation of the results supporting the decision-making process (Marakas, 1999). The objective is to compare the use of the PCA method and Kohonen neural networks (Matlabacademy, 2019) for the visualization purposes in the classification of businesses. A comparison of these methods (Brosse et al., 2001) has already been analyzed in technical fields (Blayo & Demartines, 1991). Newly, these methods are also used to analyze economic factors predicting the performance of small and medium-sized enterprises in the Czech Republic. Thus, the paper is aimed at assessing SMEs’ business performance based on Economic Value Added, calculated using the INFA build-up model.
1. THEORETICAL BASIS

1.1. Business performance assessment

There are several approaches to assessing business performance. The traditional approach deals with horizontal and vertical financial analysis (Vochozka, 2011), where it is possible to assess a wide range of indicators from activity to Return on Equity (ROE), which is the most frequently used one. ROE is calculated as follows:

\[
ROE = \frac{EAT}{E},
\]

where \(EAT\) is earning after tax, \(E\) is equity.

The approach using horizontal and vertical analysis has a number of benefits and shortcomings. The main shortcomings include an independent view of individual indicators that can often be distorted by the character of the business or high degree of risk, which is not considered in the formula.

Another possible approach is Value Based Management (Nývltová & Marinič, 2010). This method compares the overall benefit of the investment with its costs. The calculation is carried out using the following formula:

\[
Rt = \left( (Pt + 1 - Pt) + Dt + 1 \right) / Pt,
\]

where \(Rt\) is the total return to the shareholder; \(Pt + 1\) is the value (price) of investment at the end of the period (given by the share price and number of shares); \(Pt\) is the value (price) of investment at the beginning of the period (given by the share price and number of shares); \(Dt + 1\) is dividend yield.

This method is the base of the approaches based on Market value added and Economic value added. Performance can be assessed in terms of economic value added (Neumaierová, 1998), whose results can be used for business management (Neumaierová, 2003). Moreover, EVA results can be used as an input for business valuation (Mařík, 2011), as an assessment of financial health of companies (Vrbka & Rowland, 2019) or as a motivation system for managers (Kislingerová, 2007).

On the other hand, the performance can be assessed by Balanced Scorecard (Kaplan & Norton, 1992). Alternative possibilities of business performance assessment can include neural networks and others (Machová & Vochozka, 2019).

This study also focuses on Economic Value Added, since it is a clearly measurable method that is also suitable for small and medium-sized enterprises.

1.2. Economic Value Added (EVA)

EVA is calculated using the build-up model as follows (Neumaierová, 1998). There is an alternative approach based on the CAPM method (Vochozka, 2011); however, it is not suitable for small and medium-sized enterprises.

First of all, cost of equity is calculated:

\[
r_e = \frac{WACC \cdot \left( \frac{C}{A} - (1-t) \right) \cdot \frac{r_e}{D} \left( \frac{C}{A} \cdot \frac{E}{A} \right)}{E/A},
\]

where \(A\) represents total assets, \(E\) is equity, \(D\) is long-term liabilities, \(r_e\) is cost of borrowed capital, and \(WACC\) – average weighted cost of capital.

The average weighted cost of capital is calculated as follows:

\[
WACC = r_f + r_{LA} + r_{business} + r_{FinStab},
\]

where \(r_{business}\) is business risk, \(r_{FinStab}\) is financial stability risk, \(r_f\) is risk-free rate, and \(r_{LA}\) is risk involved in capital structure.

Economic value added is finally calculated as follows:

\[
EVA = (ROE - r_e) \cdot E,
\]

where \(ROE\) is return on equity, and \(r_e\) – alternative cost of equity.

1.3. Principal component analysis

Principal component analysis is a method that reduces the number of predictions. Generally, the reduction of decision problem to the key components is very important for the management,
since it clarifies the decision process and makes
the interpretation easier. The reduction is carried
out by means of converting the original predic-
tors, which are partly correlated into a new space
with a reduced number of predictors (Shaw, 2003)
that are independent of each other. Due to this
fact, complex methods with reduced data can be
applied, and new predictors can be used to visu-
alize the task more easily. The method appeared
at the beginning of the 20th century (Pearson,
1901), and was subsequently developed and named
(Hotelling, 1933). Its greater use is associated
with the development of information technology,
where visualization plays a significant role and is
not time-consuming in terms of individual partial
measurements.

