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Chapter: Perspectives on Trade Dynamics and Structural Shifts in Regional Development Transformation

EVALUATING SCALE EFFICIENCY OF INDUSTRY CLUSTERS: A DEA APPROACH

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Annotation. The paper deals with the impact of the existence of clusters on the efficiency of firms in terms of scale. The research subject is seven industries, six of which are manufacturing industries (automotive, engineering, furniture, nanotechnology, packaging and textile industries) and one service industry (IT). Technical and scale efficiencies were investigated in these industries from 2009 to 2021. The analysed firms were divided into two groups. The first group consists of members of the cluster organisation and companies operating in the same region as the cluster organisation. They may, therefore, share to some extent the positive externalities of the cluster organisation. The second group then represents other firms from more distant regions. The results show no positive impact of the existence of clusters on scale efficiency. Only in one industry - textile - a significant difference in the level of scale efficiency was found, but in reverse order. That is, non-clustered textile firms have achieved higher scale efficiency than clustered firms. Three industries (furniture, IT and packaging) are dominated by companies in conditions of increasing returns to scale. In the automotive industry, companies were on average close to optimal scale production around 2018-2019. However, the COVID-19 pandemic and subsequent sales problems in the industry marked a turning point for scale efficiency. In IT services, clustered companies in particular were close to optimal scale. In other industries, companies operating in a situation of declining returns to scale were significantly more prevalent.

Keywords: industry cluster, Data Envelopment Analysis, scale efficiency, increasing returns to scale, decreasing returns to scale

JEL classification: C61, L60, M21.

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Introduction

Since the 1990s, when Michael Porter developed and popularised his cluster theory, clusters have become an integral part of regional and innovation policy in most developed countries. However, the history of clusters, or the natural clustering and concentration of economic activities in certain areas, is much older. Von Thünen (1826) has already addressed localisation economies in agriculture. Weber (1928) investigated the optimal location of enterprises in terms of transport costs. Marshall's concept of industrial districts can be considered a precursor of cluster theory. In the late 19th century, Marshall identified three primary sources of external economies related to the proximity of economic activities. Specifically, these were the economies arising from the sharing of labour markets, the transfer of information and knowledge between neighbouring enterprises, and the sharing of specialised suppliers. These factors explain why certain regions specialise in specific production (Marshall, 1920). It is only a step from industrial districts to industry clusters. Industrial districts comprise a network of small and medium-sized enterprises mainly operating in light industry (Ketels, Memedovic, 2008). The performance of industrial districts is primarily based on local resources, the flexibility of production, and the social structure and informal ties in the local society play an important role. Clusters share several basic characteristics with industrial districts. First of all, the location and agglomeration of related economic activities and the links between economic actors positively impact performance. The network of linkages in an industrial district is limited to a specific, small region. In contrast, clusters represent a broader concept. They can consist of industrial districts, i.e. districts can be considered as one type of cluster. However, they encompass a much more comprehensive range of linkages and forms. Clusters can also include large companies that coexist with small and medium-sized enterprises. Cluster organisations tend to be much more formalised, often facilitated with the help of government organisations. Cluster members include universities, research institutions and trade associations (Becattini *et al.*, 2009).

Clusters are also a standard regional and innovation policy instrument in the Czech Republic, supported through operational programmes financed by the European Structural Funds. The first operational programme supporting the establishment and development of clusters was approved in the Czech Republic in 2004 and has since been followed up by other programmes.

The paper's main objective is to investigate whether sharing inputs and infrastructure within clustered firms positively impacts scale efficiency. A sub-objective is to find out what factors influence scale efficiency in clusters.

1. Theoretical Background

The most famous definition of a cluster comes from Porter. According to this definition, clusters are geographic concentrations of interrelated companies, specialised suppliers, service providers, and firms in related industries. Companies in the cluster compete and cooperate simultaneously (Porter, 2000). Different types of relationships between actors emerge within clusters. Rawat *et al.* (2019) identified four types of networks between enterprises: informational, collaborative technological, resource sharing, and educational. If firms are not members of a cluster, they cannot access all these networks. They cannot benefit from the direct benefits of clusters and the positive externalities associated with clusters. Companies expect cluster membership to enhance their competitiveness. Research among cluster members (Anić *et al.*, 2022) showed that this strengthening could be achieved mainly through better sectoral lobbying towards government and European institutions, developing networking and cooperation between members, shared market access (negotiation with suppliers) and logistics services.

Research on clusters over the past decades has focused mainly on the effects of knowledge sharing, fostering innovation and developing poor regions (Leick, Gretzinger, 2020). One of the more recent studies using the example of the biopharmaceutical industry in China has shown that the positive impact on innovation performance is stronger the stronger the spillover effect between companies in the cluster. And not only between companies in the core cluster but also between other actors in the network (Zeng *et al.*, 2019). Research on the impact of clusters on businesses' resilience to crises and their ability to survive in networks is also gaining importance (Andreano *et al.*, 2021). Clusters also play an important role in promoting regional development and competitiveness (Svoboda *et al.*, 2024).

Another research group focuses on measuring clusters' impact on economic performance. These studies are mainly case studies, as they depend on the availability of financial and accounting data, which varies from country to country.

Classic studies in this respect include the work (Kukalis, 2010), which examined whether companies in a cluster perform better than those outside the cluster. What is unique about the cited study is the length of the study period, which was 31 years. However, the study was limited to US companies in the pharmaceutical and semiconductor industries. The results then showed that clustered companies did not show better financial performance compared to lone non-clustered firms. More recent studies have reached the same conclusion; for example, Pavelkova *et al.* (2021) examined the financial performance difference between Czech companies in the plastics and textiles industries operating in organised clusters and non-clusters. Another similar study compared the financial performance of companies in four industries in the Czech Republic and Slovakia, where nine clusters operate (Pelloneová, 2021). The cluster organisations (COs) in these countries have very different conditions for receiving public support. While clusters in the Czech Republic are generously supported by operational programmes, support in Slovakia is very limited. Nevertheless, the financial performance of companies in the industry clusters studied has not been shown to differ significantly between the two countries.

