Company Performance Measurement with Use of Genetic Algorithm

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Abstract: This paper deals with measurement of company performance. Different methods may be used for measuring of performance of companies. In this article, the authors pay attention to the use of value-based methods in the measuring of performance, like the economic value added concept (EVA); and the traditional measuring of performance and management of companies with the use of financial analysis indicators. This traditional approach is preferred by managers, while the use of EVA is often restrained due to a lack of input information or difficulties in calculation. In the course of research, the authors inquire into a question whether a relationship between the value of EVA and the selected indicators of traditional financial analysis may be found. In order to prove that, the authors employ genetic algorithms for clustering into different groups of performance and they embark on testing of linear dependence. They show that, to a certain degree of probability, this relationship may be proved with selected parameters. Outcomes of this research may be used for performance evaluation in the business practice. Conclusions of this research also may be exploited in the construction of creditworthiness and bankruptcy prediction models.

Key-words: Performance, measurement, financial indicators, Economic value added, clustering, generic algorithm

1 Introduction

The choice of a suitable indicators for measuring company’s performance is one of the most widely discussed areas in corporate management. This paper attempts to analyse company’s performance through different indicators – selected indicators of financial analysis and complex performance indicator represented by EVA; and their mutual relationship. EVA as a value-based measure should have a leading role in corporate management strategy, and the more traditional income measures should act as facilitators of providing supporting information. Gathering of the input information for the EVA calculation does, however, face many obstacles in practice, and therefore managers tend to limit themselves to the results of ordinary financial analysis with evaluation of partial indicators. In order to evaluate the performance and financial health of a company, it is however necessary to assess all groups of indicators.
and their mutual influences. Particularly problematic may be the assessment of, for example, liquidity as a separate standpoint of management – high liquidity signalizes a solid capability to pay off debts, however it may also cause an uneconomic loss in circulating capital and therefore a decrease in profitability. A high rate of turnover in assets may be caused by a correct exploitation of equity, but also by its high amortization (a low degree of investments). The problem with traditional indicators of performance in the form of profitability indicators is that they cannot do without extra information concerning primarily the line of liquidity, indebtedness, relationships between property and financial structures or the use of assets of the company (see Chandrapala et al. 2010).

The strong point of EVA indicator (eventually including its pyramidal decomposition), is a complex measurement of the success of a company, which counters several blind spots of the traditional financial analysis. EVA may therefore be recommended, despite its relative difficulty, for analysis in those cases where the analyst may access the important inside information from the company. However, there are cases where there is no sufficient time or information for the adaptation of accounting data and thus such difficult adjustments may not be feasible. This paper deals with a question whether there may be a relationship between the EVA value and the values of selected parameters of financial analysis in order, even without the difficult EVA calculations, for a company to be categorized, with certain probability, into a specific performance group on the basis of financial analysis indicators. The authors of this paper have used for this purpose the genetic algorithms for clustering into groups of performance and tested whether a linear relationship between EVA indicator and selected financial analysis indicators may be proved (linearity has been proved on the 0.05 significance level). Conclusions of this research may be exploited in the construction of creditworthiness and bankruptcy prediction models.

2 Measuring a Company’s Performance

If a company wants to be successful, it is absolutely essential that the criteria of its performance and the ways to express and measure it are clearly defined. In the past, the main goal of a company was very often defined as maximization of profit. In last decades, the tendency has been to to accept the criterion of the growth of value (Stewart, 1993, Bacidore et al., 1997, Biddle et al., 1997 and other authors). The value-related concept then becomes the way of finding a common denominator for all activities within the company interconnecting all levels of management.

**Economic Value Added (EVA)**

1 is a widely used performance measure in Value Based Management. EVA is an indicator, which is considered by certain groups of experts to be unique with respect to the measurement of the performance of an enterprise and accepted as a management concept. Essentially, it shows what additional value is an enterprise capable to create by its activity in comparison to the use of capital for other investment opportunities with equal risk.

There are several models, which can be used to calculate EVA. Here we are using the Stern & Stewart model (Stewart, 1993):

\[ EVA = NOPAT - (C \times WACC) \]

where NOPAT - Net operating profit after tax, C - Invested capital, WACC - Weighted average cost of capital

From equation (1) it can be seen that EVA is expressed as an absolute value. In this form it complicates the possibility to compare the companies’ performance. However, after the modification of (1) and simple rearrangement we obtain the following equation:

\[ EVA = (RONA - WACC) \times C \]

and for a comparison between companies and evolution in time we may use the spread (RONA – WACC). Another possibility is to use ratios, for example EVA/Sales. The calculation of EVA is quite simple, as long as the net operation profit and capital expenses are available. Here a problem can be encountered; Stewart (1993) shows more than 160 possible modifications to evaluate net operation profit needed for the calculation of EVA. In the case of cost of capital the often occurring problem is with the calculation of cost of equity - none of the available models gives an unambiguous result. The critics of

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1 EVA is a registered mark of Stern Stewart&Co.
EVA are pointing out that adjustments for calculations are too difficult and discouraging managers from its use. Managers, on the other hand, prefer the traditional and simple financial analysis indicators. This conclusion is also supported by a survey on a sample of 402 Czech companies in 2010 (Pavelková, Knápková, Jirěšíková, 2011). Most frequently used tools are financial indicators based on the data from financial accounting, which are used on average by approx. 94% of the companies participated in the survey in comparison with using EVA by 26% of the companies (see Fig.1).

