PERFORMANCE ANALYSIS OF HUNGARIAN FOOD INDUSTRY ENTERPRISES USING THE DEA METHOD

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Abstract: *This study examines the performance of Hungarian food industry enterprises using the Data Envelopment Analysis (DEA) method. In today's rapidly evolving economic environment, assessing operational efficiency and cost-effectiveness is of paramount strategic importance. The primary objective of this research is to investigate how performance measurement and benchmarking can enhance informed decision-making and drive business development within the sector. The empirical analysis is based on secondary data retrieved from the EMIS database, covering 611 companies over the financial years from 2018 until 2023. The selected input variables include the value of tangible assets, material and personnel-related expenses, other operational costs, and interest paid. Output variables consist of total revenue and gross value added (GVA). The linear programming-based DEA model calculates a relative efficiency score for each decision-making unit, comparing firms with similar input-output structures. The study investigates efficiency differences across four dimensions: regional location, industry sub-sector, company size (based on number of employees), and enterprise age. The results reveal considerable heterogeneity. Companies in the Budapest region show the highest efficiency levels, while those in Pest County perform the weakest. Among industry sub-sectors, the efficiency gap between the best and worst performers reaches 36%. Larger firms, especially those employing more than 250 people, consistently outperform smaller ones. In terms of age, the youngest (0-5 years) and the oldest (over 50 years) enterprises exhibit the highest technical efficiency, whereas mid-aged firms tend to lag behind. The findings offer valuable insights for both academic research and practical applications by identifying key performance drivers and benchmarking opportunities within the Hungarian food industry.*

Keywords: *DEA method, data envelopment analysis, the performance of food industry enterprises, SMEs, efficiency, Hungarian economy*

JEL Classification: *C61, D24, L66, M21*

1. **Introduction**

In a rapidly changing economic environment, monitoring the operational efficiency and performance of companies is becoming increasingly important - particularly in strategically significant sectors such as the food industry. To remain competitive and ensure sustainable development, businesses require reliable and objective performance indicators to support their decision-making processes. One of the most widely used modern methods for evaluating efficiency is Data Envelopment Analysis (DEA), which enables the comparison of the relative efficiency of organizations that utilize similar resources.

This study aims to conduct an empirical and quantitative analysis of the efficiency of Hungarian food industry enterprises using the Data Envelopment Analysis (DEA) method, with a particular focus on differences by regional location, industry sub-sector, company size, and age. The research is based on secondary data obtained from the EMIS database, covering financial information from 611 domestic food industry companies over the 2018-2023 period.

Beyond mapping the current state of efficiency in the sector, the objective of this analysis is to identify key benchmarking opportunities and performance-driving factors that can support the formulation of both firm-level and industry-wide development strategies.

2. Dimensions of Corporate Performance – Theoretical Foundations and Interpretive Frameworks

The concept of corporate performance is inherently complex and multifaceted, and its interpretation and measurement remain among the most debated topics in management science. Various academic disciplines, such as economics, organizational theory, and controlling, emphasize different aspects of performance, resulting in a wide array of theoretical and practical approaches over recent decades. Traditionally, corporate performance has been assessed along two principal dimensions: effectiveness and efficiency, which Dobák et al. (1996) also identify as the cornerstones of performance management. While these dimensions can be distinguished in theory, they are often inseparably linked in practice: efficiency is only regarded as a meaningful performance metric if it contributes to effective operations.

Recent studies increasingly support a broader interpretation of corporate performance. In addition to traditional financial indicators, new dimensions—such as quality, productivity, innovation capacity, human capital, and sustainability—have gained prominence. These factors not only reflect the internal functioning of firms but also their ability to adapt to external environments, which is essential for long-term competitiveness. Wimmer (2004) emphasizes the role of profitability in evaluating business performance, not as a standalone dimension but as the cumulative outcome of effectiveness, efficiency, productivity, and innovation.

The relationship among these performance dimensions is not hierarchical but interdependent. For example, improvements in quality may enhance customer satisfaction, leading to increased revenues and, consequently, higher outputs for the same level of input - thus improving efficiency. Similarly, innovation may serve as a predictor of future performance, even if it entails short-term cost increases that temporarily lower efficiency. As a result, performance metrics must always be interpreted in context and within an appropriate time frame (Kaplan & Norton, 1992; Neely et al., 2005). Several authors, including Bititci et al. (1997) and Otley (1999), argue that performance measurement should extend beyond financial indicators to include non-financial factors that indirectly influence effectiveness. These may encompass internal elements (e.g., employee satisfaction, equipment utilization) or external ones (e.g., customer feedback, market share).