The impact of clustering on performance often depends on the industry. For example, a Russian study (Zyuzin, Demidova, 2022) found a positive and strong impact of cluster agglomeration effects on economic performance (sales margin) in the agriculture, mining and transport sectors. In contrast, a negative impact of agglomeration on economic performance was identified in the IT industry. A Chinese study focusing on the digital industry found a positive impact of spatial agglomeration on economic levels and green productivity, but the spillover effect on neighbouring regions was weak (Li *et al.*, 2022). Further research (Stojčić *et al.*, 2019) focused on the impact of clusters on business performance in the wood and furniture industries in Slovenia and Croatia. The authors examined the effect on sales, number of employees, labour productivity, export performance and business growth. They concluded that cluster member companies performed significantly better on the indicators studied than a control group represented by non-member firms in the same industry. Another recent Czech study (Zizka, Stichhauerova, 2023) found that in some industries, companies in organised clusters are more successful; in others, companies in natural industry agglomerations are more successful, but there are also industries (IT and furniture industry) where no positive effect of clustering on financial performance has been shown.

Most of the literature focuses on examining the impact of business clustering on technical efficiency (in terms of terminology, it also includes the area of economic efficiency and financial performance). Less attention is paid to the impact on scale efficiency, where we see a research gap. One of the few studies, albeit older, is Sharma and Sharma (2010), which assessed the scale efficiency of industrial districts in 26 Indian states. Of these, 21 districts were found to be experiencing decreasing returns to scale. Only two districts were scale efficient.

The novelty of our methodological approach lies in monitoring clusters from the bottom up, starting with the membership base. We do not use aggregated industry data; we work directly with company data from financial statements. Only then do we cluster the company data into individual groups.

The same factors may affect technical and scale efficiencies, but some aspects may be specific only to scale efficiency. While research examining the direct relationship of clusters on scale efficiency is scarce, a number of studies focus more generally on the determinants of scale efficiency in different industries. These studies may well be used to inspire our research and to see if some findings are transferable to the cluster domain.

Understanding technical efficiency is simple. The objective of a business is to produce the maximum output with a given volume of inputs or to achieve a given volume of output with the minimum amount of resources. The more efficient a business is, the closer it is to the efficient production frontier and the more productive it is in using its scarce resources (Anang, 2021). Several mathematical models are used to measure efficiency; among them, Data Envelopment Analysis models are widespread. The classical CCR model measures the relative efficiency of a unit under conditions of constant returns to scale. Thus, it assumes that all efficient units produce at an optimal level; that is, a proportional change in their inputs is reflected in a proportional change in their outputs (Oredegbe, Zhang, 2020). The BCC model extends the previous model with the condition of variable returns to scale, thus allowing for the investigation of scale efficiency issues. It decomposes technical efficiency into pure technical efficiency and scale efficiency (Jiang *et al.*, 2019). Pure technical efficiency shows the ability of management to properly manage inputs to the production process.

Scale efficiency then reflects management's ability to determine the optimal scale of resources or to choose the right scale or capacity of production to achieve the expected volume of output (Li and Long, 2019). In mathematical terms, scale efficiency expresses the deviation of a company from its optimal size. That is the deviation from the point on the cost curve where the company is under conditions of constant returns to scale (Majumdar, Chang, 1996). Scale efficiency can be estimated as the ratio of the average product of the company lying at the point on the efficient frontier under conditions of increasing returns to scale (IRS) and the average product at the point of the technically optimal scale on the efficient frontier under conditions of constant returns to scale (Tran Nguyen *et al.*, 2020). Thus, the loss of overall efficiency results from errors in pure technical or scale efficiency management. Units are scale inefficient if they are too small or too large. Small units have limited opportunities for specialisation of equipment, tasks and division of labour. Large units have overloaded inputs or limited managerial supervision and control over workers (Han *et al.*, 2021). The indivisibility of some inputs (then the capacity cannot be reduced) or the high specialization of workers can also cause scale inefficiency. The involvement and sharing of unique inputs or workers in cluster activities is a way to improve scale efficiency. Decreasing returns to scale (DRS) result from low management efficiency or cumbersome communication between management and ordinary staff (Kirigia, Asbu, 2013). Inefficiencies from scale also impact costs. If a company is in a situation of IRS, then an increase in production scale for a given quantity of inputs may lead to a decrease in average costs. Similarly, for companies with DRS, a reduction in capacity will lead to a decline in average costs (Majumdar, Chang, 1996).

One factor affecting scale efficiency is subsidies. These reduce the company's need to operate at an optimal scale because the subsidy guarantees part of the revenue. On the other hand, subsidies allow investment and expansion and thus can increase scale efficiency (Addo, Salhofer, 2022).

Scale efficiency also affects debt (Karagiannis, Sarris, 2005), business size (Anang *et al.*, 2016) and capital constraints (Thiele, 1999). Debt motivates company owners to improve business performance. On the other hand, they increase stress and impair owners' ability to make effective decisions. Overcapitalized companies have lower scale efficiency. Small enterprises tend to operate under conditions of IRS. In contrast, large companies often have difficulty operating at optimal scale and may not be efficient in the use of their resources. However, many of the studies cited are the result of research in the agricultural sector. There are relatively few studies from the industry sector, which can be seen as another research gap that our research is trying to narrow.

Wang *et al.* (2019) examined the efficiency of R&D expenditures in Chinese industrial companies and the factors influencing it. They identified four significant factors affecting scale efficiency. However, apart from the economic level, the remaining factors had a negative impact on scale efficiency.

The results of a historical study of the milling industry in the United States are inspiring. It showed a dramatic increase in scale efficiency driven by technological progress, which was significantly higher for larger mills. However, in the following period, large mills experienced a substantial reduction in scale efficiency due to the excessive growth in the previous period (Han *et al.*, 2021).

