A COMPARISON OF THE TRENDS IN THE FACTORS OF FINANCIAL PERFORMANCE OF COMPANIES IN CZECH CLUSTERS

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Abstract

This paper deals with the effect of clusters on trends in the financial performance of companies in seven different industries (automotive, engineering, IT, furniture, nanotechnology, packaging, textile). The companies were divided into three groups – members of cluster organisations, non-members operating in the same region, and others. Changes in companies' performance were measured using the Malmquist index based on distance functions, the values of which were obtained using Data Envelopment Analysis (DEA). The overall change in performance was decomposed into technical efficiency change – including pure technical efficiency change and scale efficiency change – and technological change**.** The companies' own equity and liabilities were used as DEA inputs; revenues gained from their own products and services and economic value added were used at the outputs. The results of the research show that the effects of clustering on performance are only partial and are felt differently in different industries. There was only one industry (nanotechnology) where clustering was found to have no effect on any component of performance. In four industries (automotive, furniture, packaging, IT**)**, companies in cluster organisations were found to enjoy faster technological progress. In the engineering and textile industries, a positive impact on scale efficiency was found.

Keywords

Industry Cluster, Cluster Analysis, Financial Performance, Data Envelopment Analysis, Malmquist Index

I. Introduction

As early as in the 19th century, Alfred Marshall discovered that spatial agglomeration resulted in benefits and positive externalities for businesses. In the 1990s, Porter determined other factors of competitiveness and explained why certain industries are more successful in some regions. He introduced the term cluster for these industry groupings. However, explaining the functioning of clusters was only the beginning – targeted support for the establishment and development of clusters has become the basis of regional and innovation policy in many countries.

In the Czech Republic, clusters have been financially supported through operational programmes since 2004. In previous programming periods up to 2013, public resources worth nearly CZK 1.3 billion had been spent on supporting clusters. In the current programming period, an additional nearly CZK 696 million (API, 2020) has been released by the Operational Programme Enterprise and Innovation for Competitiveness. Such a large amount of support logically leads to the question of how efficient it is. Žižka, Hovorková Valentová, & Štichhauerová (2019) found that public support for clusters is efficient. Efficiency was measured using the tax and non-tax revenues paid by member companies into public budgets compared to the amount of support provided. At the same time, an assumption was made that cluster membership would lead to improved financial performance by the cluster. The research

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in the present paper raises the question of whether the existence of a cluster generally leads to faster increased financial performance compared to companies that do not operate in clusters.

The main objective of this paper was to find out whether industry clusters generally have a positive effect on the growth of financial performance of companies in various industries. Seven industries were selected for the analysis, representing both traditional industries (textile, furniture, engineering, automotive, packaging) and new industries (IT, nanotechnology). An additional sub-objective was to determine whether performance varies between companies depending on the cluster type (an institutionalised cluster organisation or a natural grouping). We assumed that member companies in a cluster organisation achieve a faster rate of growth than companies outside the cluster organisation, which is also attributable to the support received. At the same time, we also assumed that the collaborative environment of a cluster and the presence of an educated workforce, and educational and research institutions in the region in which the cluster is located would have a positive effect on non-member companies in the cluster (with some simplification, this group of firms can be referred to as a natural cluster), Therefore, companies outside the cluster organisation and the region in which it operates were supposed to show the weakest increase in performance. Another sub-objective was to identify trends in financial performance factors over time.

II. Clusters and financial performance

Both in theory and in this paper, the meaning of the term cluster is twofold. First, it is an industry grouping for which the term industry cluster is used. Second, it is the result of a multivariate statistical method used to classify objects. To distinguish these from the first meaning, any groups that are found are referred to as statistical clusters.

The development of the theory of industry clusters is associated with Michael Porter, who defined four basic determinants of competitiveness in 1990 – together, these form a diamond (factor conditions, demand conditions, relating and supporting industries, firm strategy, structure, and rivalry). According to Porter (1990), competitive advantage in a global world results from and is maintained by highly localised processes. Differences in national values, culture, economic structure, institutions, and culture contribute to competitive success (Porter, 1990). In this regard, Porter built on the work of Marshall ([1890], 1920) who identified agglomeration advantages in industrial districts. These benefits result from the existence of a specifically educated workforce in the local labour market, specialised suppliers, and knowledge spillover between competing companies. The existence of hereditary skills and close informal relationships between companies is also important. According to Porter & Ketels (2009), industrial districts and clusters have one thing in common, namely that the agglomeration of related economic activities and types of interaction have an impact on economic performance. Clusters mean a broader concept, encompassing many different variations of business-institution relationships. Clusters include a configuration of businesses that can also be found in industrial districts. Industrial districts can therefore be considered as one possible type of cluster.

In general, Porter (1998) defines an industry cluster as: *"...geographic concentrations of interconnected companies and institutions in a particular field. Clusters encompass an array of linked industries and other entities important to competition. They include, for example, suppliers of specialized inputs such as components, machinery, and services, and providers of specialized infrastructure. Clusters also often extend downstream to channels and customers and laterally to manufacturers of complementary products and to companies in industries related by skills, technologies, or common inputs. Finally, many clusters include governmental and other institutions - such as universities, standards-setting agencies, think tanks, vocational training providers, and trade associations - that provide specialized training, education,* *information, research, and technical support".* Besides the location of entities within a given territory (which may comprise a city, region, state, or even cross-border areas), the central point of this definition is the cooperation between businesses, research institutions and universities. Porter linked location theory with business strategy. The result is not only a theoretical model of competitiveness, but also a practical tool of regional policy (Martin & Sunley, 2003).