An important feature of this method is that
each of the new components is a linear combi-
nation of the original predictors. This prevents
the loss of the original data. The linear combi-
nation of the individual parts of the predictors
into a component enables monitoring the vari-
cance of the relevant component. The greater the
variance, the more important is the component
for the prediction. Sorting the individual com-
ponents by variance allows dividing the compo-
nents into significant and less significant and
determining the percentage importance of the
component. Business management thus has the
information on the parameter that influences
decision making, as well as on the importance
of this parameter. In practice, it is not possible
to address absolutely all the facts in the micro
and macro environment. For this reasons, vari-
ous systems are used, such as ABC, where man-
agement is first and foremost committed to the
most important components with the greatest
impact on the result, and subsequently to other
components.

Figure 1 shows the principle of PCA. On the left
side, there is a data set whose location in space is
determined by two predictors. On the right side,
there is a line that best defined the data in the giv-
en space. The slope of the line is determined on
the basis of minimizing the distance between the
individual dots from the line.
The line in Figure 1 (the right side) is a new component (dimension) of PCA, which shows the greatest variance for the given task. Due to this, it is possible to redraw the task into a one-dimensional space (Figure 2). This redrawing causes minimal distortion of the data compared to the situation when the data is entered in the x- or y-axis (in the previous case). Thus, it was possible to reduce the number of variables with a minimum loss of information. The PCA method also allows other dimensions to be calculated and data displayed with nearly zero loss of information.

1.4. Kohonen networks

Kohonen networks (Kohonen, 1982) are neural networks that learn without a teacher (Vojáček, 2006). The basic idea consists in the random arrangement of neurons in two-dimensional space (Kohonen, 1989). In the following steps, the individual neurons are moved to represent certain data clusters on the basis of the predictors (Buhmann & Kuhnel, 1992). Each predictor is connected with an individual neuron. The strength of the connection determines the position of a given neuron (Vondrák, 2000). The principle is shown in Figure 3. Figure 3 shows Kohonen network with nine neurons (3x3), and two inputs (predictors), which are connected with the individual neurons.

2. METHODOLOGY AND DATA

After generation from the Bisnode’s Albertina database, the data set contained a total of 42,592 data rows. Each row contained the following information:

1. Identification of a company: name, company identification number, municipality, region, municipality size.

2. Information about a company: NACE, number of employees, code of NACE5A, M_NACE, OKEČ5A, year of financial statement.

3. Financial statements for the given year: balance sheet, profit and loss account, statement of cash flows.

4. Selected indicators of profitability, activity, liquidity, indebtedness, productivity, and others.

Preparation of data (MS EXCEL):

1. Calculation of EBIT (by adding taxes, interests and EAT).

2. Calculation of ROA (EBIT/Assets).
3. Calculation of ROE (EAT/Equity).

4. Calculation of EVA Equity (according to the Neumaiers methodology – MPO).

5. The data set contained all companies meeting all the following conditions.

6. Company size coding by the number of employees is in Table 1.

7. NACE 5A codes were changed into sections of CZ-NACE (i.e. only the first letter of the classification).

Table 1. Company size coding

| Original value | Code |
|---------------|------|
| 0             | 0    |
| 1-5           | 1    |
| 6-9           | 2    |
| 10-19         | 3    |
| 20-24         | 4    |
| 25-49         | 5    |
| 50-99         | 6    |
| 100-199       | 7    |
| 200-249       | 8    |
| 250-499       | 9    |

The modification reduced the data set from 42,592 rows to 29,611 rows (in Table 2).