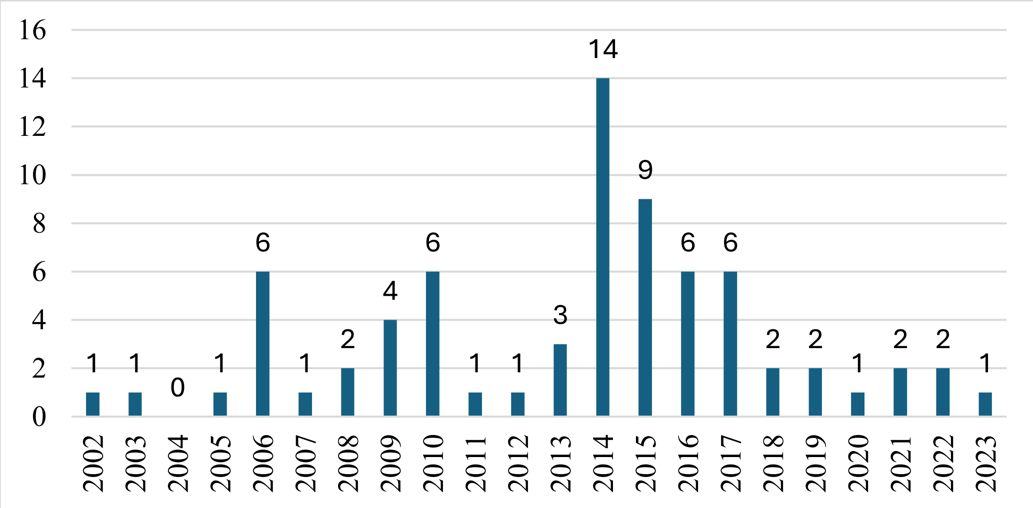
Anang (2021) found that the factor that positively influences scale efficiency in the agricultural sector is the education of entrepreneurs. Formal education contributes to companies producing at an optimal scale. Oredegbe, Zhang (2020) examined the telecommunications sector in several countries and the factors affecting its efficiency. They found that capital intensity correlated negatively with scale efficiency. High capital expenditure per unit of revenue has a negative effect on scale efficiency in some countries. From a cluster perspective, a central finding is that facility sharing and infrastructure cooperation reduce the share of capital expenditure in revenues and improve scale efficiency. Furthermore, a positive effect between inflation rate and scale efficiency has been identified, which is an exciting finding in these days of rising inflation. That is, inflation can promote operational scale. Also, an interesting finding is that companies with high labour productivity have little incentive to improve their scale.

2. Data and Methodology

Scale efficiency was measured in seven randomly selected industries where COs exist at the maturity stage. According to the National Cluster Organisation database, there are currently 101 clusters, technology platforms and industry associations in the Czech Republic, which bring together 1,577 companies and employ approximately 525,000 workers (National Cluster Association, 2023). However, the number of clusters is lower, with 87 listed in the database, of which only 72 are active. Several characteristics can identify inactive clusters. For older clusters existing before 2014, which had the legal form of a civil association, the fact that they have not transformed into a registered association is a sign of inactivity. This obligation is linked to the new Civil Code, which entered into force in 2014. Other signs of inactivity are non-functioning or long-outdated websites, and zero income and expenses in the accounts.

Figure 1 shows the number of clusters by year of formation. The figure shows that the oldest CO in the Czech Republic was established in 2002 without public support. The more significant peaks in the graph are then related to support programmes. From 2004 to 2006, clusters were supported under the Operational Programme Industry and Enterprise through the "Clusters" sub-programme. The oldest Czech COs were established in this period, with the abovementioned exception. The Clusters programme was followed in 2007 by the Cooperation - Clusters sub-programme under the Operational Programme Enterprise and Innovation until 2013. A further 18 still active clusters date from that period. Since 2014, clusters have been supported by the Operational Programme Enterprise and Innovations for

Competitiveness, which ran until 2020. From 2021, clusters can draw support from the Operational Programme Technologies and Applications for Competitiveness under the Cooperation - Clusters sub-programme.



Source: own analysis in the public register

Figure 1. **Number of COs in the Czech Republic by Year of Establishment**

The characteristics of the industry clusters studied are presented in *Table 1*. In total, 1,263 companies were included in the research for which it was possible to obtain financial statements (balance sheet, profit and loss statement) in the comprehensive time series 2009-2021. Obtaining financial statements represented a rather challenging step. According to the Accounting Act in the Czech Republic, only companies registered in the public register with assets above € 1.65 million, turnover over € 3.3 million and more than 50 employees are required to publish their full financial statements. Only abbreviated financial statements can be obtained for smaller legal entities; natural persons (sole traders) do not publish any data. Another problem is that many companies did not publish their financial statements, especially in the past. The situation has improved only in the last three years due to the introduction of sanctions and audits by the registry courts. These facts have negatively affected the analysis of industries where there are typically many micro and small companies (IT, furniture). The source of the accounting data was the MagnusWeb database (Dun & Bradstreet Czech Republic, 2023).

The actual research can be divided into the following steps:

1. **Creation of a list of companies for each industry** - Within each industry, companies were divided into two groups: companies operating in the same region (NUTS 3) as the cluster headquarters (group C), and companies operating in other regions (group O). Companies in the first group include both companies that are members of the cluster organisation and other companies operating in the cluster region. Companies in the cluster organisation were identified using the website, which lists the cluster membership. Each cluster has a core industry focus, which the NACE statistical classification can describe. Subsequently, companies that are not members of the cluster but operate in the same industry and the region where the cluster is located were identified. In the next stage, companies in the same industry but from other regions outside the cluster location were identified. The original idea was to divide firms into three groups – cluster members, non-members in the cluster region and others. However, the membership of cluster

organisations changed a lot during the period under review. Some companies that were members of a cluster organisation have left it. Conversely, other companies from the region joined the cluster organisation. If we keep in the group only those firms that were members of a cluster organisation during the whole period under review, we would obtain a very small sample that cannot be statistically analysed. Therefore, we divided the companies into only two groups: clustered and non-clustered. The MagnusWeb database was used as a data source for selecting companies.

