DOI: 10.20472/EFC.2024.023.007

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THE INFLUENCE OF THE FIELD OF BUSINESS ON THE DEVELOPMENT OF PRODUCTIVITY IN SELECTED COMPANIES OF THE CZECH CHEMICAL INDUSTRY

Abstract:

This study analyses the productivity of selected chemical industry companies in the Czech Republic through Data Envelopment Analysis (DEA). The selection of companies for analysis was based on the amount of turnover and also according to the field of business. The enterprises were grouped into 4 groups. The first group A represents qualified chemistry, followed by group B (commodity inorganic and organic chemistry), group C (processing of plastics or rubbers) and group D (distribution of raw materials). The Malmquist productivity index (MPI) was used to analyse changes in the productivity of companies, and the statistical significance of these indices was tested using. This procedure helped identify the influence of various factors on the efficiency and productivity of companies, including the influence of the area of business. The study showed other possibilities of using this procedure. E.g., in the case of inclusion of environmental costs or investments in the field of the environment.

Keywords:

Field of business of chemical industry company, data envelopment analysis, Malmquist productivity index, financial statements

JEL Classification: C10, D20

1 Introduction

The chemical industry is one of the important industries in the Czech Republic. The position of the chemical industry sector ranks 2nd - 3rd among the manufacturing industries of the Czech Republic with a share of more than 13% of total production. The Chemical Industry Association (2023) reports in the yearbook for 2022 that the total production of the chemical industry in the Czech Republic (CZ NACE 20) reached values of 360 bil. CZK at current prices, gross value added 59 182 mil. CZK and employment 33 178 people. These are figures that show that business in chemistry is one of the most important manufacturing sectors The chemical industry is therefore fundamental to the Czech economy. But chemical companies face health, safety, and environmental costs that are less dominant in other sectors. Rajeev et al. (2019) have identified that most businesses in this area provide economic benefits to the producer at the expense of negative environmental and societal impacts. Therefore, chemical enterprises for sustainable business have to incur higher costs.

The chemical industry is highly interconnected and relies on complex global supply chains to ensure a steady flow of raw materials, intermediates and finished products (Abedsoltan, 2023). The further development of the sector will therefore continue to be influenced in the period ahead by the evolution of the energy crisis, with high prices for raw materials and energy in the EU still 4 times higher than in the US, for example. Market demand and overall trade balance are significantly affected by the availability of raw materials and the ongoing war conflict in Ukraine. In addition, the competitiveness of the European chemical industry is significantly affected not only by access to cheaper goods from third countries, by restrictions on exports to third countries, but also by the limited availability and usefulness of support programmes to offset the negative effects of the gradual implementation of the European Green Agreement legislation.

This study therefore analyses the evolution of the productivity of firms in the sector. The main objective is to test the usefulness of the Data Envelopment Analysis (DEA) methodology to monitor the performance of manufacturing enterprises based on financial indicators publicly available. The aim is to determine the relationship between selected parameters characterizing business and financial performance of firms. There are significant environmental costs for businesses in the chemical industry. The answer to the question of how these costs will affect their economy and productivity is certainly important for the management of these firms, and especially for their owners. If this part of the research is positive, the authors will continue to collect environmental data to identify the impact of these costs on their productivity development.

The Data Envelopment Analysis (DEA) method has long been used to measure operational performance (Sueyoshi and Goto, 2010, Sueyoshi and Goto, 2011, Zanella et al., 2012). Sueyoshi and Goto (2010) found that large firms have managerial skills that can allow them to improve their operational and, consequently, their financial performance. At the DEA, there are several methods of measuring efficiency changes over time, such as the Malmquist Productivity Index (Färe et al., 1994). Productivity growth and its components are also calculated using the Malmquist Productivity Index.

The productivity of selected firms was monitored between 2008-2022. The entire time series was divided into 2 periods to identify the effect of the model input and output parameters used on company performance. In the study, companies are divided into four types of businesses by business line (consumer chemistry, inorganic and organic chemistry commodity, qualified chemistry, technical gases, plastic or rubber processing and raw material distribution) based on the predominant area of the production program. The classification was made to identify the effect of the model input and output parameters used on company performance.