Industry clusters may form and function perfectly naturally. Such clusters are sometimes referred to as Porterian (Pavelková et al., 2009) to emphasise the fact that they meet Porter's original characteristics, i.e. they formed with no external intervention. Such clusters result from endogenous development, which is the natural intense cooperation between companies and other institutions, and they benefit from close proximity. In addition, organised efforts expended by various actors to create and strengthen clusters began to be supported in the 1990s (Andersson et al., 2004). This process is called a cluster initiative. The result is planned or organised clusters (Lindqvist, Ketels, & Sölvell, 2012) which are also referred to as cluster organisations (Pavelková et al., 2019). The aim of cluster initiatives is to create a cluster identity, strategy, and brand, and to support innovation, research projects and networking between cluster actors. A cluster organisation is a legal entity established to facilitate and manage the development of a cluster (So, 2017). It acts as an intermediary between the various cluster members, and stimulates cooperation both within the cluster and between the cluster and the outside world (Schretlen et al., 2011).

In the European Union, support for clusters is related to the concept of smart specialisation, which results in economy of scale, knowledge transfer and networking between the various actors and infrastructures. It is in the area of networking that clusters play a central role (Pavelková et al., 2019). Various research shows that strong clusters have a positive impact on growth of employment and innovation, which can be measured e.g. through patents (Delgado, Porter, & Stern, 2014). While the positive impact of clusters on innovation is relatively well described in the literature, their impact on financial performance has received less attention. Moreover, the existing results of research in this area are not convincing, let alone unambiguous.

Kukalis (2010) examined a sample of US companies from the semiconductor and pharmaceutical industries in terms of differences in financial performance between companies operating within and outside a cluster. Performance was measured using the ROA and ROS indicators. He concluded that the difference between these groups of companies was either insignificant, or even that the non-clustered companies showed better performance than the companies in a cluster. Krželj Čolović, Milić, & Vrdoljak Raguž (2016) investigated the impact of clusters on business performance in the environment of small- and medium-sized enterprises in the tourism industry in Croatia. Business performance was evaluated using labour productivity and the income/expenditure ratio. They found that there was no difference in business performance between clustered and non-clustered companies. An extensive study of more than 4,000 companies from 86 different industries in the US on clustering's impact on corporate profitability as measured by ROA was conducted by Ruland (2013). The results showed that small companies in a cluster had worse profitability than non-clustered companies. For larger companies, the results were mixed. By contrast, in an extensive survey of 17,000 financial sector companies in the UK, Kuah (2008) proved that financial performance was better in certain types of clusters. To assess financial performance, he used return on capital employed (ROCE) and solvency. Specifically, if the companies were part of a cluster that was narrowly defined in terms of sector, their financial performance was worse than that of companies outside the cluster. However, if they were clustered in a related industry, this had a positive impact on their financial performance. A similar conclusion was found with regards to solvency. Žižka (2018) compared the financial performance of companies in the textile industry in the Czech Republic. The multi-criteria DEA method was used to measure performance, where the output was economic value added (EVA), while the inputs were the number of employees, assets, and long-term capital. The growth in financial performance was identified to be faster among member companies of a cluster as compared to other companies in the same industry outside the cluster. Also, research that was conducted on more than 200 technology companies in clusters in Taiwan concluded that knowledge sharing and collaborative innovation strategies have a positive effect on financial performance (Chen, Wang, & Wang, 2018). However, here, the improvement in financial performance was measured by the opinion of managers on a three-point scale. In this context, it should be noted that according to the research conducted by Suchánek & Částek (2019), managers' opinions on financial performance may not match performance when measured using hard accounting data.

The above research shows that there is no clear linkage between a company's membership in a cluster and its financial performance. The assumed positive effect of clustering depends on the industry, type of cluster, its age and functioning. The results that are have been determined so far point to a research gap in the area of defining the factors that – in the case of clusters – have a positive effect on improving the financial performance of their member companies.

In general, the concept of performance can be characterised as the correct deployment and management of the components of a causal model (enterprise) that lead to the achievement of set goals at the right time, within the constraints specific to each company (Lebas, 1995). Financial performance is a measure of change in a company's financial situation, i.e. in the financial flows resulting from managerial decision-making and the implementation of these decisions by individual actors within the company. The essence of financial performance is to create value in order to maintain the existence of the company (Carton & Hofer, 2006). Performance can be measured using various simple indicators (see the ROA, ROCE, ROS indicators above), pyramid indicators, composite indicators, but also multidimensional and multicriteria methods. Mono-criteria approaches, which are based on the use of a single measure, are simple and widely used in practice, but comparing companies according to different indicators may yield different results. That is why more complex linear-programming methods have been developed that can take into account various inputs and outputs that affect a company's performance. This group includes Data Envelopment Analysis (hereinafter DEA), which evaluates a company's performance (both financial and non-financial) using a larger number of inputs and produced outputs.

DEA is a tool used for evaluating the performance and efficiency of homogeneous units that are referred to as Decision Making Units (DMU). DEA uses linear-programming techniques to find an empirical efficient frontier or best-practice frontier for the set of observed units (Zhu, 2014). The first DEA model, CCR, was introduced by Charnes, Cooper and Rhodes (the name of the model is derived from the authors' names) in 1978. This model works with virtual inputs and virtual outputs, and weights that maximize efficiency are sought for each DMU, input, and output. The CCR model was developed assuming constant returns to scale (CRS). In 1984, the model was generalised to address variable returns to scale (VRS). The modified model is known as BBC, after the names of the authors Banker, Charnes and Cooper (Düzakın & Düzakın, 2007). Units can seek to achieve an efficient frontier either by maximising outputs at constant inputs (output-oriented models) or by minimising inputs at constant outputs (input-oriented models) (Yan, 2019).

In the case of the input-oriented CCR model, let us assume that we have homogeneous DMUs (companies) that consume a vector of n inputs $\boldsymbol{X}$ and produce a vector of m outputs $\boldsymbol{Y}$. For each DMU_I, this is the input vector $\boldsymbol{x_I}$ and the output vector $\boldsymbol{y_I}$. For each DMU, the rate of technical efficiency TE can be determined expressing the ratio of the weighted outputs to the weighted inputs, which are called virtual outputs and inputs, see formula (1). If the rate of technical efficiency is one, the DMU is efficient. If the rate of technical efficiency is less than one, the

DMU is inefficient (Yan, 2019). DEA thus divides the set of units into efficient and inefficient ones.