Table 1. Characteristics of the industries surveyed

Industries	Cluster name	Year of creation	Number of clustered companies	Number of other companies
Automotive	Moravian-Silesian Automotive Cluster	2006	26	60
Engineering	Czech Machinery Cluster	2003	218	243
Furniture	Cluster of Czech Furniture Manufacturers	2006	61	71
IT	IT Cluster	2006	46	69
Nanotechnology	NANOPROGRESS	2010	34	61
Packaging	OMNIPACK - Cluster of Industrial Packaging Manufacturers	2005	32	150
Textile	CLUTEX - Cluster of Technical Textiles	2006	55	137

Source: authors' results.

2. **Accounting data collection** - For companies in both groups, accounting data for 2009-2021, balance sheets and profit and loss statements were obtained. The starting year of 2009 was chosen to reflect the beginning of the cluster activity (the cluster effect occurs with a time lag). The end year 2021 has been set considering the availability of accounting data. Companies have a deadline of 12 months after the end of the accounting period to publish accounting data (i.e. for 2022, the deadline is until the end of 2023). Still, many rather smaller and medium-sized enterprises do not respect this deadline. Thus, there were various gaps in the time series of the financial statements. If a company published a financial statement more than a year late, it was usually no longer included in the MagnusWeb database. Therefore, we manually searched for the statements in the collection of documents from the commercial register. If no more than three data were missing in a time series (13 years), we used techniques to fill in the missing values (averages of adjacent values or trend functions). These techniques succeeded in increasing the sample of companies included in the survey from the original 604 units to 1,263 companies.

3. **Calculation of technical efficiency scores** - For companies where accounting data could be obtained, technical efficiency scores were determined, assuming constant returns to scale (CRS). An input-oriented Data Envelopment Analysis model was applied. Equity and liabilities were chosen as inputs to the model. Revenues from own products and services and economic value added (EVA) were used as outputs. EVA was calculated according to the Ministry of Industry and Trade methodology, see relation (2). The CRS mathematical model is presented in relation (1). In the model, x_{ij} is the model's inputs, y_{rj} is the model's outputs, λ_j is the weight of the peer unit when the unit score is 0, and the technical efficiency score is θ* (Zhu, 2014).

$$\theta^* = \min \theta$$

subject to

$$\sum_{j=1}^{n} \lambda_j x_{ij} \leq \theta x_{i0} \quad i = 1, 2, \dots, m;$$
$$\sum_{j=1}^{n} \lambda_j y_{rj} \geq y_{r0} \quad r = 1, 2, \dots, s; \tag{1}$$
$$\lambda_j \geq 0 \quad j = 1, 2, \dots n$$

$$EVA = (ROE - r_e) \cdot E \tag{2}$$

where *ROE* ... return on equity; r_e ... cost of equity; *E* ... equity

4. **Calculating pure technical efficiency** - Analogously, we determine the efficiency score under the variable returns to scale (VRS) model. The VRS model differs from the previous CRS model in the summation condition (3). MaxDEA 7 Ultra software was employed to calculate the efficiency scores.

$$\sum_{j=1}^{n} \lambda_j = 1 \tag{3}$$

5. **Determination of scale efficiency** - Scale efficiency (SE) was determined for each company according to relation (4). The average SE score was then calculated for both groups of companies. The homoskedasticity condition was tested using Levene's variance check test. If the variances of the two groups were identical, One-way ANOVA analysis was used to verify the existence of statistically significant differences in the mean SE score between the two groups of companies. On the other hand, if Levene's test indicated unequal variances between the groups, the non-parametric Welsch test was applied instead of One-way ANOVA. All tests were performed at the 0.05 significance level.

$$SE = \frac{\theta^*{}_{CRS}}{\theta^*{}_{VRS}} \tag{4}$$

6. **Determining the type of returns to scale** - Dual models were solved and lambda values were determined. For each company, it was determined whether it operated under CRS, IRS, or DRS. If the unit is in the CRS area, the efficiency scores under the CRS and VRS models are always the same. If the efficiency scores are different and condition (5) is met, the company is in the area of IRS. If the efficiency scores are different and condition (6) is met, the unit is in the area of DRS (Zhu, 2014).

$$\theta^*{}_{CRS} \neq \theta^*{}_{VRS} \; and \sum\nolimits_{j}^{n} \lambda_j^* < 1 \rightarrow IRS \tag{5}$$

$$\theta^*{}_{CRS} \neq \theta^*{}_{VRS} \; and \sum\nolimits_{j}^{n} \lambda_j^* > 1 \rightarrow DRS \tag{6}$$

The correctness of the determination of the type of returns to scale can be verified by the proportion of technical efficiency scores calculated by DEA models under constant and non-increasing returns to scale

(NIRS) conditions. The company is in the IRS area if condition (7) holds and in the DRS area if relation (8) holds (Bielik and Rajčániová, 2004).

$$\frac{\theta^*_{CRS}}{\theta^*_{NIRS}} = 1 \tag{7}$$

$$\frac{\theta^*_{CRS}}{\theta^*_{NIRS}} < 1 \tag{8}$$

7. **Investigation of factors influencing scale efficiency** - Correlation analysis was used to determine whether the value of SE depends on the capital structure of the company (the level of indebtedness measured as the share of liabilities in total capital) or on the business size (measured by turnover and the size of total capital).

3. Research Results

Table 2 shows the development of average SE scores in each industry depending on the group of companies. In three industries, there is a cyclical trend with a discontinuity in the time series in 2020. The COVID-19 pandemic had a significant negative impact on SE in two industries. The most significant SE decline occurred in 2020 in the automotive and engineering industries, where SE decreased by 0.19 and 0.18, respectively. Conversely, in the nanotechnology industry, SE increased by 0.15, possibly related to the increased consumption of protective materials (e. g. nano-masks and respirators) during the pandemic. In the IT branch, the SE is practically unchanged in 2020 and in the remaining industries (furniture, packing and textiles) it increased slightly.