Table 2. Number of companies in original and modified data set

| Year | Original data set | Modified data set |
|------|------------------|-------------------|
| 2013 | 7,976            | 5,705             |
| 2014 | 8,059            | 5,492             |
| 2015 | 8,046            | 5,449             |
| 2016 | 8,803            | 5,982             |
| 2017 | 9,708            | 6,983             |
| In total | 42,592       | 29,611            |

The resulting data set also contains a complete financial statement with several calculated data stated above. The data can thus be considered predictors (more than 100). For these reasons, the resulting set of companies will be reduced to the main components, and in accordance with the Neumaiers’ methodology (Ministry of Trade and Industry, 2019), a category of the companies will be determined following the scheme below.

- Value-generating companies (positive EVA value) – \( \text{ROE} > r_e \).
- Companies with positive profit and negative EVA value, but exceeding the risk-free rate \( r_f - r_e > \text{ROE} > r_f \).
- Companies with positive profit, where \( \text{ROE} \) does not achieve the risk-free rate – \( r_e > r_f > \text{ROE} > 0 \).
- Companies with negative profit.

The data will be involved in further analyses. The main predictors are as follows:

- Total assets – CZK thousands.
- Fixed assets – CZK thousands.
- Current assets – CZK thousands.
- Equity – CZK thousands.
- Borrowed capital – CZK thousands.
- Short-term liabilities.
- Personnel costs – CZK thousands.
- Fixed intangible and tangible assets depreciation – CZK thousands.
- Operating result – CZK thousands.
- Interest payable – CZK thousands.
- Financial result – CZK thousands.
- Economic result for accounting period (+/-) – CZK thousands.
- Income tax on ordinary and extraordinary activity – CZK thousands.
- Turnover – CZK thousands.
- Company category.

Displaying more than 20,000 companies was complicated because their high number caused the
creation of continuous color clusters that covered less frequent clusters in groups. For these reasons, the number of companies was reduced to 4,000. The percentage of individual categories remained the same. The data was normalized for the methods, as otherwise, the methods would provide erroneous results (Abdi & Williams, 2010). The normalization was carried out using the "normalize" command. Furthermore, extreme values were removed using the "outliers" command.

3. RESULTS AND DISCUSSION

In the first phase, the PCA analysis was carried out. With the normalized data set, the following command was executed:

\[
dimension, score, \sim, \sim, percentage = pca(table\{;6:end-1\}),
\]

where \(dimension\) represents new coordinates for PCA space; \(score\) – values of individual companies in new space; \(percentage\) – importance (variance) of individual components; \(pca\) – command for execution of analysis; \(table\) – data source, where the individual rows represent the companies and columns are the predictors described in the methodology.

By means of pareto (procenta) command, a new graph was generated (Figure 4). Figure 4 clearly shows that it is possible to obtain about 80% of the information from the first three components, and more than 70% from the first two components. The remaining components are thus of relatively negligible importance.

By means of the “biplot” command, it is possible to see how the individual parts participate in a given component. A positive value represents a positive correlation, while a negative value represents a negative correlation. The result is shown in Figure 5. There are only two components. It is clear from the figure that most components are dependent on each other. For example, the economic result (marked as VH in the figure), Tax, and Operating result are positively correlated both for the fist and the second component. On the contrary, interest payable is negatively correlated with the 2\textsuperscript{nd} component and positively correlated with the 1\textsuperscript{st} component. Similarly, it is possible to interpret other components of the predictors.

Using the “gscatter” command, the position of companies in two-dimensional space can be visualized.

In the next stage, Kohonen neural network with the dimensions of 5x5 was created. When creating this network, it is possible to see the mutual dependence of the individual predictors. The result can be seen in Figure 7. The more different color for each node, the less dependent the relevant pre-
dictors are on each other. For example, predictors 1 and 5 are highly correlated for most neurons. On the contrary, predictor 11 is very little correlated to predictor 12.

Figure 8 shows the position of the companies and neural networks. On the left side, there are neurons in space by companies. The right side shows a standardized graph showing the percentage of a company category for the given neuron. Particularly the right part of the graph shows that for certain clusters, Kohonen network allows creating a representative element (neuron), which will be in the relevant category by company performance.