The financial analysis is a traditional and well-known tool in business practice for measuring of financial position of the company and its financial condition. Results are used for evaluating the past processes, detecting trends and should be used even for the evaluation of profitability and feasibility of accomplishment of future plans in the development of companies. The financial analysis should play a role of a tool that may help with evaluation of financial performance of the company as a follow-up to the development in financial indicators. The financial analysis indicators measure particular areas of company management aimed at monitoring of profitability, liquidity, indebtedness and activities of an enterprise. The performance of the company generally encompasses all areas of business activity, which must be coordinated in order to get a functional and prosperous enterprise with a perspective of existence in the long run. To assess the performance and financial condition of the company, it is essential to consider all those groups of indicators. Some partial evaluations may be, however, contradictory – a big amount of cash is advantageous from the perspective of company’s liquidity, but decreases its profitability; high indebtedness may lead to higher values in return on equity (and thereby to a positive evaluation in performance development), but decreases the ability to pay off debts, etc. One of the major problems with these indicators is the exclusion of risks from their calculations.

The EVA indicator (eventually with its pyramidal decomposition), on the other hand, presents a complex measurement of successfulness of a company whereby eliminating the weak points of financial analysis; it is therefore highly beneficial to employ this concept for evaluation of performance (despite its relative difficulty) mainly in a case where an analyst has access to a bunch of important inside information on the company. Nevertheless, there may be cases where the arduous adjustments may not be feasible (due to insufficient time or lack of information for adjustment of accounting data). It would be therefore appropriate to analyse, whether there can be found a relationship between the EVA value and the values of selected parameters of financial analysis in order, even without the difficult EVA calculation, for a company to be categorized, with certain probability, into a specific performance group on the basis of financial analysis indicators. For this purpose, the authors use genetic algorithms for clustering into performance groups and test this zero hypothesis:

$H_0: A \text{ linear relationship is proved between EVA and selected financial analysis indicators by means of clustering calculated with use of genetic algorithms.}$

3 Methodology of research

During the research, the authors tested a sample of 258 companies from the plastic industry sector (CZ NACE 22) with following parameters measured:

- $P_0 = \text{spread (RONA – WACC)}$
- $P_1 = \text{return-on-assets (EBIT/assets)}$
- $P_2 = \text{current ratio (current assets/short term liabilities)}$
- $P_3 = \text{indebtedness (equity/assets)}$
- $P_4 = \text{assets turnover (sales/assets)}$

The sample includes companies’ economic results achieved in 2007 (i.e. economic conditions before the start of financial and economic crisis). Companies with extreme figures in individual parameters had been excluded. The authors focused only on one sector of industry for reasons of a better compatibility in margins, property and financial structure, risk and business conditions.

These companies were grouped into clusters with use of genetic algorithms. Cluster analysis problems can be solved by means of genetic algorithms. The advantages of the use of genetic algorithms in economy were described by Safarzyńska (2010), Chen (2005), Shin and Lee (2002), Thawornwong and Enke (2000) and other authors.

The aim of a genetic algorithm as an optimization task is to divide a set of $N$ existing objects into $M$
groups. Each object is characterized by the values of \( K \) variables of a \( K \)-dimensional vector. The aim is to divide the objects into groups so that the variability inside those groups is minimized.

The software MATLAB and its Global Optimization Toolbox are used for the software applications that can be utilized to solve these types of problems. The input data are represented by coordinates \( x_1, x_2, \ldots, x_K \) that characterize the objects. It is possible to define any number of groups.

The fitness function is the sum of squares of distances between the objects and centroids. The coordinates of centroids \( c_{j1}, c_{j2}, \ldots, c_{jK} \) are changed. The calculation assigns the objects to their centroids. The whole process is repeated until the condition of optimum (minimum) fitness function is reached. The process of optimization ensures that the defined coordinates \( x_{i1}, x_{i2}, \ldots, x_{iK} \) of objects and assigned coordinates \( c_{j1}, c_{j2}, \ldots, c_{jK} \) of groups have the minimum distances. The fitness function is expressed by following formula:

\[
\min_{j=1}^{M} \sum_{i=1}^{N} \left( \sum_{l=1}^{K} (x_{il} - c_{jl})^2 \right),
\]

where \( N \) is the number of objects, \( M \) the number of groups, and \( K \) the dimension. In the course of research, following parameters had been tested: \( N = 258, M = 3 \) a successively tested one-, two- and three-dimensional tasks.