Suppose we exclude 2020 as an atypical year from the analysis. In that case, the most significant improvements in SE in terms of industries over the period 2009-2021 are shown by the IT industry (0.17), nanotechnology (0.06) and packaging (0.06). On the other hand, only a tiny improvement in SE occurred in the engineering (0.04), furniture (0.04) and textile (0.03) industries. Only in the automotive industry did the SE decrease (-0.06), but this branch was still affected by the COVID-19 pandemic in 2021. In terms of the affiliation of companies to a cluster, an improvement in SE can be observed in all industries, except for the automotive cluster (a drop of 0.11). The greatest improvement in SE occurred in the group of clustered enterprises in the IT (0.23), nanotechnology (0.13) and textile industries (0.08). However, in the same industries, SE also improved in the group of other enterprises. Therefore, it was necessary to test in which industries and years the differences were significant.

The results of the analysis of the differences between the average SE scores in the industries are shown in *Table 3*. The table contains two rows in each year. The first row shows the type of difference regarding the company's membership in one of the two groups (C, O). The second row gives the p-value. In order to save space, only significant differences are reported in this table. That is, in five industries (automotive, engineering, furniture, nanotechnology and packaging), no significant differences between groups of companies in relation to cluster membership were found at all for the whole period 2009-2021. *Table 3* shows that significant differences were most often found between groups of enterprises in the textile industry. Throughout the whole period under review, non-clustered companies in this industry in other regions had higher SE rates than clustered firms in other regions. In only one year (2011), a significant difference in SE was found in the IT branch, in the same direction as in the textile industry. However, the identification of a difference in a single year cannot be considered a systematic phenomenon. It is rather a random fact. The results show that there is no evidence of a positive effect of firm clustering on SE in any industry.

Table 2. Average SE scores by industry and company group

Industry	Type	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021
Auto	C	0.9049	0.8883	0.8975	0.9133	0.8663	0.8194	0.8808	0.9146	0.8768	0.9507	0.8590	0.6755	0.7949
	O	0.8963	0.9202	0.8959	0.8970	0.8458	0.8281	0.9103	0.9342	0.8966	0.9674	0.9123	0.7356	0.8309
	ALL	0.8812	0.8949	0.8875	0.9002	0.8437	0.8275	0.9140	0.9186	0.8865	0.9448	0.9004	0.7107	0.8228
Eng	C	0.6355	0.5232	0.8106	0.4855	0.4645	0.8052	0.8193	0.6746	0.7287	0.7807	0.6489	0.4848	0.6885
	O	0.6517	0.5172	0.8139	0.4915	0.4486	0.7806	0.8087	0.6521	0.7386	0.7722	0.6540	0.4712	0.6763
	ALL	0.6367	0.5136	0.8100	0.4874	0.4566	0.7913	0.8193	0.6648	0.7311	0.7786	0.6557	0.4752	0.6797
Furniture	C	0.7940	0.5805	0.5172	0.6733	0.8496	0.8464	0.8756	0.8474	0.8017	0.8341	0.8513	0.8590	0.8358
	O	0.8046	0.6240	0.5449	0.6600	0.8217	0.8297	0.8717	0.8247	0.7719	0.8283	0.8125	0.8581	0.8296
	ALL	0.8092	0.6044	0.5334	0.6801	0.8500	0.8410	0.8864	0.8498	0.8009	0.8564	0.8296	0.8623	0.8498
IT	C	0.6964	0.7343	0.6649	0.7968	0.8725	0.8660	0.8588	0.5587	0.8050	0.8588	0.8739	0.9827	0.9232
	O	0.6616	0.7098	0.7510	0.8349	0.8700	0.8297	0.8728	0.5244	0.7880	0.8075	0.8455	0.8580	0.8540
	ALL	0.6781	0.7346	0.7360	0.8310	0.8822	0.8372	0.8742	0.5501	0.8117	0.8379	0.8707	0.8727	0.8490
Nano	C	0.6248	0.8240	0.7428	0.8206	0.6957	0.5322	0.7551	0.7710	0.8733	0.8815	0.7164	0.8689	0.7539
	O	0.6866	0.8399	0.7558	0.8016	0.6699	0.5113	0.7555	0.8158	0.8518	0.8547	0.7131	0.8990	0.7432
	ALL	0.6765	0.8123	0.7396	0.7833	0.6778	0.5074	0.7320	0.7762	0.8311	0.8511	0.7104	0.8633	0.7397
Pack	C	0.6948	0.7004	0.6769	0.6712	0.6889	0.6768	0.7178	0.7129	0.8028	0.7660	0.7054	0.7285	0.7483
	O	0.6590	0.7262	0.7242	0.6975	0.7112	0.6546	0.7241	0.7211	0.8034	0.7428	0.7179	0.7596	0.7244
	ALL	0.6686	0.7338	0.7295	0.6993	0.7160	0.6610	0.7297	0.7315	0.8126	0.7591	0.7318	0.7650	0.7299
Textile	C	0.5561	0.4789	0.4085	0.4316	0.5498	0.4364	0.5416	0.6050	0.4747	0.5226	0.6078	0.6474	0.6395
	O	0.7046	0.6328	0.5187	0.5516	0.6817	0.5704	0.6502	0.7417	0.6148	0.6880	0.7079	0.7471	0.7394
	ALL	0.6938	0.6153	0.4954	0.5264	0.6611	0.5459	0.6213	0.7193	0.5833	0.6543	0.6867	0.7253	0.7230

Source: authors' results.

Table 3. Significant differences between the average SE scores for different company groups by industry

Industry/Year	2009	2010	2011	2012	2013	2014	2015	2016
IT			O > C * (<.007)					
Textile	O > C * (<.001)	O > C (<.001)	O > C (.009)	O > C (.003)	O > C (<.001)	O > C (<.001)	O > C * (<.001)	O > C (<.001)

Industry/Year	2017	2018	2019	2020	2021
Textile	O > C (.004)	O > C (<.001)	O > C (.013)	O > C * (.039)	O > C (.012)

Note: parametric tests: ANOVA; with asterisk due to mismatch of variances non-parametric Welsch test.

Source: authors' results.