1.1 Literature Review

The Malmquist Index (MI) finds uses in a number of industrial areas. It has also been used in recent years to measure economic and environmental efficiency in the chemical industry, when assessing changes in individual EU member countries (Lennort et al., 2019). The authors found that the chemical industry increased its productivity in 20 EU countries between 2010 and 2016. But how individual firms from the countries surveyed contributed to the growth was not ascertained.

The Malmquist index is also used separately to measure productivity growth. Simar and Wilson (1999) expanded Färe et al. (1994) by providing a statistical interpretation of their Malmquist Productivity Index and submitting a bootstrap algorithm that can be used to estimate confidence intervals for indices.

The Malmquist index is an indicator that was created in 1953 by Swedish entrepreneur Staffan B. Malmquist (Farnoudkija, 2024). It is a non-parametric productivity indicator that is still widely used. Because it is based on the technical formulation of efficiency, tracking input and output data (Walheer, 2022) is sufficient. However, it can also be broken down into different components, the most common of which is the technical eficiency change and technological change. The original index was thus modified by Färe et al (1992) and subsequently in 1994 by Färe et al (1994). It can be constructed as input or output oriented and calculates the change in productivity between two periods.

$$M(xt+1,yt+1,xt,yt)=[Dt(xt+1,yt+1)Dt(xt,yt)\times Dt+1(xt+1,yt+1)Dt+1(xt,yt)]1/2=Dt+1(xt+1,yt+1)Dt(xt,yt)[Dt(xt+1,yt+1)Dt+1(xt+1,yt+1)\times Dt(xt,yt)Dt+1(xt,yt)]1/2=effch\times techch \quad (1)$$

Equation (1) is the expression of the Malmquist exponent from time t to time t+1, where xt+1 and xt denote the input vectors at time t+1 and t, respectively, yt+1 and yt represent the output vectors at time t+1 and t, respectively, and Dt and Dt+1 are distance functions. When $M(xt+1,yt+1,xt,yt)>1$, it indicates that the TFP in period t+1 has increased compared with that in period t (He et al, 2024).

The drawback of MI is its great sensitivity to, or completeness of, the data used (Akbarian, 2020). Other drawbacks include that it is based on a technical formulation of effectiveness, although a structural approach would be more appropriate in many situations (Walheer, 2022). Its design, as an indicator of change between two states, also makes it impossible to directly compare change over a longer, consecutive period (Wahleer, 2022). For these reasons, the Malmquist index has been modified differently. Wahleer (2022) defines two new indices - Global MI (GMI) and Global Cost MI (GCMI) to compare groups. Chen et al. (2023) again proposed the novel Malmquist-type green total factor productivity index for measuring green total factor productivity (GTFP).

Development also continues in the search for the production option boundary (operational performance). Development also takes place in the search for production option boundaries (operational performance). By default, mathematical programming models are used for these purposes. There is even implementation of stochastic non-matrix programming within Data Envelopment Analysis (DEA). Frontier analysis (SFA), see Odeck and Schøyen, 2020 or even the stochastic nonparametric envelopment of data (StoNED), designed by Yu and Hiroshi (2024) by Kuosmanen (2006) and Kuosmanen and Kortelainen (2012), which combines the DEA and SFA approach.

However, most of the study remains with the use of the standard MI under Färe et al (1994) and the DEA approach. Therefore, this combination will also be used in our article.

2 Methodology

2.1 Data Acquisition

The selection of companies for research was made on the basis of statistical yearbooks of the Union of Chemical Industries of the Czech Republic. The association represents the bulk of the Czech chemical industry in terms of turnover, profit generation and contribution to the state budget of the Czech Republic. It was established in 1992 as a voluntary professional organization of entities active in the oil refining, chemical, pharmaceutical, rubber and plastics sectors in areas whose remit is related to activities such as producer, research institute, university, professional association, engineering, consulting, intermediary and commercial legal and natural persons (Chemical Industry Union, 2023).