The optimal weights can be obtained by solving the following model (1), see e.g. Coelli & Coelli (2005). We are seeking $\boldsymbol{u}$ and $\boldsymbol{v}$ weights that maximise the efficiency of a given decision-making unit U_I.

$$\text{Maximising eff}(U_I) = \frac{\boldsymbol{u}\boldsymbol{y}_{\boldsymbol{I}}}{\boldsymbol{v}\boldsymbol{x}_{\boldsymbol{I}}} \qquad (1)$$

under the constraints

$$\frac{\boldsymbol{u}\boldsymbol{y}_{\boldsymbol{j}}}{\boldsymbol{v}\boldsymbol{x}_{\boldsymbol{j}}} \leq 1, j = 1, 2, \ldots, I$$

$$\boldsymbol{u}, \boldsymbol{v} \geq 0$$

However, the model is not linear. Using the Charnes-Cooper transformation, the model can be easily linearised, see formula (2).

$$max_{\mu,w}(\boldsymbol{\mu}\boldsymbol{y}_{\boldsymbol{i}}) \qquad (2)$$

under the constraints

$$\boldsymbol{w}\boldsymbol{x}_{\boldsymbol{i}} = 1$$

$$\boldsymbol{\mu}\boldsymbol{y}_{\boldsymbol{j}} - \boldsymbol{v}\boldsymbol{w} \leq 0, j = 1, 2, \ldots, I$$

$$\boldsymbol{\mu}, \boldsymbol{w} \geq 0$$

where μ and w are also weights, but they are obtained by solving a different linear-programming problem.

To manage the economy of inefficient units, a dual model can be used. The output of the dual model are the weights λ of peer efficient units, which can be used to obtain information on what changes need to be made to the amounts of inputs for inefficient units.

For the dual problem, it is necessary to solve model (3).

$$min_{\theta,\lambda}\theta \qquad (3)$$

under the constraints

$$-\boldsymbol{y}_{\boldsymbol{i}} + \boldsymbol{Y}\boldsymbol{\lambda} \geq 0$$

$$\theta\boldsymbol{x}_{\boldsymbol{i}} - \boldsymbol{X}\boldsymbol{\lambda} \geq 0$$

$$\boldsymbol{\lambda} \geq 0$$

where θ is a scalar that expresses the efficiency score of a given firm.

In the case of a model that assumes variable returns to scale, the rate of technical efficiency is called pure technical efficiency (PTE). The ratio of technical efficiency to pure technical efficiency is called scale efficiency (Yan, 2019), see formula (4).

$$SE = \frac{TE}{PTE} \qquad (4)$$

In the case of BCC, the input-oriented model used in our research, a convexity constraint needs to be added (5).

$$\sum_{j=1}^{n} \lambda_j = 1 \qquad (5)$$

The rate of technical efficiency or, where relevant, pure technical efficiency, can be determined in each period. However, it is important to realise that there are innovations that are taking place over time, resulting in a shift of the efficient frontier. The Malmquist index is used to measure changes in efficiency over time.

Designed in 1953 by Malmquist, the index evaluates changes in relative productivity between different time periods. One of the advantages of the Malmquist index is its identification of the components that lead to a change in productivity. The index breaks down overall productivity change into technical efficiency change *EFFCH* and technological change *TECH*, see formula (6). On the one hand, companies strive to come closer to the efficient frontier (the best companies in an industry) through various internal organisational measures. This effort is expressed by the *EFFCH* component (Li, Crook, & Andreeva, 2017). At the same time, however, innovations lead to an efficiency frontier shift over time. This shift is expressed by the *TECH* component. In general, it is desirable that the *MI*, *EFFCH*, and *TECH* values be greater than one. In such a case, industry productivity increases, efficiency improves and there is technological progress.

The change in internal technical efficiency *EFFCH* can be further decomposed into the product of pure technical efficiency change *PECH* and scale efficiency change *SECH*. *PECH* expresses the DMU's ability to improve its internal technical efficiency between two periods t and z under variable returns to scale. *SECH* measures scale efficiency change between these periods. The optimal value of *SECH* is one, because in that case a company is operating under constant returns to scale and its production at the its technically best (Pantzios, Karagiannis, & Tzouvelekas, 2011).

$$MI^{t,z}(x^z, y^z, x^t, y^t) = EFFCH_I TECH_I = (PECH_I SECH_I) TECH_I \qquad (6)$$

Similar to the previous description of the CCR/BCC models, let us assume there is a company (DMU) that operates with a vector of n inputs $\boldsymbol{x}^t$ and produces m outputs $\boldsymbol{y}^t$ in period t. Then (x^t, y^t) denotes an input-output pair for the given DMU in period t and (x^z, y^z) is an input-output pair for the same unit in period z. The Malmquist index (MI) between periods z and t is given by the formula (7), or (8).

$$MI^{t,z}(x^z, y^z, x^t, y^t) = \sqrt{\frac{D^t(x^z,y^z) D^z(x^z,y^z)}{D^t(x^t,y^t) D^z(x^t,y^t)}} \qquad (7)$$

$$MI^{t,z}(x^z, y^z, x^t, y^t) = \frac{D^z(x^z,y^z)}{D^t(x^t,y^t)} x \sqrt{\frac{D^t(x^z,y^z) D^t(x^t,y^t)}{D^z(x^z,y^z) D^z(x^t,y^t)}} \qquad (8)$$

$$EFFCH^{t,z} \; TECH^{t,z}$$

The expressions $D^t(x^t, x^t)$ and $D^z(x^t, x^t)$ in formulas (7) and (8) are distance functions. They express the distances between a DMU with inputs and outputs in period t and the efficient frontiers in periods t and z. Another pair of distance functions $D^z(x^z, x^z)$ and $D^t(x^z, x^z)$ measures the distances between a DMU with inputs and outputs in period z and the efficient frontiers in periods z and t (Wang, 2019). The values of distance functions D are determined using Data Envelopment Analysis (DEA). In general, the distance between the periods may not be one, but instead may be wider.