The specific characteristics of the food industry, such as high seasonal volatility, stringent food safety standards, and short supply chains, make multidimensional performance evaluation particularly relevant. Therefore, the application of the DEA method enables the integrated assessment of various performance dimensions, including material usage, labour input, asset efficiency, and output value. The empirical research presented in this study thus explores not only the interrelation between effectiveness and efficiency but also their regional, structural, and temporal variations within the DEA framework.

3. Theoretical Foundations of the DEA Method

The Data Envelopment Analysis (DEA) is one of the most widely used non-parametric methods for measuring production efficiency. It facilitates the comparison of the relative performance of units operating under similar resource conditions, referred to as Decision-Making Units (DMUs). The theoretical foundation of DEA is based on linear programming, aiming to define an efficiency frontier against which the performance of individual units can be assessed. Initially developed by Charnes, Cooper, and Rhodes (1978), the methodology and its application areas have expanded substantially in subsequent decades.

The original CCR model assumes constant returns to scale (CRS), while the later BCC model introduced by Banker et al. (1984) allows for variable returns to scale (VRS). The choice between these models significantly influences the results of efficiency assessments, especially in sectors characterized by a wide range of firm sizes, such as the food industry. One of the key strengths of DEA lies in its flexibility: it requires no prior assumptions about the form of the production function and can simultaneously accommodate multiple input and output variables. These characteristics make it particularly suitable for complex, multi-criteria performance evaluations.

As Emrouznejad and Yang (2018) highlight, the widespread adoption of DEA is due not only to its methodological flexibility but also to its applicability across diverse sectors, including healthcare, public services, and the agriculture and food industries. However, Luo et al. (2012) caution that DEA's effectiveness may be limited by dataset size and by an imbalanced ratio of variables to observations. An excessive number of input-output variables relative to the sample size can reduce discriminatory power and lead to biased efficiency estimates.

The DEA is often compared to Stochastic Frontier Analysis (SFA), another prominent method for evaluating efficiency. Unlike DEA, SFA is a parametric model that incorporates statistical noise. As Zhu (2021) notes, DEA's advantage lies in its freedom from distributional assumptions; however, its main limitation is its inability to distinguish between random error and inefficiency, making it sensitive to data variability.

The application of DEA is particularly appropriate for analyzing enterprises in the food industry, where production processes are complex, firm sizes vary widely, and performance must be assessed across several dimensions, including efficiency, quality, and innovation. According to a comprehensive literature review by Dutta, Jaikumar, and Arora (2022), DEA has been extensively used between 2000 and 2020 to evaluate the efficiency of food industry producers and suppliers, often segmented by region or firm size.

4. Presentation of the Analyzed Database and the Input-Output Variables

One of the critical aspects of applying the DEA method lies in the careful selection of input and output variables, as well as the use of a reliable and representative dataset to populate the analytical framework. This study is based on data from 611 Hungarian food industry enterprises drawn from the financial records provided by the EMIS (Emerging Markets Information Service) database. The sample includes companies classified under code 311 of the North American Industry Classification System (NAICS), corresponding to the food manufacturing sector. The data spans the financial years 2018 to 2023, enabling an assessment of temporal changes in corporate efficiency.

The success of a DEA analysis depends heavily on the appropriate choice of input and output variables. Luo et al. (2012) emphasize that this is not merely a technical consideration but a conceptual one, as the selected variables fundamentally define the scope and interpretive framework of performance assessment. Poor variable selection can distort results, diminish the model's discriminative capacity, and lead to misleading conclusions.

The input variables used in this study are:
- Value of tangible assets,
- Material-type expenditures,
- Personnel-type expenditure,
- Other expenditures,
- Value of interest paid.

These variables represent the resources employed in the companies' production processes and can be objectively quantified using financial statements. The inclusion of interest paid allows for the consideration of financial efficiency, which is particularly relevant in capital-intensive sectors.

The output variables are:
- Total revenue,
- Gross value added (GVA).

Total revenue is a commonly used output metric in corporate performance evaluation (Cook & Seiford, 2009), while Gross Value Added (GVA) has gained increasing prominence in recent years, especially in sectors where final profitability may not accurately reflect operational efficiency (Zhu, 2021).