Companies were included in the research in terms of their turnover and by business line. The selected companies represent all areas of activity of Czech chemical industry companies. The companies were grouped into 4 groups. The first group A represents qualified chemistry, then group B (inorganic and organic commodity chemistry), group C (plastic or rubber processing) and group D (raw material distribution).

The data collection was completed in June 2024, when the 2023 accounts of all monitored firms were not yet available. Therefore, the time series analysed was terminated in 2022. It was not possible to work with environmental data at this stage of the research, as the only publicly available information of this kind is available at the Czech Statistical Office only in an aggregated form.

2.2 Selection of adequate data

All data were obtained from the annual reports of selected enterprises in the selected time period 2008-2022. The annual reports were downloaded from the web portal Justice.cz. It is therefore clear that the authors used balance sheet and result data.

The selected data has been broken down into inputs and outputs for modelling needs (see Table 1). Inputs were represented primarily by balance sheet items such as business assets (total assets) and then sub-amounts, fixed and current assets. Shares of resources, i.e., equity and foreign capital, were also included in the examination. The last entry was a result item, output consumption.

Operating sales were included among outputs, but limited to sales of products, services and goods. Furthermore, value added, operating result and pre-tax income (EBT) result were worked on. The data obtained was then subjected to statistical processing.

Table 1: Descriptions of input and output variables in the DEA model

Variables	Description
Inputs	
I1	business assets, the total sum of assets
I2	fixed assets
I3	current assets
I4	equity capital
I5	foreign capital
I6	power consumption, material, energy and service costs
Outputs	
O1	operating sales, only products, services and goods
O2	added value
O3	accounting result, operational
O4	Earnings-before-tax (EBT)

Sources: own adjustment based on research data

2.3 Descriptive statistic

The research period was 2008 to 2022. Table 2 provides descriptive statistical characteristics of the population used, giving average values and standard deviations for each year for all input and output variables. All values are given in units of mil. CZK.

The average input variable I1 in the period from 2008 through 2022 ranged from 2595.4 mil. CZK to 5126.1 mil. CZK, the trend is growing. The average of the input variable I2 ranged from 1179.6 mil. CZK to 2659.6 mil. CZK during the research period. The other input variable I3 has been growing fairly steadily throughout the research period, with an average of 1082.3 mil. CZK up to 2462.3 mil. CZK. Input variable I4 averages from 1091.1 mil. CZK up to 3052.8 mil. CZK. The average of the input variable I5 is in a relatively narrow range from 1294.17 mil. CZK up to 2184.27 mil. CZK. The average values of the last input variable I6 range from 3025.5 mil. CZK up to 6409.9 mil. CZK, with values tending to stagnate over the reference period, the significant increase only occurs in the last year of the period.

The average of the O1 output variable acquires values from 3646.2 mil. CZK up to 8026.6 mil. CZK, the rapid increase occurs again only in the last year of the reporting period. Output variable O2 ranges from 360.6 mil. CZK on average up to 1616.7 mil. CZK. The average of the O3 output variable is in the range of 1.9 mil. CZK up to 769.6 mil. CZK. The average of the last input variable O4 ranges from 7.9 mil. CZK up to 755.5 mil. CZK, significant growth only occurs in the last year of the reporting period. Table 3 shows the variability of input and output variables through Standard Deviation.

Table 2: Average values of the indicators used for the monitored period (mil. CZK)

