VALUE GENERATORS IN METALLURGICAL INDUSTRY

Jakub HORÁK, Veronika MACHOVÁ, Tomáš KRULICKÝ

Abstract

Metal industry product, especially steel, represent a key raw material in the Czech Republic for other industries (automotive, mechanical engineering, energy industry or electronics industry). Between 2008 and 2010, the financial crisis affected a number of industries, including metal industry. This caused a decrease of demand for metal industry companies, which implied the fall in their value and affected Czech economy. In today´s constantly changing economic environment, there is a high risk of a fall in the value and performance of companies. Changes in company value can be predicted based on monitoring the company value generators. The objective of the contribution is to identify value generators of companies operating in mining in the CR in 2016. For this purpose, the data of complete financial statements for the given year were used. For each company, EVA Equity value was calculated. Practical methodology for which the value generators were identified was created. For the identification of the value generators, sensitivity analysis within artificial neural networks was used. A total of 13 financial statements items were chosen that are greatly involved in creating a metal industry company value in the Czech Republic.

Key words:

company, metal industry, value generators, performance, EVA Equity

JEL Classification: G32, C45, M21

Introduction

The annual turnover of the EU metallurgical industry is EUR 200 billion, employing 400,000 people. In a year, it produced approximately 200 million tons of steel in more than 500 production plants in a total of 23 states within the EU. The products of this industry, in particular steel, are a key raw material of many industries – automotive, mechanical engineering, power engineering, and electronics (Vilamová et al., 2012). In the CR, metallurgical industry can be considered key in terms of the export base in the Moravian-Silesian region (Sucháček et al., 2017).

Literature overview

Vilamová et al. (2013) evaluated the success and development of the companies operating in metallurgical industry in the CR by analysing individual accounting items. On the basis of this analysis, they found out that if the annual GDP increase is at least 3 %, there is a notable rise of metallurgical industry. It can thus be said that the rise of metallurgical industry is a direct indicator of the GDP growth. According to Kula et al. (2012), the financial crisis in the years 2008 - 2010 affected the majority of industries, including metallurgical industry in the CR. The reflection of this crisis was a decrease in the neighbouring countries´ demand for the metallurgical industry products, which significantly affected the CR economy. In the future, it can be assumed that the growth of the CR economy will be linked to innovations and growth of the metallurgical industry production (Vilamová et al., 2013). Innovations of the manufacturing process are the key to production innovations in all industries using the metallurgical industry products as key components for manufacturing their own products (Vilamová et al., 2012). Innovations in metallurgical industry also increase the competitiveness of such companies (Bakalarczyk et al., 2011). According to Dufek and Šarman (2005), the entry of foreign companies from the EU to the Czech market has been a great contribution for the CR since 2005.

Kafka (2010) tried to evaluate the assumed development of the metallurgical industry in the coming years. He claims that the most important thing for all employees is to be aware of the economic aspects of the company in which they work. Employees even at the least important positions shall be aware of the fact that they do not work with materials, semi-finished products, and machinery, but that they have company money in their hands, and not only the material object to perform their work tasks.

In today´s ever-changing economic environment, there are great risks of a decrease of corporate value and performance. A change in the value of the business can be predicted on the basis of monitoring business value generators (Kazlauskiene, Christauskas, 2008). Value generators influence the success of each business (Vochozka, Machová, 2017), (Zareba, 2014). Setting value generators is a very complex issue, and it has been little addressed in scholarly literature so far. (Kazlauskiene, Christauskas, 2008). Microeconomic theory and journalistic practice is limited to maximizing the profit only, which is insufficient given the structure of income over time. It does not take the aspect of managerial decisions risks into account, either (Zareba, 2014). Value generators differ by industries, with the exception of revenues and earnings per share, which are constant in all industries (Tiwari, Kumar, 2015). In recent years, several methods of measuring a business performance have appeared: EVA, economic profit, EFQM, BSC, performance prism. Each of the methods have their strengths and weaknesses (Rylková, Bernatík, 2014). Hall (2016) focused on 5 manufacturing industries, including metallurgical industry, and tried to determine the individual value generators using statistical methods. For metallurgical industry, the following generators have been determined: earnings per share (EPS), return on assets (ROA), net operating profit after taxes (NOPAT), and economic value added (EVA).