Formula (8) indicates the decomposition of the Malmquist index into two components. Technical efficiency change $EFFCH^{t,z}$ assumes an efficient frontier in the same period and expresses the ratio of a given DMU's efficiency in period z to its efficiency in period t. This means that the DMU tried to improve its internal performance through various work organisation and production measures. Technological change $TECH^{t,z}$ characterises the frontier shift. If the efficient frontier shifts from its position in period t towards the position in period z, the $TECH^{t,z}$ value will be greater than one and there will be technological progress taking place. The $TECH^{t,z}$ component expresses a group change in efficiency brought about by all DMUs, i.e. by innovations in the industry (Wang, 2019).

III. Data and Methodology

The research included clusters from seven industries – furniture (the group designation starts with the letter F), IT (I), packaging (P), engineering/machinery (E), automotive (A), nanotechnology (N), and textile (T). These industries were selected because they have existing cluster organisations in the mature phase (active for at least 10 years). At the same time, they represent a mix of different industries, both traditional and modern. The companies in each industry were divided into three groups:

- companies in a cluster organisation (the letter C appears second in the group designation),
- companies that operate in the same industry and region as the cluster organisation, but are not members of the cluster organisation (the letter N appears second in the group designation),
- companies operating in the same industry, but outside the region where the cluster operates (the letter O appears second in the group designation).

The basic characteristics of each industry are listed in Table 1. Before the slash is the number of companies in each of the relevant groups; after the slash is the number of companies for which financial data were successfully obtained for the entire 2009–2016 time series. The number of analysed companies is affected by the fact that entrepreneurs – natural persons – are not obliged to publish financial statements. Business corporations in the category of micro- and small-accounting entities publish condensed financial statements without any profit and loss statement, which also makes performing an in-depth analysis of financial performance impossible. At the same time, these two categories of businesses are the most common in the economy: according to CZSO (2019), 97.5% of all entities in the manufacturing industry had fewer than 20 employees in 2018.

Table 1 Characteristics of the industries under examination

Industry	Region of operation of CO	Core NACE	Year of establishment of CO	Number of companies in CO	Number of companies in the region outside CO	Number of companies outside the region
Automotive	Moravian-Silesian	293	2006	11/9	25/13	135/52
Engineering	Moravian-Silesian, Olomouc, South Bohemian	251, 28	2003	10/6	1,011/167	1,836/197
IT	Moravian-Silesian	620	2006	8/6	718/21	3,409/85
Furniture	South Bohemian	161, 162, 310	2006	16/12	1,794/46	9,125/68
Nanotechnology	Central Bohemian, Pardubice	721	2010	6/3	357/19	790/45
Packaging	Hradec Kralove	172, 222	2005	16/9	104/15	764/162
Textile	Liberec, Hradec Kralove, Pardubice	13, 141	2006	19/19	275/38	1,430/138
Total				86/64	4,284/319	17,489/747

Source: Prepared by the authors (2020)

The research was divided into the following steps.

Step 1: Compiling a list of companies in all seven industries – a list of member organisations was compiled for each cluster organisation. The data were sourced from the cluster website or from the cluster organisation manager. For each organisation, the main line of business according to the NACE statistical classification was determined using the MagnusWeb database (Bisnode, 2019). Since the research focused on evaluating the financial performance of companies, only business entities were included in further analysis. Since DEA analysis requires the evaluated DMUs to be homogeneous, i.e. that they operate in similar markets (**Soteriou & Zenios, 1999**), the cluster core that determines the main focus (industry) of the entire cluster was identified for each cluster organisation, (see the NACE column in Table 1). Subsequently, the MagnusWeb database was used to identify companies that operate in the same industry and region in which the cluster organisation is based, but are not member of the cluster organisation. Finally, companies operating in the same industry in other regions were also identified.

Step 2: Determining the inputs and outputs for Data Envelopment Analysis – capital, namely equity and liabilities, was used as the input, whereas revenues from their own products and services and economic value added (EVA) were used as the outputs. EVA is based on economic profit that respects all the costs of the capital invested, i.e. both equity and liabilities (Grant, 2003). EVA is considered a modern measure of a firm's success because it expresses the company's true profitability and it is associated with the need to maximise shareholder wealth (Stewart, 1994). Since the transformation of accounting profit into economic profit is a relatively complicated process that is affected, among other things, by national accounting standards, Neumaierová & Neumaier (2002) created a model for calculating the EVA indicator, see formula (9). The same calculation methodology has been used by the Ministry of Industry and Trade since 1999. This is an equity-based approach where EVA is defined as the product of equity and spread (i.e. return on equity minus alternative cost of equity):

$$EVA = (ROE - r_e).E \qquad \textbf{(9)}$$

ROE … Return on equity

r_e … alternative cost of equity

E … Equity

The alternative cost of equity (r_e) can be calculated using formula (10), where a risk premium is added to the risk-free rate (r_f). According to the Ministry of Industry and Trade (2017), the risk premium consists of a risk premium for business risk (r_{pod}), financial structure (r_{finstr}), financial stability ($r_{finstab}$) and the size of the company or the liquidity of its shares (r_{la}).

$$r_e = r_f + r_{pod} + r_{finstr} + r_{finstab} + r_{la} \qquad (10)$$

Step 3: Collecting data for each group of companies in each industry – for all three groups of companies in each industry, financial data were obtained from their balance sheets and profit and loss statements. The data were collected for the 2009–2016 period. The initial year of collection was determined taking into account the process of establishing cluster organisations, so that at least three years have passed since the establishment of the cluster organisation. It is assumed that the cluster's positive effect on performance would be felt with a certain amount of delay. 2016 was determined taking into account the number of financial statements obtained, as the number of available statements dropped in subsequent years. Only those companies for which a complete time series of financial statements was obtained were included in the research. Accounting data were sourced from the MagnusWeb database (Bisnode, 2019) and the collection of documents available in the public register (Department of Justice, 2020). As mentioned above, the problem is that micro and small businesses do not publish their accounting data. That said, even some large corporations do not comply with their legal obligation and either do not publish their accounting data at all, or do so with a significant amount of delay. As Table 1 shows, obtaining accounting data for member companies in cluster organisations was the most successful, as these were mostly business corporations which have to publish their annual reports and financial statements in the public register.