	I1	I2	I3	I4	I5	I6	O1	O2	O3	O4
2008	2750.1	1644.3	1086.2	1373.9	1395.9	3976.1	4795.2	510.0	69.5	44.8
2009	2595.4	1496.8	1082.3	1237.7	1364.2	3025.5	3646.2	360.6	1.9	7.9
2010	2649.7	1412.6	1225.6	1387.0	1294.2	3719.3	4511.0	538.1	191.5	204.8
2011	2759.0	1282.3	1462.7	1335.9	1487.2	4218.1	5243.4	546.8	109.4	129.1
2012	2734.1	1236.0	1475.2	1300.9	1433.2	4127.1	5139.9	502.4	197.9	181.3
2013	2691.2	1179.6	1429.4	1148.9	1467.1	3920.6	4756.0	425.7	99.3	97.1
2014	2758.6	1273.6	1486.1	1091.1	1626.3	4589.5	5476.0	579.4	225.8	227.0
2015	2730.4	1317.9	1383.1	1450.7	1415.8	3757.4	4686.3	706.2	360.5	362.1
2016	3282.5	1643.6	1607.5	1709.9	1526.7	4337.2	4048.8	468.8	320.6	330.7
2017	3729.6	1931.3	1735.5	2222.3	1491.1	4274.7	5119.6	846.6	509.3	484.9
2018	4137.4	2234.0	1831.1	2470.1	1660.4	4600.9	5340.8	740.2	416.2	456.1
2019	4192.1	2318.1	1873.6	2539.0	1539.1	4462.4	5160.3	697.4	234.2	233.7
2020	4082.2	2546.1	1529.1	2455.2	1623.3	3095.2	3829.2	731.6	344.9	344.8
2021	4872.0	2734.0	2121.3	2676.4	2184.3	4668.3	5666.8	1000.1	386.5	412.8
2022	5126.1	2659.6	2462.3	3052.8	2137.9	6409.9	8026.6	1616.8	769.6	755.5

Sources: own adjustment based on research data

Table 3: Standard deviations (mil. CZK)

	I1	I2	I3	I4	I5	I6	O1	O2	O3	O4
2008	5482.5	3265.6	2220.0	2329.3	3371.4	14499.4	15646.1	738.6	322.1	394.8
2009	5535.4	3072.4	2476.3	2001.0	3724.8	11079.8	11530.6	487.3	400.9	477.8
2010	5572.1	2877.1	2721.2	2131.7	3684.2	13573.0	14373.6	769.7	386.8	459.9
2011	5757.9	2526.4	3267.5	1885.2	4387.1	15325.8	16629.2	764.8	906.3	958.9
2012	5767.0	2473.5	3256.4	1982.7	4214.4	14318.7	15703.8	628.9	432.0	480.2
2013	5704.0	2164.4	3222.5	1599.5	4527.3	13388.1	14354.0	528.7	417.7	464.4
2014	5932.1	2502.1	3509.1	1711.8	4564.6	16649.6	18043.3	861.7	494.0	518.4
2015	5972.3	2457.4	3590.7	2517.5	3754.3	13364.1	15569.2	1515.9	1031.7	1062.9
2016	8791.6	4214.4	4622.7	3843.4	5165.0	13276.2	12441.4	542.2	984.6	1059.0
2017	10770.7	5656.7	5161.2	6377.0	4499.4	15430.5	17486.9	2107.4	1739.8	1563.8
2018	12707.1	7038.9	5726.2	7696.3	5110.2	17322.9	18796.2	1560.7	1463.3	1642.0
2019	13264.4	7874.4	5443.4	7733.4	4702.3	17096.8	18439.4	1422.2	392.1	439.8
2020	12281.4	8459.2	3876.7	6849.3	5548.5	10149.9	11574.9	1494.7	1026.9	1121.6
2021	15089.8	9218.2	5915.1	7363.7	7879.0	16637.8	19080.0	2489.9	769.0	782.4
2022	15940.4	9208.4	6803.4	8744.6	7270.9	23976.8	3025.2	6311.5	2801.6	2762.7

Sources: own adjustment based on research data

Table 4 shows the correlation coefficients characterizing the correlation between input and output variables used for DEA. The results show that all correlations are significant and all variables are positively correlated. This suggests that an increase in the value of the input variable should not lead to a decrease in the value of the output variable. Compliance with this condition indicates the appropriateness of using selected input and output variables to measure corporate efficiency (Charnes et al., 1985; Talluri et al., 1997).