Based on the value generators, the overall performance of a business is determined. According to Rylková and Bernatík (2014) it is necessary for companies to measure their performance sufficiently and properly; otherwise they will not be able to control their business activities adequately. This method of company management is in the literature referred to as a Value-based Management. Introducing this company management method is not easy in terms of the correct identification of value generators. After identification of these generators and focusing on their improvement, there is an increase in their value for the owner. Value generators can change over time depending on the company´s current goals. What is important is to be able to measure these goals and their comparing with the previous goals. With increasing value of these indicators, the value of the company also increase during the identification (Šalaga, 2015). Firk et al. (2016) noted the positive impact of Value-based Management on companies and the related companies´ performance increase.

Currently, there is no common approach to addressing the issue of identifying the key value generators. So far, the most widely used method for determining the company value indicators is sensitivity analysis. Sensitivity analysis, however, can assess the influence of one value generator only, without a complex involvement of other generators (Kazlauskiene, Christauskas, 2008).

Goal and Methodology

The aim of this article is to identify value generators of the enterprise engaged in the sphere of mining in the Czech Republic in 2016.

The analyzed data are stored in Albertina database. What is going to be dealt with are enterprises engaged in metallurgical engineering such as mining and extraction that operated on the Czech market in 2016. CZ NACE classification of economic activities categorizes it in section B: Mining and extraction, paragraph 05 – mining and refinement of black coal and lignite, 06 – oil and natural gas extraction, 07 – extraction and refinement of ore, 08 – other mining and extraction, 09 – supporting activities while mining. The whole data set contains records on 135 enterprises. The data on their complete financial statements (without attachments) are available. From this information, we use the hard data on their balance sheets, profit and loss statements and cash flow statements. The data are recorded in one table; each line contains data on one enterprise. The enterprises are further classified according to the years on the market. Individual columns contain information from financial statements. Subsequently, Economic Value Added for shareholders (owners) of each enterprise in each year on the market, i.e. EVA Equity, is calculated.

At first, the weighted average cost of capital needs to be calculated. The calculation is done according to Equation No. 1 (Neumaierová, Neumaier, 2008):

$$WACC = r_f + r_{LA} + r_{enterprise} + r_{FinStab} \quad (1)$$

Where: WACC – Weighted Average Cost of Capital, r_f – risk free profit, r_{LA} is a function defining the size of the enterprise, $r_{enterprise}$ is a function defining the development of production power, $r_{FinStab}$ is a function defining relationships between assets and liabilities of the enterprise.

Furthermore, costs of equity need to be calculated according to Equation No. 2 (Neumaierová, Neumaier, 2008):

$$= \frac{WACC \cdot \frac{UZ}{A} - (1-d) \cdot \frac{U}{BU+O} \cdot \left(\frac{UZ}{A} - \frac{VK}{A}\right)}{\frac{VK}{A}} \quad (2)$$

Where: r_e – costs of equity (rate of equity), WACC – Weighted Average Cost of capital, UZ – payable resources (equity and interest-yielding liabilities), A – assets, VK – equity, BU – bank loans, O – debentures, $\frac{U}{BU+O}$ – interest rate, also i (interest), d – income tax rate also (t - tax).

EVA Equity for shareholders is calculated according to Equation No. 3 (Neumaierová, Neumaier, 2008):

$$EVA\ Equity = (ROE - r_e) * VK \quad (3)$$

Where ROE is Return on Equity.

Enterprises in which EVA Equity calculation could not be made – as a result of unknown or zero values of entries that are necessary for the calculation to be done – were removed from the data set. The final table is subsequently uploaded to Statistica Software version 12 where the degree of dependence of EVA Equity ratio on individual entries of financial statements is examined.

Afterwards, the raw data statistics and correlation matrix is produced. In case that the correlation between two quantities is found, a close relationship of the two variables is very likely. As a result, particular entries are selected with respect to this close correlation. Regression is then used as a means of automated neural network. EVA Equity is considered as a dependent quantity and the selection of variables is subject to the economic theory of factors of production. This issue has already been dealt with by Wöhe and Kislingerová (2007). The data are subsequently divided into three subsets. The first one is training data. This subset contains 60% of input data. The second one is testing data that contain 20% of input data. The last one is a validation subset with remaining 20% of input data. The purpose of the training subset is to generate neural structures; testing and validation subset assess the reliability of identified structures. It is 10,000 neural networks that were generated in total. Five of them, which showed the best results, have been preserved. The networks that do not demonstrate improvement by lowest square method and entropy when being created are considered as the best identified structures. Two types of neural structures are used: Multi-Layer Perceptron neural networks (MLP) and Radial Basic Function neural networks (RBF). In the hidden and output layer, the following distribution functions are considered: linear, logistic, atanh (hyperbolic tangents), exponential and sinus.