Step 4: Calculating the Malmquist index and decomposing it – businesses were divided into a total of 21 files (7 industries, each comprising 3 groups of companies). For each group, the DEA-score-based Malmquist index was determined, including its components (EFFCH – technical efficiency change under CRS; PECH – pure efficiency change under VRS; TECH – technological change and SECH – scale efficiency change). An input-oriented model with radial distances was used. The MI compares a DMU's performance between periods t and z, see formula (7). The analysis was performed at one-year periods. The geometric means of the Malmquist index and its components were determined for each industry and for each group of companies within the industries. DEA scores were calculated using the MaxDEA 7 Ultra software.

Step 5: Comparing the Malmquist Index and its components between groups of companies and industries – since the final output of step 4 was geometric means, the companies' original values of the MI and its components were logarithmised. This is because the geometric mean is a monotonic function of the mean of logarithms. Thus, if there is a significant difference between the means of the logarithmised data, there is also a significant difference between the geometric means of the original variables (**Alf & Grossberg, 1979**). The Shapiro-Wilk test proved that the data did not have a normal distribution and, for some groups of companies, Levene's variance check test found that the homoscedasticity constraint was not met. For these reasons, the non-parametric Games-Howell post-hoc test was used to identify the differences between all groups of companies. The Games-Howell test works with the order of original values and examines the differences in the means for the various groups. The differences were tested using the Statgraphics XVIII software. The significance level alpha was 5%.

Step 6: Statistical cluster analysis of groups of companies – a hierarchical cluster analysis was performed to identify similarities between the various groups of companies in different industries. Ward's method of clustering with squared Euclidean distances was used. First, the similarity of groups of companies was assessed using a dendrogram of objects. Then, the basic characteristics of the MI and its components EFFCH and TECH were calculated for each statistical cluster.

IV. Research Results

Table 2 shows the average annual changes in the Malmquist index and its components in the industries under evaluation, by group of companies according to their cluster and region affiliation. Table 2 shows that performance in the industries under review decreased by 1.4% year-on-year, over the entire 2009–2016 monitoring period. The reasons for the decrease were both on the part of the companies, namely a decline in their internal efficiency, and in the shift of the efficient frontier in an undesirable direction. The decline in technical efficiency was caused by a decrease in scale efficiency, which means that the companies were not operating at the optimum scale of production.

Table 2 Average scores of the Malmquist index and its components by industry in the 2009–2016 period

Group	Count	MI	EFFCH	TECH	PECH	SECH
AC	9	1.082	1.018	1.063	1.005	1.013
AN	13	1.108	1.020	1.086	1.045	0.977
AO	52	1.011	1.030	0.981	1.050	0.981
Auto total	**74**	**1.036**	**1.027**	**1.009**	**1.043**	**0.984**
EC	6	1.073	1.104	0.972	1.020	1.082
EN	167	0.984	1.006	0.978	1.103	0.913
EO	197	1.021	1.015	1.006	1.061	0.957
Engineering total	**370**	**1.005**	**1.013**	**0.993**	**1.079**	**0.939**
IC	6	1.023	0.978	1.046	0.989	0.989
IN	21	0.926	1.009	0.917	0.992	1.018
IO	85	0.972	0.949	1.023	1.004	0.945
IT total	**112**	**0.966**	**0.962**	**1.004**	**1.001**	**0.961**
FC	12	1.032	0.994	1.038	0.985	1.009
FN	46	0.976	0.990	0.986	1.015	0.976
FO	68	0.980	0.981	0.999	1.060	0.925
Furniture total	**126**	**0.984**	**0.986**	**0.998**	**1.036**	**0.951**
NC	3	0.971	1.021	0.951	1.021	1.000
NN	19	0.996	0.975	1.022	0.960	1.015
NO	45	0.994	1.010	0.984	1.026	0.985
Nano total	**67**	**0.994**	**1.000**	**0.993**	**1.007**	**0.994**
PC	9	0.978	0.926	1.055	0.998	0.928
PN	15	1.022	1.011	1.011	0.998	1.013
PO	162	0.982	1.032	0.952	1.120	0.922
Packaging total	**186**	**0.985**	**1.025**	**0.961**	**1.103**	**0.929**
TC	19	1.012	1.008	1.004	1.006	1.003
TN	38	0.961	0.935	1.028	1.048	0.892
TO	138	0.934	0.936	0.998	1.084	0.863
Textile total	**195**	**0.947**	**0.942**	**1.005**	**1.069**	**0.881**
Core total	64	1.025	1.001	1.024	1.001	1.000
Natural total	319	0.984	0.994	0.989	1.059	0.939
Other total	747	0.984	0.994	0.991	1.068	0.930
Industry Total	**1,130**	**0.986**	**0.994**	**0.992**	**1.062**	**0.937**

Source: Prepared by the authors (2020)

The automotive and engineering industries were an exception, as their performance grew at an average annual rate of 3.6% and 0.5% respectively. In the automotive industry, both components contributed positively to performance growth, i.e. both improved internal organisation and technological progress resulted in a shift of the industry's efficient frontier. In the engineering industry, performance growth was driven by improved internal efficiency. As far as the other industries are concerned, it should be noted that packaging showed an average annual increase in technical efficiency of 2.5%. However, at the same time, there was a negative shift in the efficient frontier in this industry. In the remaining industries, both components of performance declined or stagnated.