By means of the “gscatter” command, the position of companies in two-dimensional space can be visualized. Moreover, it is possible to distinguish the individual sets of companies from each other by means of color (see Figure 6). Figure 6 clearly shows 4 groups of companies created in the graph. These groups represent the category of a company according to the INFA methodology. Thus, to
a certain extent, the method can categorize the companies according to their performance.

Figure 8 shows the position of companies and neural networks. On the left side, there are neurons in space by companies. The right side shows a standardized graph showing the percentage of a company category for the given neuron. Particularly the right part of the graph shows that for certain clusters, Kohonen network allows you to create a representing element (neuron), which will be in the relevant category by company performance.

Both methods allow visualizing business performance, which is important for decision-making systems in business management. Both methods have their advantages and disadvantages. The PCA method eliminates mutually correlated pre-
dictors and can determine the amount of data lost by the reduction and visualization of only two PCA components. Unlike PCA, there is no loss of information in visualization in the case of Kohonen networks. However, their interpretation is significantly more complicated and thus less applicable for the management in practice in this case.

CONCLUSION

This study calculated business performance based on Economic Value Added, which is the key information for business management. The calculation method was based on the INFA build-up model. On the basis of this value, performance of these enterprises was visualized using selected items of accounts. Despite its spatial complexity, it was possible to carry out the visualization so that it is useful for the management.

Both methods can be used to visualize company performance. Performance visualization can facilitate the decision-making process in a number of cases (e.g. about the cooperation with a given company, equity investment, etc.). Both methods can provide analytic tools to identify which parameters were used to decide on the classification in a concrete group. With regard to the allowed extent of the paper, these analytic methods were presented and described from the perspective of the most important outcomes.

The objective of the analysis was to simplify the decision-making process by means of visualization. In other words, the visualization was supposed to lead to a segmentation that could be easily interpreted. Given the purpose of the analysis, PCA seems to be a more effective visualization method in this particular case due to easier and more unambiguous identification of the classification of individual companies into sets that express company performance. It is also easier to understand and interpret a company’s position in a given space.

The limitation of the study is mainly in the input data, which is based on the obligation of companies in the Czech Republic to publish their financial statements. Nevertheless, the statements are subject to tax optimization, which can be quite easy to implement in the case of small enterprises. In other words, a category 3 or 4 company may, in fact, bring a sufficient return on resources for the owner. However, this return is not shown in the financial statement with respect to the tax deduction. Finally, it shall be mentioned that, despite the legal obligations, not all companies complete financial statements. This is especially true for companies in difficulty. This distorts a number of companies in individual categories.

AUTHOR CONTRIBUTIONS

Conceptualization: Vojtech Stehel, Jakub Horak.
Data curation: Jakub Horak, Tomas Krulicky.
Formal analysis: Jakub Horak, Tomas Krulicky.
Funding acquisition: Vojtech Stehel.
Investigation: Vojtech Stehel.
Methodology: Vojtech Stehel.
Project administration: Vojtech Stehel.
Resources: Jakub Horak.
Software: Vojtech Stehel, Tomas Krulicky.
Supervision: Vojtech Stehel.
Validation: Vojtech Stehel.
Visualization: Vojtech Stehel.
Writing – original draft: Vojtech Stehel, Jakub Horak.
Writing – review & editing: Vojtech Stehel.

http://dx.doi.org/10.21511/ppm.19(3).2021.35
ACKNOWLEDGMENT

This study has been supported by the Technology Agency of the Czech Republic under project No TL01000349.