Selected neural structures are considered to be the research results. These structures are able to predict EVA Equity based on input data from which we are able to predict the likely value of EVA Equity. This model considers only these variables with a profound influence on the final value of EVA Equity ratio. It is a neural network whose ability to predict is the greatest based on the highest efficiency in the training, testing and validation data set that is chosen. Moreover, this network contains only a minimum error in all data sets and thereby makes a true economic interpretation. Sensitivity analysis is then carried out by means of which variables that need to be calculated and that significantly influence the result are identified. Value generators of the enterprise engaged in the sphere of mining are the results.

Findings

After the enterprises for which EVA Equity ratio could not be calculated have been removed from the input data, figures in financial statements of 135 enterprises engaged in the mining and extraction in the Czech Republic are to be calculated. The methodology determined independent variables that are calculated (according to the discovered correlation of the data and economic interpretation). These are as follows: total assets, fixed tangible assets, fixed financial property, inventories, long-term liabilities, short-term liabilities, business relation liabilities, registered capital, bank loans and financial aids, material and energy consumption, depreciation of fixed tangible assets, amortization of fixed intangible assets, other operating incomes, and income tax on ordinary and extraordinary activities. Table No. 1 shows the five best generated and preserved neural networks.

Table 1. Preserved neural structures

	Network	Training efficiency	Testing efficiency	Validation efficiency	Training error	Testing error	Validation error	Training algorithm	Error function	Activation of hidden layer	Output activation function
1	MLP 13-13-1	0.976236	0.722904	0.989862	5.544183 E+08	7.272184 E+10	1.761796E +08	BFGS 10	Total squares	Sinus	Exponential
2	MLP 13-5-1	0.870682	0.896288	0.988916	2.866814 E+09	4.711732 E+10	3.044458E +08	BFGS 4	Total squares	Exponential	Sinus
3	MLP 13-5-1	0.923346	0.551301	0.987651	1.139886 E+10	1.282867 E+11	1.344766E +09	BFGS 2	Total squares	Identity	Exponential
4	MLP 13-17-1	0.953240	0.902236	0.988849	1.217160 E+09	6.176602 E+10	1.727418E +08	BFGS 4	Total squares	Identity	Sinus
5	MLP 13-14-1	0.900491	0.078517	0.988693	1.072166 E+10	1.285218 E+11	1.088074E +09	BFGS 2	Total squares	Identity	Exponential

Sources: Authors.

The table suggests that all preserved neural structures are multilayer perceptron networks; therefore, they demonstrate the best characteristics. Variants of Quasi-Newton (2, 4 and 10) Algorithm were used as a training algorithm. The method of the lowest squares was used as an error function for each preserved network. The hidden neural layer was activated by the identity function (sinus and exponential) in three cases. Output activation function was activated by exponential function in three cases and other two neural networks were activated by sinus function. The first layer of all preserved neural networks contains the identical number of neurons – 13. What is evident is that the structure of hidden layers is highly variable. The relevance of generated networks is depicted in Tab. No. 2.

Table 2. The efficiency of generated networks

Network	Training	Testing	Validation
MLP 13-13-1	0.976236	0.722904	0.989862
MLP 13-5-1	0.870682	0.896288	0.988916
MLP 13-5-1	0.923346	0.551301	0.987651
MLP 13-17-1	0.953240	0.902236	0.988849
MLP 13-14-1	0.900491	0.078517	0.988693

Source: Authors

This table illustrates efficiencies of individual networks in all three data sets (training, testing and validation). Ideally it is the highest efficiency value (correlation coefficient) that is looked for;

at the same time, what is also looked for is the identical value of all data sets. As could be evident at the first glance, MLP 13-13-1 neural network achieves the highest efficiency in the training data set. At the same time, this neural network shows the best efficiency result in the validation data set. The table also suggests that all the remaining preserved neural networks demonstrate a decrease in efficiency in the training network. As far as the similarity of values of all data sets is concerned, MLP 13-5-1 neural network, i.e. the second preserved network, manifests a high and relatively constant efficiency in all data sets. Of importance might also be that the testing data set of the last preserved network (MLP 13-14-1) shows several times lower efficiency than other preserved networks.

In order to properly evaluate the result, the following table (Table No. 3) suggests parameters of predictions that have been made by individual networks.