As noted by Emrouznejad and Yang (2018), DEA model variables must be both economically meaningful and statistically sound, and they must also be accessible. Accordingly, the variable selection in this study reflects not only data availability but also the structural characteristics of the food industry, such as its high proportion of material costs, labour intensity, and capital-intensive requirements.

An additional consideration is the ratio between the number of variables and the sample size. Cooper, Seiford, and Zhu (2011) recommend that the total number of input and output variables should not exceed one-third of the number of decision-making units to avoid an inflated number of efficient observations. According to this guideline, the current study utilizes five input and two output variables across 611 DMUs, ensuring both proportionality and adequate discriminatory power.

5. Research Objectives and Analytical Dimensions in the Application of DEA

One of the primary objectives of this research is to assess the technical efficiency of Hungarian food industry companies using the Data Envelopment Analysis (DEA) method and to facilitate a comparison of their relative performance across different structural dimensions. The study aims not only to generate aggregate efficiency indicators but also to identify the structural and environmental factors influencing performance, thereby serving both theoretical and practical purposes.

A key advantage of DEA lies in its ability to accommodate multiple input and output variables simultaneously, making it particularly well-suited for multidimensional performance analysis (Cook & Seiford, 2009; Zhu, 2021). This feature makes DEA especially suitable for complex sectors, such as the food industry, where outputs are not solely financial and where diverse structural factors shape operations.

The present study examines DEA-based efficiency along four key dimensions:

- Regional location,
- Industry sub-sector,
- Company size (measured by number of employees),
- Company age.

This structured analytical framework aligns with contemporary research trends that emphasize the role of environmental and organizational context in DEA studies (Färe et al., 2007; Emrouznejad & Yang, 2018). The regional dimension is particularly relevant in the context of national economic development strategies, given the strategic objective of reducing regional disparities (Lengyel & Rechnitzer, 2013). A central aim of the study is to determine whether infrastructural, economic, and institutional differences across regions influence technical efficiency.

Analyzing performance by industry sub-sector (e.g., meat processing, bakery, dairy, and beverage production) enables the identification of vertical differences in efficiency. As highlighted by Jamasb and Pollitt (2003), efficiency scores can vary significantly across sectoral contexts due to differences in operational logic, technology, and input intensity.

The analysis by company size is among the most frequently applied dimensions in DEA, as it facilitates the examination of returns to scale (Banker et al., 1984). This is particularly relevant in the food industry, where SMEs often operate under structurally different conditions compared to capital-intensive, vertically integrated large enterprises.

Company age, while less frequently examined in DEA literature, is also included as a relevant dimension. Drawing on the findings of Rossi (2016), it is hypothesized that accumulated experience, organizational routines, and capital formation capacity may influence firm-level efficiency. The inclusion of this factor adds novelty to the research framework.

Thus, the purpose of this study is not only to identify efficiently performing companies but also to establish a foundation for benchmarking and to uncover structural, regional, and managerial determinants of performance. By doing so, the findings will provide both scientific insights and practical support for informed strategic decision-making and the formulation of economic policy.

6. Results of the Analysis

6.1. Distribution of the Sample by NAICS Code, Regional Location, and DEA Score

The dataset analyzed in this research contains data from 611 food industry companies over six financial years, making the database complex both in terms of time and structure. Presenting the composition of the sample is an essential step in establishing the foundations for the DEA-based efficiency analysis, as performance measurement can only be meaningfully interpreted if the types of companies included in the study are clearly understood. Figure 1 illustrates the distribution of the sample according to NAICS codes.