If we look at the type of returns to scale for the companies surveyed, the automotive industry was dominated by companies operating in DRS conditions at the end of the period (2021) in both groups of companies. The trend towards a shift to DRS conditions tended to strengthen since 2019, in both groups of companies. As noted above, there was a sharp drop in output in 2020, and 88% of businesses were in a

DRS situation. Similar, though not as severe, crisis years in the automotive industry were also 2010, 2011, 2013, 2016, 2017 and 2019, when the share of firms in a DRS situation also increased.

In the engineering industry, it was found that the dominant part of enterprises in both groups operate in conditions of DRS. In both groups of firms – clustered and others – throughout the period under review the shares of companies in a DRS were around 85%. It cannot be concluded that there was any significant improvement in returns to scale in these two groups.

The furniture industry was characterised by relatively strong fluctuations in scale efficiency in the period analysed. In the group of clustered firms, the share of firms in IRS conditions increased from 18% in 2009 to a maximum of 62% in 2015. By the end of the analysed period in 2021, it was 52%. A different situation prevailed in the group of other companies, where the average share of companies with DRS was around 62%.

IT industry is also one of the branches in which returns to scale fluctuated strongly during the period under review. However, the highest proportion of companies across both groups (around 52%) over the period under review was in an environment of DRS. Of these, most such companies (about 59%) were in the group of other companies outside the cluster region. In contrast, the group of clustered companies tended to be dominated by firms (51% share) still in a situation of IRS. Indeed, the core members of the CO are mostly large companies. This suggests that an informal group of other companies has formed around this core, drawing on the positive externalities of the cluster, which contributes to their growth. The group of other companies is then internally quite inhomogeneous - just about one third of the companies in this group are operating in IRS conditions.

In the nanotechnology industry, we can observe a rapidly increasing proportion of companies operating in the IRS area in 2020. However, by the following year, the proportion of businesses operating in the IRS had returned to virtually the level before the outbreak of COVID-19. At the beginning of the time series in 2009, only a third of such companies were in an IRS situation; by the end of the period under review, in 2021, this proportion was practically the same. However, differences can be observed between the groups of clustered and non-clustered enterprises. In the group of clustered firms, the share of firms in IRS conditions was on average 28%, but in the group of other firms it was 41%.

Overall, in the packaging industry, the development in the period under review was relatively calm from in terms of scale efficiency. However, the two groups of enterprises show differences. In the group of clustered companies, the share of those in an IRS situation has been around 60% for a long time, with the remaining 40% of companies operating in DRS conditions. A significantly higher proportion of companies (67%) in DRS was in the group of non-clustered firms. Just a third of the companies in this group operated in IRS conditions.

The textile industry is also dominated by companies in DRS conditions, in both groups of firms. The share of companies in DRS in the cluster has long been around 67%. This share was slightly lower in companies outside the cluster, approaching approximately 62%. The proportion of businesses in an IRS situation increased in both groups of companies in 2020, probably related to the increased demand for protective equipment in the context of COVID-19. However, it returned to its previous level in the following year.

In the last research step, the Pearson correlation coefficient was used to investigate the relationship between SE and business size (measured by revenues and total capital) and between SE and the level of indebtedness of companies in each industry. The results are shown in *Table 4*. *Table 4* omits the years 2012, 2016 and 2018, where no significant correlations were found.

Table 4. Dependence of SE on individual industry characteristics

	2009			2010			2011			2013			2014			2015		
Industry	TC	D	R	TC	D	R	TC	D	R	TC	D	R	TC	D	R	TC	D	R
Auto	-.511 (<.001)	.	-.297 (.005)	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.
Eng	-.403 (<.001)	.	-.420 (<.001)	.	-.118 (.012)	.	.	-.116 (.013)	.	.	-.108 (.021)	.	.	.	.	.	-.094 (.043)	.
Furniture	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.
IT	-.290 (.002)	,202 (,030)	-.184 (.049)	.	.	.	.	.	.	.	.	.	.	.194 (.038)	.	.	.	.
Nano	.	.	.	.	.	.	.	.	.	.248 (.015)	-.223 (.030)	.	.	.	.	.	.	.
Pack	-.541 (<.001)	.	-.548 (<.001)	.	-.243 (<.001)	.	.	.	.	.	.	.	.	.	.	.	.	.
Textil	-.380 (<.001)	,167 (,021)	-.440 (<.001)	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.

	2017			2019			2020			2021		
Industry	TC	D	R	TC	D	R	TC	D	R	TC	D	R
Auto	.214 (.048)	.	.	.278 (.009)	.	.237 (.028)	.321 (.003)	.	.230 (.033)	.297 (.005)	.	.231 (.032)
Eng	.	-.117 (.012)	.	.	-.101 (.029)	.	.105 (.024)	.	.	.	-.104 (.026)	.
Furniture	.	.	.	.	.	.	.	.	.	.	.	.
IT	.	.	.	.	.	.	.	.	.	.	.222 (.017)	.
Nano	.	.221 (.031)	.	.	.	.	.	.	.	-.375 (<.001)	.	-.378 (<.001)
Pack	.	.	.	.	.	.	.	.	.	.	.	.
Textil	.	.	.	.	.	.	.	.	.	.	.	.

Notes: R - revenues from own products and services, TC - total capital, D - debt ratio.

Source: authors' results.

Table 4 shows a significant moderate inverse relationship between SE and business size characteristics in most cases at the beginning of the study period. This means that SE generally decreases as business size increases. However, in most industries, the correlation was only found in a small number of periods. In the case of the furniture industry, then, no dependence at all was found between SE and the observed characteristics. In the automotive industry, a weaker, but significant, direct relationship between SE and firm size was found towards the end of the period. In general, however, there is no evidence of a stronger link between SE and firm size.