Table 4: Correlation

	I1	I2	I3	I4	I5	I6	O1	O2	O3	O4
I1	1									
I2	.959**	1								
I3	.911**	.757**	1							
I4	.980**	.961**	.857**	1						
I5	.857**	.763**	.874**	.747**	1					
I6	.621*	.421	.829**	.546*	.718**	1				
O1	.587*	.402	.780**	.516*	.714**	.943**	1			
O2	.836**	.733**	.870**	.811**	.824**	.790**	.842**	1		
O3	.782**	.660**	.840**	.788**	.689**	.713**	.681**	.899**	1	
O4	.797**	.674**	.853**	.801**	.709**	.709**	.670**	.891**	.996**	1

**. Correlation is significant at the 0.01 level (2tailed).
*. Correlation is significant at the 0.05 level (2tailed).

Sources: own adjustment based on research data

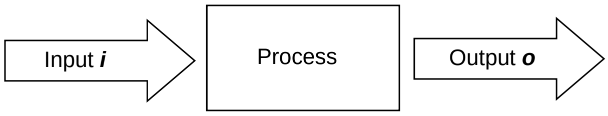
2.4 Malmquist index

The Malmquist Index can be calculated in several ways. In this study, we estimate an output-oriented Malmquist Productivity Index, based on DEA. Output-oriented efficiency measurements are appropriate if we assume that chemical companies act in a competitive market. In output-oriented models, such as the one adopted in this paper. DEA allows for the estimation of total productivity change in the form of a Malmquist Index.

The software DEAP version 2.1 was used to calculate the Malmquist index (The University of Queensland, 2024). Individual combinations of outputs and inputs for selected groups of companies were gradually inserted into software. The processing followed the general model (see Fig. 1). The output module allows to obtain the following Malmquist Index indicators for each of the firms analysed in each year:

1. technical efficiency change (relative to a CRS technology),
2. technological change,
3. pure technical efficiency change (relative to a VRS technology),
4. scale efficiency change,
5. total factor productivity (TFP).

Figure 1: A general model for calculating the Malmguist index



Sources: own processing

The output from software contains further aggregated tables from which to identify the development of the Malmquist Index over a period of time for all firms surveyed and for individual firms over the entire period of time. In the tables presented in the next chapter, Malmquist's index of development (efficiency) by time period is presented for groups of firms A, B, C, D.

3 Results and discussion

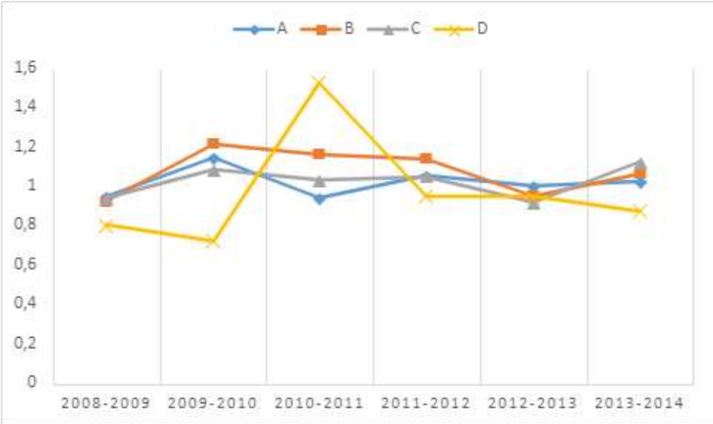
Under the solution in software DEAP version 2.1, calculations were performed sequentially for different combinations of input and output factors per model (see Fig. 1). To illustrate the results in this post, a model was chosen where the input value was total assets and the output value represented operating revenues. Table 5 shows the total factor productivity (TFP) values for each pair of years. The results are organised not only within two different time periods (between 2008-2014 and beyond 2015-2022), but are also divided into 4 groups into which selected firms have been divided. Both trends are also demonstrated in Figures 3 and 4.