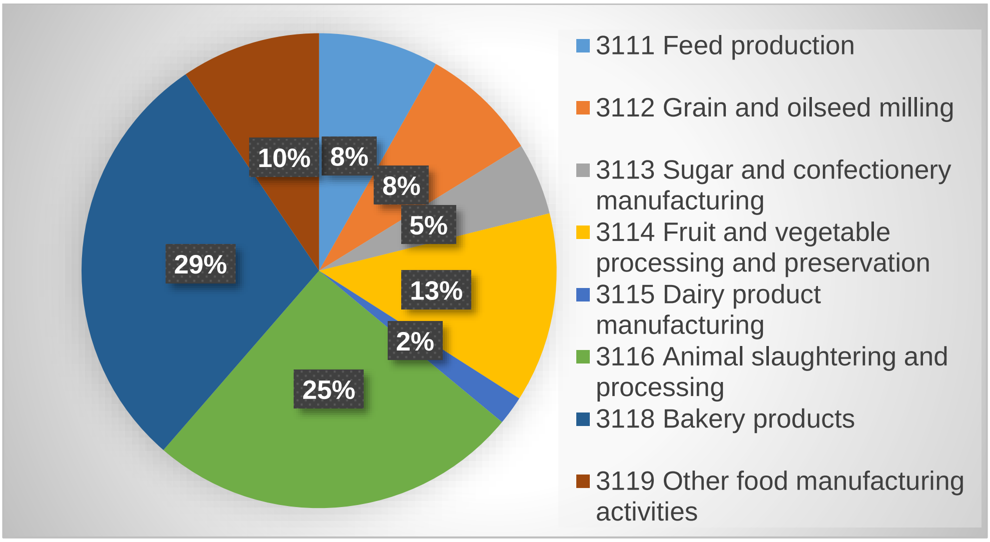

Figure 1: Distribution of the Sample by NAICS Code
Source: Own compilation based on the conducted analysis

Based on Figure 1, it can be concluded that in terms of sub-sector distribution by NAICS code, the largest portion of the sample belongs to the Bakery Products sub-sector (3118), which comprises 178 companies, representing 29.13% of the entire dataset. This is followed by Animal Slaughtering and Processing (3116), with 155 companies (25.37%), and Fruit and Vegetable Processing and Preservation (3114), with 79 companies (12.93%). Other components of the food industry structure appear in smaller proportions, such as Feed Production (3111), with 8.18%, Grain and Oilseed Milling (3112), with 8.02%, and Sugar and Confectionery Manufacturing (3113), with 4.91%. The Dairy Product Manufacturing sub-sector (3115) represents the smallest share, comprising only 1.96% of the sample. This distribution reflects the structural characteristics of the domestic food industry, where bakery and meat processing dominate, while underrepresented sectors such as dairy may influence the outcomes of comparative efficiency analyses.
Figure 2 illustrates the regional distribution of the sample.

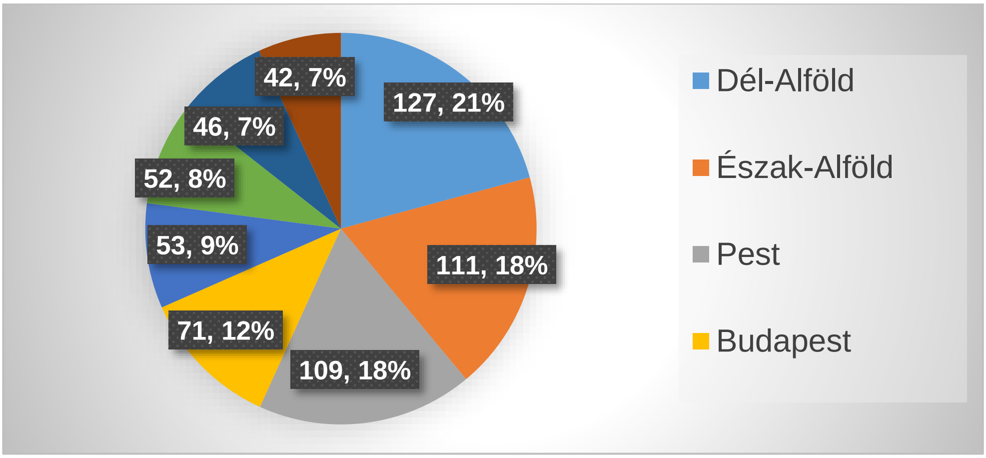

Figure 2: Regional Distribution of the Sample
Source: Own compilation based on the conducted analysis

From a regional perspective, the majority of the sample is linked to the Alföld regions: most companies are located in Dél-Alföld (20.79%), Észak-Alföld (18.17%), and Pest (17.84%), while Budapest accounts for 11.62%. The Dunántúl regions - Közép-Dunántúl, Nyugat-Dunántúl, and Dél-Dunántúl - together represent 24.7%, while Észak-Magyarország has the smallest share (6.87%). Based on this regional concentration, a crucial question arises as to whether economic performance and efficiency are related to geographical location and whether the dominance of the Alföld areas could skew the results. The examination of such questions is fully enabled by the relative efficiency indicators calculated using DEA models, which provide a valuable basis for comparison not only at the company level but also at the regional level.