REFERENCES

1. Abdi, H., & Williams, L. J. (2010). Principal component analysis. Wiley Interdisciplinary Reviews: Computational Statistics, 2(4), 433-459. https://doi.org/10.1002/wics.101

2. Blayo, F., & Demartines, P. (1991). Data analysis: How to compare Kohonen neural networks to other techniques? In A. Prieto (Ed.), Artificial Neural Networks (Lecture Notes in Computer Science) (pp. 469-476). Springer, Berlin, Heidelberg. https://doi.org/10.1007/BFb0035929

3. Brosse, S., Giraudel, J. L., & Lek, S. (2001). Unsupervised and supervised data clustering with competitive neural networks. In IJCNN International Joint Conference on Neural Networks (pp. 796-801). https://doi.org/10.1109/IJCNN.1992.227220

4. Buhmann, J., & Kuhnel, H. (1992). Unsupervised and supervised data clustering with competitive neural networks. In IJCNN International Joint Conference on Neural Networks (pp. 796-801). https://doi.org/10.1109/IJCNN.1992.227220

5. Hotelling, H. (1933). Analysis of Artifical Neural Networks. Berlin: Springer-Verlag.

6. Kohonen, T. (1989). Self-organizing and associative memory (3rd ed.). Berlin: Springer-Verlag.

7. Kohonen, T. (2001). Self-organizing and associative memory (3rd ed.). Berlin: Springer-Verlag.

8. Kislingerová, E. (2007). Manažerské finance [Managerial Finance] (2nd revised and expanded edition). Prague: C. H. Beck.

9. Marínková, E. (2007). Financial management: modern methods and trend. Prague: Grada.

10. Maráková, G. M. (1999). Decision support systems in the twenty-first century. Upper Saddle River, N.J.: Prentice Hall.

11. Mařík, M. (2011). Finance – základní metody a postupy [Business valuation methods: valuation process – basic methods and procedures] (3rd ed.). Prague: Ekopress.

12. Mařík, M. (2011). Finance – základní metody a postupy [Business valuation methods: valuation process – basic methods and procedures] (3rd ed.). Prague: Ekopress.

13. Matlabacademy. (2019). Machine Learning with MATLAB. USA: The MathWorks. Retrieved from https://matlabacademy.mathworks.com

14. Ministry of Industry and Trade. (2019, December 12). Machine Learning with MATLAB. USA: The MathWorks. Retrieved from https://matlabacademy.mathworks.com

15. Ministry of Industry and Trade. (2019, December 12). Machine Learning with MATLAB. USA: The MathWorks. Retrieved from https://matlabacademy.mathworks.com

16. Nývltová, R., & Marinič, P. (2010). Finanční řízení podniku: moderní metody [Financial management: modern methods and trend]. Prague: Grada.

17. Pearson, K. (1901). On Lines and Planes of Closest Fit to Systems of Points in Space. Philosophical Magazine, 2(11), 559-572. https://doi.org/10.1080/14786440109462720

18. Pearson, K. (1901). On Lines and Planes of Closest Fit to Systems of Points in Space. Philosophical Magazine, 2(11), 559-572. https://doi.org/10.1080/14786440109462720

19. Pearson, K. (1901). On Lines and Planes of Closest Fit to Systems of Points in Space. Philosophical Magazine, 2(11), 559-572. https://doi.org/10.1080/14786440109462720

20. Pearson, K. (1901). On Lines and Planes of Closest Fit to Systems of Points in Space. Philosophical Magazine, 2(11), 559-572. https://doi.org/10.1080/14786440109462720

21. Pearson, K. (1901). On Lines and Planes of Closest Fit to Systems of Points in Space. Philosophical Magazine, 2(11), 559-572. https://doi.org/10.1080/14786440109462720

22. Pearson, K. (1901). On Lines and Planes of Closest Fit to Systems of Points in Space. Philosophical Magazine, 2(11), 559-572. https://doi.org/10.1080/14786440109462720

23. Pearson, K. (1901). On Lines and Planes of Closest Fit to Systems of Points in Space. Philosophical Magazine, 2(11), 559-572. https://doi.org/10.1080/14786440109462720

24. Pearson, K. (1901). On Lines and Planes of Closest Fit to Systems of Points in Space. Philosophical Magazine, 2(11), 559-572. https://doi.org/10.1080/14786440109462720

25. Pearson, K. (1901). On Lines and Planes of Closest Fit to Systems of Points in Space. Philosophical Magazine, 2(11), 559-572. https://doi.org/10.1080/14786440109462720