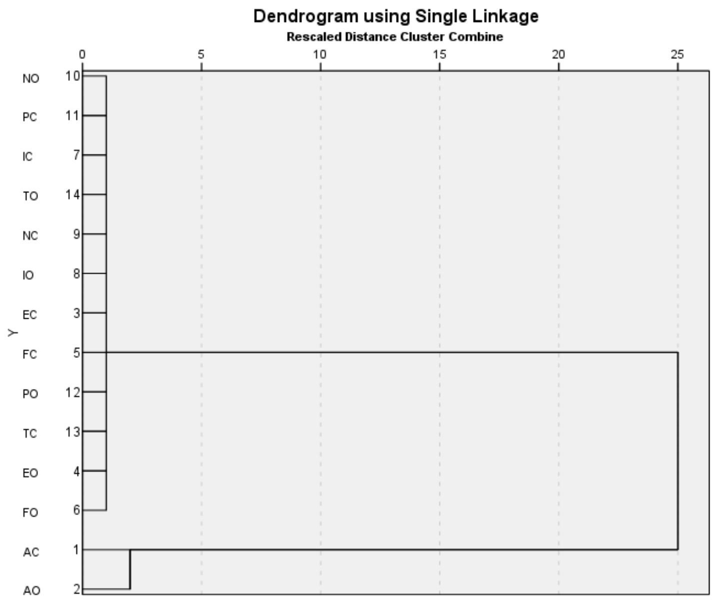
Regarding indebtedness, the results can be divided into three categories. The first category represents industries where, with a few exceptions, no significant relationship between SE and indebtedness could be found. This category includes the automotive, furniture, packaging, nanotechnology and textile industries. In the packaging and textile industries, the dependencies between SE and indebtedness were identified in only one year (2010 resp. 2009) and as relatively weak. In the nanotechnology industry, a significant correlation was found in two years, but each time in a different direction. Such an occurrence can be described as rather coincidental. The second category is represented by the engineering industry, where an inverse relationship between SE and debt levels has been identified. That is, SE decreases as indebtedness increases. This correlation was found in seven observation periods. Finally, the third category consists of industries with a direct proportionality, i.e. SE increases with increasing indebtedness. Such a trend was found in the IT services; however, only in three periods.

4. Discussion

It can be concluded that the research results did not show a significant effect of clusters on scale efficiency. However, such a result does not mean that clusters do not positively impact business performance and innovation. The stimulation of innovation activities is not dependent on the scale of operation (Peng and Wang, 2025). A company may not be scale-efficient and still be economically efficient to some extent. This is true in a situation of variable returns to scale. However, in such a case, the company does not reach its optimal size or manage its resources and capabilities optimally.

The groups of clustered and non-clustered enterprises studied do not represent homogeneous groups. The similarities and differences between the enterprises' groups were identified through hierarchical cluster analysis using the nearest neighbour method. *Figure 2* shows the 2021 dendrogram. This analysis divided the observed groups of enterprises into two main statistical clusters. Note: we use the term "statistical cluster" to distinguish the term cluster to refer to an industry grouping from the statistical analysis results.

This analysis shows that the automotive industry is a cluster of its own, with both groups of companies. If we look at the characteristics of the automotive industry, it includes, by a wide margin, large companies (with an average annual turnover of over EUR 140 million). Companies in the cluster have a medium level of indebtedness (50%). Firms outside the clusters have an indebtedness level of just over 61%. The industry has a very good capital intensity ratio (in the range 0.54-0.58). Unfortunately, as of 2019, companies in the automotive industry are in a DRS situation, which means a problem of underutilised capacity. All other groups of enterprises from other industries then form one cluster.



Source: authors' results.

Figure 2. **Cluster Analysis of Individual Enterprise Groups in 2019**

The finding that most clustered companies surveyed were operating under DRS conditions in 2021, and therefore, their size is larger than optimal, corresponds with the findings of the EU study (Franco *et al.*, 2021). Franco *et al.* (2021) analysed COs in the EU-27 with updated profiles in the ECCP database (for the Czech Republic, automotive, nanotechnology, furniture and engineering clusters were included). Of the total 73,000 members across the EU-27, about 70% belong to the SME category, 10% are large companies, and 8% are research organisations; however, Czech clusters are still atypically dominated by large firms (with a share of about 20%). Similarly, a study by Sharma and Sharma (2010) examining the scale efficiency of small businesses in Indian districts found that most clusters operated under DRS conditions. This finding points to the limited effect of network cooperation in terms of optimal production scale. However, it should be noted that the study examined naturally existing districts, not purpose-built cluster organisations.

The highest capital intensity (measured by total capital per unit of sales) can be observed in the nanotechnology industry (in cluster 1.26, outside the cluster, even 1.23) and the textile industry (cluster companies 0.94, outside the cluster 1.33). On the contrary, it is very low for companies in the IT cluster (only 0.48), then in the IT services sector outside the cluster (0.57). However, it is also relatively low in the automotive industry (0.53-0.58).

The textile manufacturing industry confirms the findings (Thiele, 1999) that high capital intensity tends to impact scale efficiency negatively. However, this is not true for nanotechnology, where the technological complexity of production drives capital intensity. On the contrary, rapid technological progress and the predominance of smaller clustered companies in the industry lead to scale efficiency improvements here. At the same time, the results for the nanotechnology, IT and packaging industries confirm the conclusions (Anang *et al.*, 2016; Karagiannis, Sarris, 2005) that small enterprises mainly operate in IRS conditions.

One of the latest studies dealing with scale efficiency in relation to technological progress in the energy sector (Zhu *et al.*, 2025) points out that traditional companies generally have limited potential for improving resource utilisation. The scale efficiency of traditional companies is usually stable, and changes in internal efficiency mainly drive changes in total factor productivity. The situation is different for newly established companies, where there is strong polarisation. Some companies are growing rapidly and improving their efficiency. Changes in total factor productivity are driven by technological progress and, to a lesser extent, by improvements in organisational efficiency. However, up to half of new companies experience a decline in returns to scale, which is caused by insufficient capacity utilisation. Scale efficiency is significantly influenced by available financial resources, liquidity, profitability, and intellectual property protection. Our research shows that new companies have a noticeable impact on scale efficiency, particularly in the nanotechnology sector. In contrast, scale efficiency in the automotive and packaging industries is relatively stable over time.