Table 3. Parameters of predictions

Prediction parameter	**1. MLP 13-13-1**	**2. MLP 13-5-1**	**3. MLP 13-5-1**	**4. MLP 13-17-1**	**5. MLP 13-14-1**
Minimal prediction (Training)	-332737	-11657	33365	-328448	18799
Maximal prediction (Training)	1139052	814848	43806	968213	58589
Minimal prediction (Testing)	-2091	-802304	33558	-9437	18896
Maximal prediction (Testing)	2293621	1056179	42898	944392	187082
Minimal prediction (Validation)	-4971	-11424	33556	-9796	18890
Maximal prediction (Validation)	155994	134345	35553	163141	25472
Minimal residua (Training)	-110313	-469257	-402296	-312916	-387730
Maximal residua (Training)	152257	301099	1049914	125507	1035635
Minimal residua (Testing)	-1953519	-93106	-530167	-723386	-674443
Maximal residua (Testing)	321264	1558706	2571987	1670493	2544035
Minimal residua (Validation)	-15272	-4406	-48468	-7198	-33850
Maximal residua (Validation)	87192	108841	207633	80045	217714
Minimal standard residua (Training)	-5	-9	-4	-9	-4
Maximal standard residua (Training)	6	6	10	4	10
Minimal standard residua (Testing)	-7	0	-1	-3	-2
Maximal standard residua (Testing)	1	7	7	7	7
Minimal standard residua (Validation)	-1	0	-1	-1	-1
Maximal standard residua (Validation)	7	6	6	6	7

Source: Authors

Table No. 3 strongly suggests that values of maximal and minimal predictions in the third and fifth neural structures bear remarkably similar values in all data sets. On the other hand, they have highest values in maximal and minimal standard residua. Of interest might also be that these two networks, as contrasted to the three remaining preserved networks, have positive minimal values as opposed to standard residua where these values are negative – although extremely low.

Sensitivity analysis was subsequently carried out. Results of this analysis are depicted in Table No. 4.

Table 4. Sensitivity analysis

Ratio	1. MLP 13-13-1	2. MLP 13-5-1	3. MLP 13-5-1	4. MLP 13-17-1	5. MLP 13-14-1	Average
Total assets	3.748769	2.134657	1.005125	1.916584	1.023933	1.965814
Registered capital	5.362169	1.005736	0.999091	0.936063	0.996042	1.859820
Material and energy consumption	2.493298	1.148591	1.002088	1.059412	1.002833	1.341244
Depreciation of fixed tangible assets, amortization of fixed intangible assets	1.846339	1.278299	0.999882	1.212942	1.009398	1.269372
Fixed intangible assets	1.836384	1.044906	1.000454	1.022727	1.001631	1.181220
Fixed financial property	1.799239	1.009912	1.000900	1.011264	0.999214	1.164106
Bank loans and aids	1.345822	0.934230	1.000132	0.999833	1.000544	1.056112
Business relation liabilities	1.152275	1.034692	1.000600	1.027410	1.001798	1.043355
Short-term liabilities	1.116033	0.999931	0.999763	0.998747	1.002010	1.023297
Other operating incomes	1.012090	1.044928	1.000012	1.020638	1.000059	1.015545
Inventories	1.022545	0.995388	1.001033	0.996093	1.000649	1.003142
Income tax on ordinary and extraordinary activities	1.014457	0.984404	1.000025	1.014892	1.000074	1.002770
Long-term liabilities	0.461567	1.295562	0.999459	1.148378	0.984292	0.977851

Source: Authors

The table demonstrates that levels of importance of individual variables differ in each preserved network. In the first preserved network, it is registered capital that is on the first place; in the second one it is total assets of the enterprise; the same applies to the third and fifth network. Material and energy consumption, depreciation of fixed tangible assets and amortization of fixed intangible assets are other important entries. Other entries see a decrease in their importance together with a position in the imaginary table of winners.

Discussion and Conclusion

The aim of this article was to identify value generators of the enterprise engaged in the sphere of mining in the Czech Republic in 2016. In order to achieve this, a practical methodology by means of which value generators of the enterprise were identified was devised. Thirteen quantities that participate in creating enterprise value to the largest extent were chosen in total. This value is measured by EVA Equity ratio. These most important variables were identified as generators: total assets, registered capital, material and energy consumption, depreciation of fixed tangible assets and amortization of fixed intangible assets and fixed intangible assets. Mining enterprises engaged in mining and extraction in the Czech Republic should thereby focus on these entries in their financial statements. What is strongly evident is the parallel between this type of enterprises and value generators. As a result of a large accumulation of fixed assets in which the mining enterprises accumulated probably the most financial resources, the total assets are obviously the key generator; what also plays an important role are depreciations of fixed tangible assets and amortization of fixed intangible assets. What also should not be omitted are entries from Table No. 4 that also participate in creating enterprise value. The aim of the article was thereby fulfilled. Of major importance is also the potential of results which means that a further in-depth research can be carried out. Currently, it is relevant to identify the degree of influence of individual variables on EVA Equity and, also, the relationship between these variables and EVA Equity in regard to the growing popularity of these ratios. The next essential step is to decompose constituent ratios and integrate them into tactical and operational objectives of the enterprise. The strategic objective of all existing enterprises is generally known – the increase of its value for shareholders. All the same, the same applies to all manufacturing and non-manufacturing economic sectors.