Table 5: Resulting values of the company's productivity index by group

	2008-2009	**2009-2010**	**2010-2011**	**2011-2012**	**2012-2013**	**2013-2014**	**2015-2016**	**2016-2017**	**2017-2018**	**2018-2019**	**2019-2020**	**2020-2021**	**2021-2022**
TFP-A	0.949	1.144	0.941	1.054	1.001	1.024	1.054	0.997	0.988	1.172	0.812	1.011	1.065
Mean			1.016							1.009			
TFP-B	0.924	1.218	1.163	1.142	0.954	1.064	0.847	1.205	0.798	1.005	0.939	1.010	1.391
mean			1.072							1.011			
TFP-C	0.941	1.085	1.031	1.050	0.917	1.121	0.993	0.905	0.925	0.430	0.940	1.096	0.091
mean			1.021							0.316			
TFP-D	0.806	0.725	1.528	0.954	0.947	0.876	1.142	1.118	1.047	1.028	0.895	1.006	1.041
mean			0.944							1.037			

Sources: own adjustment based on research data

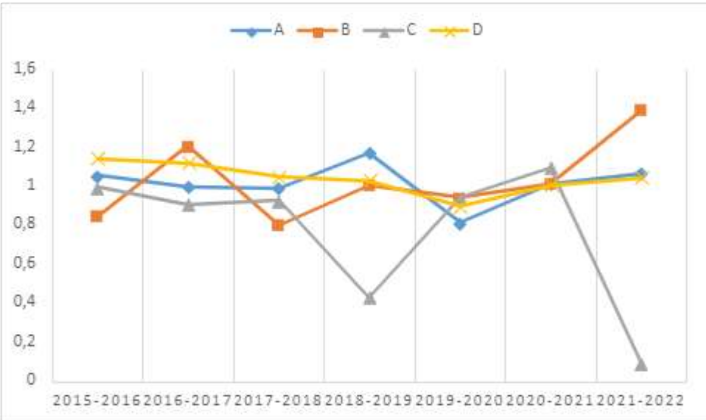
Figure 3: Development of company efficiency values by group in 2008 - 2014



Sources: own adjustment based on research data

Figure 4: Development of company efficiency values by group in 2015 - 2022

Okomentoval(a): [SD1]: Pro druhý článek



Sources: own adjustment based on research data

4 Conclusion

In conclusion, the methodology of modelling through the Data Envelopment Analysis (DEA) Malmquist Productivity Index is well utilised to monitor the performance of manufacturing enterprises based on available financial indicators. The authors in Chapter 3 have produced a number of results that can demonstrate the relationship between selected parameters characterizing business and financial performance of firms.

The models for the DEA Malmquist Productivity Index in this research did not include all inputs and outputs, although correlations were demonstrated in the Descriptive Statistics chapter. It was necessary to test the suitability of individual parameters for processing. Two-parameter models were always verified within the calculations. Given the nature of the data, merchant property (i.e., total assets) proved to be the most appropriate input and either operating revenues or value added was the most appropriate output. E.g., EBT values proved unsuitable for the DEA MI method.

The contribution focused on the development of productivity indices for selected Czech chemical companies in two consecutive time segments. As a result, major trends could be demonstrated from the results presented.

The results obtained could be used to analyse in more detail the differences in efficiency across the businesses surveyed. The results, however, would not yield significantly different conclusions than experienced financial analysts can draw from the annual accounts themselves, from which the data were drawn. It was essential for the authors to test the DEA's methodology so that the next stage of research could be pursued, where data would be included to better track differences in company performance. Only then will the meaning apply more parametric models. Such a challenge is primarily the environmental costs, which significantly affect businesses in the chemical industry. It is certainly important for the management of these firms, and especially for their owners, to answer the question of how these costs will affect their management. The existing RU statement 1-01 requested by the Ministry of Environment is not delivered responsibly enough to the competent authorities. The challenge, then, is for authors to obtain this data in structured form for individual businesses.

Finally, it is important to mention the limitations that the DEA methodology entails. First of all, it is a matter of selecting businesses, grouping them on the basis of an analysis of the production programme, selecting appropriate input and output values. Last but not least, it is also a question of an appropriately chosen time period.

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