The results of this research tend to side with the sceptical studies (e.g. Kukalis, 2010; Pavelkova *et al.*, 2021) that question the positive economic effects of clustering. If economic impacts of clusters exist, they are often not generalizable and vary across industries (see, e.g., Zizka, Stichhauerova, 2023; Zyuzin, Demidova, 2022). However, such a conclusion is logical, as the motives for establishing cluster organisations have varied, and clusters operate accordingly. The formation of some clusters in the Czech Republic was mainly motivated by national subsidy programmes, while in some cases, there was enthusiasm at the beginning, which gradually faded away. Some clusters are no longer functioning at all or only formally for a period of sustainability (Žižka, Pelloneová, 2019).

The agglomeration effects resulting from clusters are widely recognised in the literature, and the theoretical basis of Porter's theory itself is not fundamentally disputed, but this alone is insufficient to justify their politically driven implementation (Duranton, 2011). Some critics point to the vagueness and difficult operationalisation of the term "cluster," whose boundaries are not clearly defined, limiting the possibility of unambiguous testing and application (Martin, Sunley, 2003). The most significant doubts concern the effectiveness of the so-called cluster policy. Empirical evaluations show that political initiatives often bring only short-term effects, such as increased cooperation or the number of joint projects, but not long-term growth in productivity or innovation performance of companies (Aboal *et al.*, 2020; Giuliani, Pietrobelli, 2011). Some authors even argue that attempts to create "new Silicon Valleys" fail because they ignore the historical, cultural, and institutional context that is key to the emergence and sustainability of successful clusters (Hospers *et al.,* 2009). Sceptics are thus particularly critical of the assumption that agglomeration advantages can be replicated or artificially enforced through universalistic policy instruments.

Conclusions

The main objective of the research was not confirmed: sharing inputs and infrastructure would not positively impact the SE of clustered companies. No significant differences were found between clustered and non-clustered firms regarding scale efficiency. The only exception was the textile industry, where non-clustered firms achieved higher levels of scale efficiency than non-clustered ones.

In some industries, a correlation between SE and debt ratios was found. In the case of the IT services, this dependence is direct. An inverse relationship has been identified in the engineering industry. In contrast, there has been no significant relationship between the level of turnover and total capital and scale efficiency, except for a few periods in the automotive industry.

Three industries (furniture, IT and packaging) were dominated by clustered companies operating in an area of IRS. In the automotive industry, both groups of companies (clustered and non-clustered) were, on average, close to the optimal production scale around 2018-2019. However, the COVID-19 pandemic and the subsequent fall in companies' turnover in this industry brought a turning point. In IT services, clustered companies, in particular, were close to optimal scale in 2018-2021. In all other industries, companies operating in an environment of DRS were significantly more prevalent, irrespective of cluster membership.

In conclusion, the impact of Czech clusters on optimising the inputs and outputs of member companies is minimal. This may also be due to the actual functioning of clusters, which were often established from the top down and their creation was supported by public subsidies. Clusters can improve SE by sharing expensive (especially research) infrastructure, knowledge spillovers, and by increasing the education of employees and managers of member companies. However, the actual state of Czech clusters is not good. Only about a third of clusters are members of a national association; many do not even have a website or a completed profile (National Cluster Association, 2023). Logically, these clusters cannot be expected to have any significant impact on improving the activities of their members. The results of our research do not dispute the positive effects of clusters described in the literature. Still, they point out that the politically motivated application of cluster policy in specific cases may not bring about the expected improvements in business performance.

The fact that only seven industries are included in the research should be considered a research limitation. Extending the research to other industry sectors and the tertiary sector of the economy can be viewed as a possible future direction of research, as the study may suggest that clusters in the service sector may behave differently from clusters in manufacturing industries. Similarly, a detailed examination of why clusters do not bring about increased efficiency is a topic for further research. However, the change in data availability from the Magnusweb database may also be a limitation for further research. This database has changed ownership, and the new proprietor has stopped updating it in its original form. The alternative database has a different data structure, making retrieving accounting data very difficult. Therefore, the suggested direction for further research will be based directly on empirical studies in companies.

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PRAMONĖS KLASTERIŲ MASTO EFEKTYVUMO VERTINIMAS: DEA METODAS

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Santrauka. Straipsnyje nagrinėjamas klasterių egzistavimo poveikis įmonių efektyvumui masto atžvilgiu. Tyrimo objektas yra septynios pramonės šakos, iš kurių šešios yra gamybos pramonės šakos (automobilių, inžinerijos, baldų, nanotechnologijų, pakavimo ir tekstilės) ir viena paslaugų pramonės šaka (IT). Techninis ir masto efektyvumas šiose pramonės šakose buvo tiriamas nuo 2009 iki 2021 m. Analizuojamos įmonės buvo suskirstytos į dvi grupes. Pirmąją grupę sudaro klasterio organizacijos nariai ir įmonės, veikiančios tame pačiame regione kaip ir klasterio organizacija. Todėl jos gali tam tikru mastu patirti teigiamą klasterio organizacijos išorinį poveikį. Antroji grupė atstovauja kitoms įmonėms iš tolimesnių regionų. Rezultatai nerodo teigiamo klasterių egzistavimo poveikio masto efektyvumui. Tik vienoje pramonės šakoje – tekstilės – nustatytas reikšmingas masto efektyvumo lygio skirtumas, tačiau atvirkštine tvarka. Tai reiškia, kad nesusijusios su klasteriais tekstilės įmonės pasiekė didesnį masto efektyvumą nei susijungusios su klasteriais įmonės. Trijose pramonės šakose (baldų, IT ir pakavimo) dominuoja įmonės, kurių masto grąža didėja. Automobilių pramonėje įmonių gamybos mastas vidutiniškai buvo artimas optimaliam maždaug 2018–2019 m. Tačiau COVID-19 pandemija ir vėlesnės pardavimo problemos pramonėje žymėjo lūžio tašką masto efektyvumo srityje. IT paslaugų srityje ypač dažnos klasteriuose veikiančios įmonės buvo artimos optimaliam mastui. Kitose pramonės šakose gerokai dažniau pasitaikė įmonių, veikiančių mažėjančios masto grąžos sąlygomis.

Reikšminiai žodžiai: pramonės klasteris; DEA; masto efektyvumas; didėjanti masto grąža; mažėjanti masto grąža.