Table 1 shows the distribution of the sample according to DEA scores.

Table 1: Distribution of the Sample by DEA Scores

Efficiency coefficient intervals		2018	2019	2020	2021	2022	2023
	=1.0	79	77	81	84	97	57
>= 0.9	< 1.0	55	43	41	54	74	15
>= 0.8	< 0.9	109	112	102	82	101	21
>= 0.7	< 0.8	138	128	156	130	139	32
>= 0.6	< 0.7	116	112	122	145	107	37
>= 0.5	< 0.6	69	78	53	74	57	48
>= 0.4	< 0.5	23	40	35	32	23	52
>= 0.3	< 0.4	13	12	13	6	10	99
>= 0.2	< 0.3	9	8	8	2	3	111
>= 0.1	< 0.2	0	1	0	2	0	100
>= 0.0	< 0.1	0	0	0	0	0	39
Average		0,7488	0,7368	0,7457	0,7445	0,7740	0,4343
Sample size		611	611	611	611	611	611

Source: Own compilation based on the conducted analysis

Based on the DEA results presented in Table 1, it can be concluded that the technical efficiency of Hungarian food industry companies remained relatively stable between 2018 and 2022, with annual average efficiency values ranging from 0.7368 to 0.7740. This suggests that the sector's operations were considered balanced, even during the COVID-19 pandemic period. The moderate improvement in efficiency in 2022 (average: 0.7740) may suggest that companies successfully adapted to the post-pandemic economic environment. However, the year 2023 brought a significant decline in efficiency: the average DEA score dropped to 0.4343, while the number of companies with technical efficiency below 0.3 increased dramatically. The number of companies achieving full efficiency (DEA=1) also fell to 57, marking the lowest figure over the six years analyzed. The decline in efficiency is likely attributable to several interrelated economic factors, particularly the inflationary pressures emerging after 2022, the rise in energy and raw material costs, and the increase in interest rates, which directly impacted the results through the "paid interest" input variable. The extreme dispersion of efficiency values also highlights that the adaptability of individual companies varied significantly: while some firms maintained high-performance levels even in the face of difficulties, others experienced marked declines. The radical drop observed in 2023 thus reflects not only the worsening external economic environment but also reveals internal vulnerabilities of the sector, particularly in terms of financing structures, operational efficiency, and innovation capabilities. All of this underscores the importance of benchmarking and efficiency-enhancing measures to sustain the future competitiveness of food industry companies.

6.2. Regional Efficiency Ranking Based on DEA Scores

Table 2 presents the regional efficiency ranking based on DEA scores. The table aims to provide a comprehensive overview of which regions operated more efficiently in technical terms based on the average performance between 2018 and 2023.

Table 2: Regional Efficiency Ranking Based on DEA Scores

Region	2018	2019	2020	2021	2022	2023	Aver.	Rank.
Észak-Magyarország	0,7140	0,7009	0,7273	0,7307	0,7160	0,4189	0,6680	8
Észak-Alföld	0,7305	0,7164	0,7151	0,7055	0,7534	0,4029	0,6706	7
Dél-Alföld	0,7708	0,7658	0,7597	0,7658	0,8019	0,4763	0,7234	2
Pest	0,7435	0,7293	0,7325	0,7372	0,7573	0,3906	0,6817	6
Budapest	0,7585	0,7578	0,7886	0,7936	0,8126	0,4660	0,7295	1
Közép-Dunántúl	0,7574	0,7408	0,7698	0,7746	0,7487	0,4697	0,7101	3
Nyugat-Dunántúl	0,7543	0,7350	0,7526	0,7257	0,7913	0,4343	0,6988	4
Dél-Dunántúl	0,7453	0,7221	0,7274	0,7209	0,7892	0,4223	0,6879	5
Average	0,7488	0,7368	0,7457	0,7445	0,7740	0,4343	0,6974	