In terms of the various groups of companies, the fastest growth in performance (almost 11 % per year) was found in the automotive industry in the region in which the cluster organisation is based. This group was followed by companies in the cluster organisation with an average growth rate of over 8 % per year. In both cases, both components contributed to the growth, but the *TECH* component – which can be interpreted as a result of innovation activities in the industry – contributed more significantly. It is apparent that there is a competitive and collaborative environment in the automotive industry in the Moravian-Silesian Region, which contributes to the growth in company performance.

By contrast, the sharpest decline in performance was identified in IT companies in the region in which the cluster organisation exists. In this group of companies, performance declined by an average of 7 % per year. This was caused by technological change. Interestingly, in the same industry, IT companies in the cluster organisation grew at an average rate of 2.3 % per year and, conversely, their growth was driven by technological progress. Given these trends, it can be concluded that the existence of the IT cluster had a positive effect. Similar trends can be observed in the furniture industry, where the performance of companies in the cluster organisation also grew (by an average of 3.2 % per year) due to innovation. In contrast, furniture companies outside the cluster showed a decline in performance in both components.

The following Tables 3 to 5 show the results of the Games-Howell post-hoc test, which was used to compare the average values of the *MI* and its components in each group of companies. Given the extent of the outputs, the tables are only provided for those components where more frequent differences between groups were found. The other differences are only commented on in the text.

In terms of the overall Malmquist index, significant differences (at a significance level of 5%) were only identified between three groups of companies (AN > AO, AN > IN, AN > FN). This means that the hypothesis that clustered companies had faster performance growth rates was only confirmed in one case, namely in the automotive industry. However, the hypothesis that members of the automotive cluster organisation would perform better than non-member companies was not confirmed. This conclusion is also apparent when making a comparison of the *MI* values for the AC and AN groups of companies in Table 2. For the *EFFCH* component, a significant difference was only found for one pair of values (PC < PO). This means that in the packaging industry, companies outside the cluster showed a significantly lower rate of decline in technical efficiency than companies in the cluster organisation. No significant difference was confirmed for the other pairs of values.

A higher incidence of significant differences was found in the case of the *TECH* component, see Table 3. On the diagonal, groups of companies within the same industry are compared. Above the diagonal, pair differences between industries are shown. The assumption that the trends in the *TECH* component would be better for clustered companies was confirmed in three industries. In the automotive industry, companies in a cluster organisation and in a natural cluster showed faster technological change than companies in other regions. In the furniture industry, technological progress was found in companies within the cluster organisation, both in comparison to other companies within the same region and in comparison to companies in other regions. However, unlike the automotive industry, the technological growth of companies within the natural regional cluster was not significantly better than that of other companies in other regions. All three assumptions were confirmed in the packaging industry. Technological progress was strongest among companies within the cluster organisations. At the same time, it was also stronger in non-member companies operating near the cluster as compared to packaging companies from other regions. Only companies from other regions showed technological regress. In the IT industry, significantly stronger technological progress was identified in companies within the cluster organisation as compared to other companies outside the region in which the cluster operates. However, technological change in the natural IT cluster was negative, even in comparison to companies in other regions. At the same time, an analysis of the *TECH* component revealed industries that showed trends that were opposite than expected. Engineering companies in the cluster organisation experienced a shift of the efficient frontier in an undesirable direction, in contrast to companies outside the region of the cluster. In the nanotechnology cluster, technological progress was achieved by companies in the region in which the cluster organisation exists, but not directly by its member companies.

An inter-industry comparison of the *TECH* component is more difficult. If we look directly at cluster organisations, the IC group of companies showed significantly faster technological growth compared to EC and NC, and the PC group compared to EC. In the group of natural clusters, companies in the automotive industry (AN) grew faster compared to the EN, FN, IN, and PN groups.

Table 3 Significant differences in the TECH component between groups of companies over the 2009–2016 period

Industry	A	E	I	F	N	P	T
A	AN > AO, AC > AO	AN > EN, AN > EO	AC > IN, AN > IN	AC > FN, AN > FN	AN > NC	AN > PN	x
E		EC < EO	EC < IC, EO < IC, EO > IN,	EN < FC	x	EC < PC, EO < PC	EN < TN
I			IC > IN, IN < IO	FN < IC, FO < IC	IC > NC	IC > PO, IN < PC	IN < TC, IN < TN
F				FC > FN, FC > FO	x	FC > PO	x
N					NC < NN	x	x
P						PC > PO, PC > PN, PN > PO	x
T							x

Source: Prepared by the authors (2020)

Table 4 Significant differences in the PECH component between groups of companies over the 2009–2016 period

Industry	A	E	I	F	N	P	T
A	x	x	x	x	x	AC < PO	x
E		x	x	x	EN > NN, EO > NN	x	x
I			x	x	x	IO < PO	x
F				x	x	x	x
N					x	NN < PO	x
P						PC < PO, PN < PO	x
T							x

Source: Prepared by the authors (2020)

In the *PECH* component (see Tab. 4), significant differences were only identified within one industry (packaging), but they were opposite to the original assumption. Packaging companies outside the region in which the cluster operates showed an increase in pure technical efficiency, in contrast to member companies of the cluster organisation and other companies in the region in which the cluster operates. In the group of natural clusters, engineering companies achieved significantly better improvement in efficiency than companies in nanotechnology. Other differences between industries can be seen in Table 4.

Significant differences in scale efficiency change *SECH* are shown in Table 5. The original assumption that the existence of a cluster organisation would have a positive effect on economies of scale was confirmed in two industries – engineering and textile. In the first case, the difference is significant compared to non-member companies of the cluster. In the textile industry, the difference is significant compared to other textile companies that operate in other regions than that in which the cluster operates.