The calculation of correlation was executed with help of Pearson correlation coefficient. The hypothesis on linear relationship was verified by a test on 0.05 significance level.

4 Results and discussion

By use of genetic algorithms, clusters of subjects were created according to the results of their financial performance parameters under:

1) EVA (spread RONA – WACC)

2) the results of financial analysis indicators in the form one-, two- and three-dimensional task. The examples in a graphic form are presented in Fig. 2. (with centroids highlighted).²

On the basis of linear relationship testing between EVA and selected financial analysis indicators with use of clustering on the basis of genetic algorithms it is possible to conclude that this relationship is proved on the 0.05 significance level for following parameters (see more in Table 1):

a) one-dimensional tasks:
   - return-on-assets (P1)
   - assets turnover (P4)

b) two-dimensional tasks:
   - return-on-assets and current ratio (P1, P2)
   - return-on-assets and assets turnover (P1, P4)
   - current ratio and assets turnover (P2, P4)

c) three-dimensional tasks:
   - return-on-assets, current ratio and indebtedness (P1, P2, P3)
   - return-on-assets, current ratio and assets turnover (P1, P2, P4),
   - current ratio, indebtedness and assets turnover (P2, P3, P4).

A group of relationships under scrutiny demonstrated the linear relationship and it is possible to utilize these parameters and their combinations for evaluation of performance of the companies. The most frequently represented parameters, which well illustrate the performance of a company, proved to be return-on-assets (P1) and assets turnover (P4). It is also evident that indicator P3 (indebtedness expressed as equity share on capital) is not in correlation with EVA measured by spread. That is confirmed by a theoretical assumption that low indebtedness increases costs on capital and thus reduces the value of the spread. Only in combination of P3 with the groups of indicators P1, P2 and P2, P4 the performance of a company correlation with the spread (EVA) development may be inferred.

The results of this research verify the hypothesis that finding indicators and their combinations, which in the framework of cluster groups demonstrate a

² The aim of using genetic algorithm is to find a matrix that minimizes the sum of the squares of distances in groups from their centroids.
linear relationship with the complex performance indicator EVA (calculated in a form of spread), is possible. These results may be used mainly when there is no sufficient input information indispensable for EVA calculation available, i.e. mainly by external evaluators (analysts), or eventually in the situation of a lack of will or room for implementation of EVA type of indicators into the system of enterprise management. This solution is indeed simplified and substitutive, but it can yield better results than the partial evaluation of particular areas of management with no awareness of the mutual interconnections.

The weak spot of this research is a limited sample of companies under scrutiny, evidential quality and dependability of the reported data (in view of, for example, optimization of taxation).

5 Conclusion
The research dealt with measuring of performance of companies. It pointed out the importance in use of complex indicators such as for instance the EVA concept; and at the same time it showed that the business practice clearly lingers with popular traditional financial analysis indicators that provide partial evaluation of particular areas of management in the companies. This popularity stems from unsophisticated character of calculations and seemingly simple interpretation of the results. This simplicity in construction has been discussed in the first part of this paper – the results and evaluation of partial indicators are not always clearly connected. The results of this research moreover proved that even in spite of the disadvantageous use of partial indicators, it is possible to use those indicators for measurement of performance of a company and overcome the abovementioned weak spot of the analysis with the use of clustering on the basis of genetic algorithms. Output results then may be used in the business practice of companies in various evaluation processes, notably conducted by external entities. Furthermore, they also may be exploited in the construction of creditworthiness and bankruptcy prediction models.

Acknowledgement
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References:
Figure 1 - Utilization of concepts and tools for measurement and management of performance in corporate practice in the Czech Republic. Source: Pavelková, Knápková, Jirčíková (2011)

Figure 2: Examples of two-dimensional graph (P1,P2) and three-dimensional graph (P1,P2,P4) for three clusters

Table 1 - Results of testing of linear dependence of $P(00) = f(Px,Py,Pz)$

<table>
<thead>
<tr>
<th>3 clusters (P00)</th>
<th>$P(00) = f(P1)$</th>
<th>$P(00) = f(P2)$</th>
<th>$P(00) = f(P3)$</th>
<th>$P(00) = f(P4)$</th>
<th>$P(00) = f(P1,P2)$</th>
<th>$P(00) = f(P1,P3)$</th>
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<td>Pearson</td>
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<td>0,0748</td>
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<tr>
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<td>yes</td>
<td>yes</td>
<td>yes</td>
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<table>
<thead>
<tr>
<th>3 clusters (P00)</th>
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<th>$P(00) = f(P2, P4)$</th>
<th>$P(00) = f(P3, P4)$</th>
<th>$P(00) = f(P1,P2,P3)$</th>
<th>$P(00) = f(P1,P2,P4)$</th>
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<td>linearity</td>
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