Source: Own compilation based on the conducted analysis

Based on Table 2, it can be concluded that the efficiency of Hungarian food industry companies showed significant regional disparities between 2018 and 2023. The best performance was achieved by Budapest, which consistently recorded high DEA values, while Észak-Magyarország proved to be the weakest region, with the lowest average efficiency scores. The Dunántúl regions—especially Közép-Dunántúl and Nyugat-Dunántúl—demonstrated moderate performance, while the Alföld regions, despite the outstanding results of Dél-Alföld, were generally positioned in the lower half of the ranking. The year 2023 brought a sharp decline in every region, as reflected by the marked drop in DEA values and the dominance of red color codes in the table. This overall deterioration can be attributed to adverse changes in the economic environment—particularly rising inflation, energy prices, and interest costs. It is particularly concerning that the eastern regions (Észak-Alföld, Észak-Magyarország, Pest) not only maintained persistently low efficiency indicators, but also experienced further decline during the crisis year, highlighting weaknesses in adaptability and limited capacity to leverage internal resources. Overall, the results indicate that regional differences stem from deeply embedded structural and developmental disparities, and that stable organizational operations, technological advancement, and financial flexibility play a critical role in mitigating economic shocks.

6.3. Industry Efficiency Ranking Based on DEA Scores

Table 3 presents the industry efficiency ranking based on DEA scores. The table examines the average performance of each sub-sector between 2018 and 2023, providing an opportunity to identify which sectors operate with relatively higher resource efficiency.

Table 3: Industry Efficiency Ranking Based on DEA Scores

Industry sub-sector	2018	2019	2020	2021	2022	2023	Aver.	Rank.
3111	0,8114	0,8051	0,8052	0,7842	0,8197	0,4300	0,7426	2
3112	0,7662	0,7466	0,7789	0,7929	0,8447	0,4291	0,7264	4
3113	0,6207	0,6259	0,5951	0,6684	0,6336	0,3653	0,5848	8
3114	0,7072	0,7033	0,6918	0,7141	0,7519	0,3852	0,6589	7
3115	0,7794	0,7608	0,7748	0,7894	0,8436	0,6289	0,7628	1
3116	0,8099	0,7946	0,7805	0,7747	0,8075	0,4016	0,7281	3
3118	0,7060	0,6887	0,7203	0,7028	0,7336	0,4690	0,6701	6
3119	0,7575	0,7544	0,7914	0,7848	0,7906	0,4495	0,7214	5
Average	0,7488	0,7368	0,7457	0,7445	0,7740	0,4343	0,697	

Source: Own compilation based on the conducted analysis

Based on the industry DEA scores, it can be observed that there are significant differences in technical efficiency among the various food industry sub-sectors. Dairy product manufacturing (3115) proved to be the most efficient, with an average DEA score of 0.7628. This outstanding performance is primarily attributable to the highly mechanized and regulated processing operations in the dairy sector, combined with a high level of technological advancement, resulting in optimized input-output ratios. Feed production (3111) and animal slaughtering and processing (3116) also show high efficiency, where the benefits of mass production and industrial-scale economies are strongly evident. Grain and oilseed milling (3112) and other food manufacturing activities (3119) also perform well, although they slightly lag behind the top three sectors, indicating greater technological diversity and varying company sizes.

Bakery products manufacturing (3118), fruit and vegetable processing and preservation (3114), and sugar and confectionery manufacturing (3113) are positioned in the lower third of the efficiency ranking. These sub-sectors are typically characterized by smaller-scale, labour-intensive production, higher specific labour costs, and less standardized technologies, which may reduce technical efficiency. The particularly low-efficiency score of the sugar and confectionery sector (0.5848) may also suggest that this industry finds it more challenging to adapt to the changing economic environment, including fluctuations in raw material and energy prices, as well as rapidly shifting consumer demands. Overall, it can be concluded that sub-sectors with higher technological intensity, mechanization, and economies of scale are more competitive and operate more efficiently, whereas traditional, labour-intensive areas exhibit greater efficiency variability and higher development potential.

6.4. Efficiency Ranking Based on Number of Employees

Table 4 presents the efficiency ranking of the analyzed companies based on the number of employees. The goal is to explore the relationship between company size specifically the number of employees - and technical efficiency.