Table 5 Significant differences in the SECH component between groups of companies over the 2009–2016 period

Industry	A	E	I	F	N	P	T
A	x	x	x	x	x	x	AC > TO, AO > TO,
E		EC > EN	x	x	x	EC > PC	EC > TN
I			x	x	x	x	x
F				x	x	x	FC > TO
N					x	x	x
P						x	x
T							TC > TO

Source: Prepared by the authors (2020)

In terms of the overall comparison of all three groups of companies across all industries (members of cluster organisations, non-members operating within the same region, and companies in other regions), some differences can be observed in the trends in performance and its components (see Table 2). However, most differences are not significant at a 5% level. This applies both to the overall trends in performance *MI*, and to changes in internal efficiency *EFFCH*. The Games-Howell post-hoc test (see Table 6) only identified significant differences in the *TECH* component between member and non-member companies of the cluster organisation. This means that in the group of cluster organisations, there was a significant desirable shift in the efficient frontier. For the *PECH* component, trends opposite than those originally assumed were identified. Specifically, the change in pure technical efficiency was significantly worse in the group of cluster organisations (it practically stagnated) in contrast to the group of non-member companies or other companies, where there was a year-on-year increase in pure internal efficiency (by an average of 6 % to 7 % per year). In terms of scale efficiency *SECH*, a significant change was identified in the group of cluster organisations in comparison to the group of other companies.

Table 6 Results of Games-Howell post-hoc tests for each group of companies

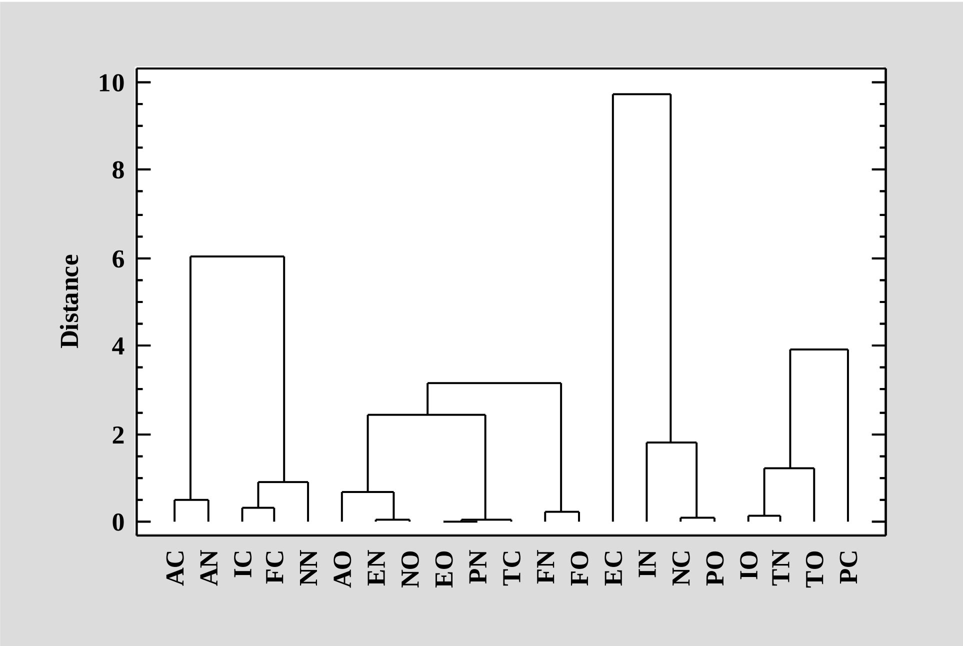
Group	TECH			PECH			SECH		
Contrast	Sig.	Difference	+/- Limits	Sig.	Difference	+/- Limits	Sig.	Difference	+/- Limits
C - N	*	0.034422	0.01912	*	-0.05653	0.052338		0.063431	0.06461
C - O		0.032952	0.036918	*	-0.06471	0.042283	*	0.072267	0.071872
N - O		-0.00147	0.034231		-0.00818	0.051469		0.008836	0.078706

* denotes a statistically significant difference
Source: Prepared by the authors (2020)

Making a comparison of the trends in performance and its components across industries is also difficult, because the DMUs cannot be considered homogeneous – they operate in different markets, are of different sizes, work with different inputs and produce different outputs. A statistical cluster analysis provides a certain amount of insight. This is a multivariate statistical method that seeks to create natural clusters that are as homogeneous as possible internally and as different as possible from each other.

Figure 1 shows a dendrogram of groups of companies that was created based on clustering according to two variables, *EFFCH* and *TECH*. At clustering level 9, four larger clusters of objects can be identified in the figure. The scatterplot in Figure 2 shows the position of each group of companies according to the *EFFCH* and *TECH* indicators. At the same time, it divides the groups of companies into four statistical clusters of groups. To facilitate interpretation, average characteristics were determined for each statistical cluster according to the magnitude of the *MI*, *EFFCH* and *TECH*, see Table 7.

Figure 1 Dendrogram of groups of companies

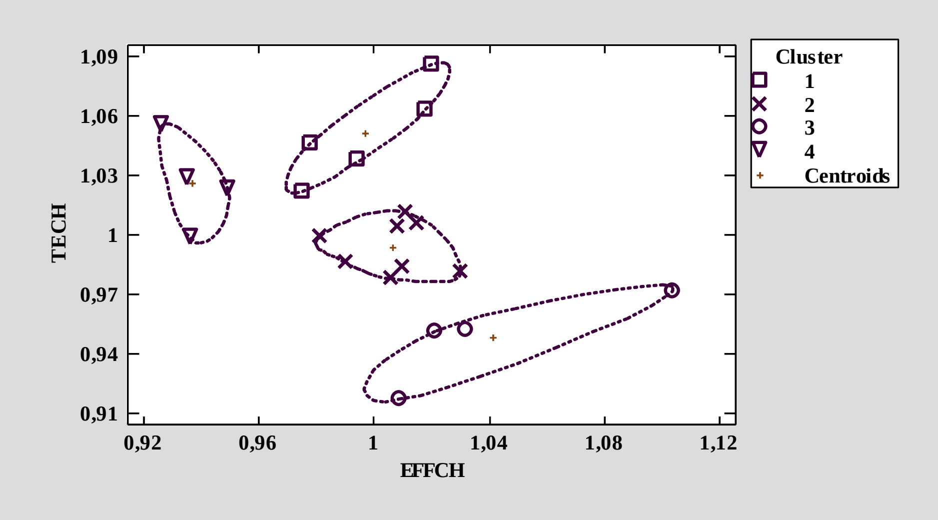


Source: Prepared by the authors (2020)

The first statistical cluster consists of groups of companies AC, AN, FC, IC, NN. It contains three cluster organisations and two natural clusters. It can be characterised as being oriented towards innovation and technological progress, with a rather constant level of internal technical efficiency.