References

Bakalarczyk, S., Pomykalski, P. and Weiss, E. (2011). Innovativeness of metallurgical production enterprises. *20th Anniversary International Conference on Metallurgy and Materials (METAL), 18. – 20. 5. 2011.* Brno: Czech Republic, pp. 1298-1302.

Dufek, V. and Šarman, L. (2005). Powder metallurgy in the Czech Republic. *Powder Metallurgy*, 48 (3), 212-215.

Firk, S., Schrapp, S. and Wolff, M. (2016). Drivers of Value Creation – The Role of Value-Based Management and Underlying Institutions. *Management Accounting Research*, 33, 42-60.

Hall, J. H. (2016). Industry-specific determinants of shareholder value creation. *Studies in Economics and Finance*, 33 (2), 190-208.

Kafka, V. (2010). Creation of economic awareness in czech metallurgy – indispensable prerequisite for reduction of its costingness. *19th International Conference on Metallurgy and Materials, 18. - 20. 5. 2010*. Roznov pod Radhostem: Czech Republic, EU, pp. 20-27.

Kazlauskiene, V. and Christauskas, C. (2008). Business Valuation Model Based on the Analysis of Business Value Drivers. *Inzinerine Ekonomika – Engineering Economics*, (2), 23-31.

Kula, D., Bobek, M., Čamská, D. and Hájek, J. (2012). Impact of the financial crisis on profitability and liquidity of companies in metallurgical industry in the Czech Republic. *21st International Conference on Metallurgy and Materials, 23. – 25. 5. 2012*. Brno: Czech Republic, pp. 1781-1788.

Rylková, Ž. and Bernatík W. (2014).Performance Measurement and Management in Czech Enterprises. *Procedia - Social and Behavioral Sciences*, 110, pp. 961-968,

Šalaga, J. (2015). Value-based management and value drivers in worldmarket. *Proceedings of the 15th International Scientific Conference Globalization and its Socio-Economic Consequences* – Rajecké Teplice, Slovakia, pp.743-747.

Sucháček, J., Samolejová, A., and Seďa, P. (2017). Metallurgy in the Czech Republic: a spatio-temporal view. *Metalurgija*, 56 (1-2), 249-251.

Tiwari, R. and Kumar, B. (2015). Drivers of Firm’s Value: Panel Data Evidence from Indian Manufacturing Industry. *Asian Journal of Finance & Accounting*, 7 (2), 1-22.

Vilamová, Š., Janovská, K., Kozel, P, Vozňáková, I. and Švecová E. (2012). New trends in the management within the metallurgy firms. *21st International Conference on Metallurgy and Materials, 23. – 25. 5. 2012*. Brno: Czech Republic, pp. 1897-1903.

Vilamová, Š., Janovská, K., Vozňáková, I. and Kozel, R. (2013). Selected specific aspects of marketing analyses and management in the conditions of metallurgy firms. *22nd International Conference on Metallurgy and Materials (Metal), 15. -17. 5. 2013*. Brno: Czech Republic, pp. 2043-2049.

Vochozka, M. and Machová V. (2017). Enterprise value generators in the building industry. *Innovative Economic Symposium 2017, SHS Web of Conferences 39,* České Budějovice, Czech Republic.

Wöhe, G. and Kislingerová, E. (2007). *Úvod do podnikového hospodářství [Introduction to business management]*. 2. ed. Prague: C.H. Beck, 928 p. ISBN 978-80-7179-897-2.

Contact:

Ing. Jakub Horák
Faculty of Operation and Economics of Transport and Communications
University of Žilina, Univerzitná 8215/1
010 26 Žilina, Slovakia
e-mail: horak@mail.vstecb.cz

Ing. Veronika Machová, MBA
School of Expertness and Valuation
Institute of Technology and Business in České Budějovice, Okružní 517/10
370 01 České Budějovice
Czech Republic
e-mail: machova@mail.vstecb.cz

Ing. Tomáš Krulický, BBA
Faculty of Operation and Economics of Transport and Communications
University of Žilina, Univerzitná 8215/1
010 26 Žilina, Slovakia
e-mail: krulicky@mail.vstecb.cz