The second and largest statistical cluster includes eight groups of companies (AO, EN, EO, FN, FO, NO, PN, TC). It includes only one cluster organisation, three natural clusters and four industries that are not spatially localised. It can be described as being stable, with no significant changes in internal work organisation or innovation.

Figure 2 Cluster Scatterplot



Source: Prepared by the authors (2020)

The third statistical cluster contains four groups of companies (EC, IN, NC, PO), i.e. two cluster organisations, one natural cluster and one industry that is not spatially concentrated. This cluster is characterised by an increase in internal technical efficiency and a negative technological change. It can be characterised as being oriented towards internal managerial measures to improve efficiency.

The fourth statistical cluster also comprises four groups of companies (IO, PC, TN, TO). It contains one cluster organisation, one natural industry grouping and two other industries that are spatially fragmented. On average, this cluster shows the largest decline in internal technical efficiency but, on the other hand, it shows a positive technological shift. It can therefore be described as being oriented towards change in technology.

Table 7 Average values of the MI, EFFCH and TECH in statistical clusters

Cluster No.	MI	EFFCH	TECH
1	104.76 %	99.68 %	105.10 %
2	100.00 %	100.65 %	99.35 %
3	98.65 %	104.09 %	94.78 %
4	96.11 %	93.65 %	102.62 %

Source: Prepared by the authors (2020)

V. Conclusions

The objective of the research was to find out whether cluster initiatives that aim to provide targeted support for the establishment and development of cluster organisations bring any economic benefits to companies. The research that was carried out did not generally confirm the above assumption. In none of the industries was it found that member companies of a cluster organisation experienced faster growth in overall performance over the entire 2009–2016 period.

In terms of the type of cluster of a company's membership, it was not confirmed that the change in overall performance differed for all monitored industries over the period under examination. Therefore, it cannot be concluded that industry clusters generally have a positive effect on the financial performance of companies. In terms of internal technical efficiency change, no significant difference was found between cluster members and non-members. The group of cluster organisations even showed a stagnation of pure technical efficiency, while other groups of companies experienced improvement. However, cluster organisations were found to have a positive impact on the shift of the efficient frontier, which is usually attributed to the effects of innovation within the specific industry. The group of companies in cluster organisations achieved a significantly faster pace of technological progress in comparison to non-member companies. Cluster organisations were also found to have a positive effect on scale efficiency change as compared to other companies. Overall, however, these partial positive effects of clustering were not strong enough to suggest that the group of clustered companies experienced a significantly faster rate of financial performance growth.

From the perspective of the various industries, some benefits were identified in four industries in the component expressing technological shift. This applied to the automotive, furniture, packaging and IT industries, where the group of companies in cluster organisations showed faster growth in the efficient frontier in comparison to companies that are not members of a cluster organisation (furniture, packaging, IT), or in comparison to other companies outside the region (automotive, furniture, packaging). This suggests that cluster organisations have a positive effect on innovation within each industry. When forming cluster organisations, an additional benefit could also be expected in the area of economies of scale, e.g. due to the joint organisation of the procurement of raw materials and other materials, joint usage of research infrastructure, or the joint promotion of production. This effect was successfully demonstrated in the case of the engineering and textile industries.

Besides the targeted establishment of cluster organisations in the given regions, the natural business environment, research infrastructure, specialised schools, workers with specialised knowledge and skills leads natural knowledge spillover. These positive externalities have been found to contribute to performance growth in the automotive industry, including technological progress. A positive effect on innovation was also identified in the natural packaging industry grouping.

There was only one industry (nanotechnology) for which clustering was not found to have any effect on performance at all. This may be due to the specific nature of that industry. It is a new industry that is highly innovative and progressive in and of itself. Businesses in this industry are innovative regardless of whether or not they are clustered. In two industries (IT, engineering), companies operating outside locations with a high concentration of industry reported faster technological progress.

In summary, it can be concluded that in most industries (i.e. six), partial positive effects of clustering were demonstrated, yet they were not strong enough to significantly affect the overall performance of the companies under review. These positive effects mainly concerned the area of innovation. This finding is in line with existing knowledge published in literature, which sees the main role of clusters as being the support of innovation (Delgado, Porter, & Stern, 2014). Somewhat surprisingly, clustering was found to have a weaker impact on improving internal technical efficiency. At least a partial effect on scale efficiency was identified in only two industries (engineering, textile). It can thus be concluded that cluster organisations do not have a significant impact on the internal functioning of their members.

The research results confirm the rather sceptical views contained in literature that the existence of clusters has only a minor impact on company performance (Kukalis, 2010; Krželj Čolović, Milić Beran, & Vrdoljak Raguž, 2016; Ruland, 2013). However, the finding that the clustering of companies has a positive impact of the shift of the efficient frontier in some industries suggest that, in the long term, clusters might prove to have a positive effect on overall company performance. Some foreign studies (Branco & Lopes, 2018) found that the clusters' positive effect on performance was not felt until 20 years later. From this point of view, Czech clusters are still too young, and therefore it will be desirable to monitor trends in the performance of companies in clusters in future periods.

Even though the research was conducted on a sample of seven industries and involved more than 1,100 companies, the limitations of the research should be noted. These mainly concern micro and small businesses for which accounting data cannot be obtained. From this perspective, the research focused mainly on medium-sized and larger businesses, which were much more represented in the group of members of cluster organisations. Therefore, the research provides information on the impact of clusters mainly on the performance of this category of companies.

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