Table 4: Efficiency Ranking of the Analyzed Companies Based on Number of Employees

Employee category	2018	2019	2020	2021	2022	2023	Aver.	Rank.
1. <5	0,8101	0,7808	0,7976	0,8285	0,8082	0,3529	0,7319	3
2. 5-10	0,7167	0,7188	0,7282	0,7598	0,7462	0,2417	0,6371	7
3. 11-20	0,7218	0,7156	0,7149	0,7116	0,7118	0,2989	0,6502	6
4. 21-50	0,7413	0,7007	0,7221	0,7100	0,7316	0,3774	0,6628	5
5. 51-100	0,7190	0,7153	0,7141	0,7172	0,7889	0,4715	0,6888	4
6. 101-250	0,7630	0,7841	0,7845	0,7820	0,8578	0,6536	0,7709	2
7. >250	0,8802	0,8908	0,9088	0,8782	0,9130	0,8526	0,8872	1
Average	0,7488	0,7368	0,7457	0,7445	0,7740	0,4343	0,6974	

Source: Own compilation based on the conducted analysis

Based on Table 4, it is evident that the technical efficiency of Hungarian food industry companies shows a strong correlation with the size of the workforce. Companies with more than 250 employees have the highest average DEA score (0.8872), indicating that large enterprises are more capable of operating with economies of scale, better utilizing input resources, and likely possess more advanced technologies and organizational structures. Similarly, high efficiency is observed in the 101-250 employee category (average: 0.7709), suggesting that some medium-sized companies already reach an operational scale where the combination of resources becomes optimal. In contrast, the smallest categories (5-10, 11-20, and 21-50 employees) achieved average efficiency scores between 0.6371 and 0.6628, indicating that micro- and small enterprises are less capable of efficiently converting available inputs into outputs. This may be attributed to limited technological capabilities, the lack of specialized labour, and underdeveloped internal management systems. Interestingly, the smallest companies with fewer than five employees showed slightly better efficiency (0.7319) compared to small businesses, which may suggest that these firms benefit from more flexible operations, lower fixed costs, or specialized production. One of the key lessons from the analysis is that in the food industry, company size growth - up to a certain point - favours efficiency as economies of scale emerge, which the DEA method reliably detects. However, the year 2023 brought a decline across all categories, particularly among small businesses (e.g., the DEA score for companies with 5-10 employees fell to 0.2417), indicating that economic shocks—such as inflation, rising energy, and interest costs—most adversely affected smaller enterprises. In contrast, the relatively stable efficiency scores of large enterprises (e.g., 0.8526 for companies with more than 250 employees even in 2023) suggest that these players were better able to cope with the negative market environment. Overall, the results indicate that company size is a key determinant of technical efficiency in the food industry and that without targeted support and development programs, smaller firms may struggle to achieve competitive operations.

6.5. Efficiency Ranking Based on Age Category

Table 5 illustrates the efficiency ranking of the analyzed companies based on age category. It is worth noting that company age is a less frequently examined yet relevant factor in performance-based comparisons, as firms operating for a longer period may possess greater experience, established process systems, and accumulated capital, while newly founded companies may exhibit greater flexibility and a higher propensity for innovation.

Table 5: Efficiency Ranking of the Analyzed Companies Based on Age Category

Age category	2018	2019	2020	2021	2022	2023	Aver.	Rank.
1. 0-5 y.	0,8057	0,7708	0,7516	0,7689	0,6927	0,4666	0,7609	1
2. 5-10 y.	0,7429	0,7439	0,7698	0,7864	0,8321	0,5101	0,7421	3
3. 10-20 y.	0,7435	0,7365	0,7557	0,7559	0,7815	0,3707	0,6959	4
4. 20-50 y.	0,7467	0,7303	0,7323	0,7297	0,7650	0,4464	0,6841	5
5. over 50 y.	0,6959	0,7709	0,8229	0,7640	0,8060	0,7067	0,7607	2
Average	0,7488	0,7368	0,7457	0,7445	0,7740	0,4343	0,6974	

Source: Own compilation based on the conducted analysis

Based on Table 5, it can be concluded that the technical efficiency of food industry companies shows a strong yet non-linear relationship with company age. The highest average DEA score was achieved by companies aged 0-5 years (0.7609), closely followed by companies older than 50 years (0.7607). This duality suggests that both young, dynamic enterprises and long-established, experienced companies can achieve high levels of technical efficiency, albeit through different operational logic. Young companies may benefit from flexible adaptation, an innovative mindset, and the rapid adoption of modern technologies, while older companies can leverage their stable operations, well-established processes, and greater capital resources to gain efficiency advantages. In contrast, mid-aged companies - particularly those aged 20-50 years - show lower average DEA scores (0.6841), indicating that they often struggle to maintain innovation while not yet thoroughly enjoying the advantages of stability characteristic of older firms. The average efficiency of companies aged 10-20 years (0.6959) is also lower compared to the full sample, reinforcing the assumption that mature but not veteran firms may be especially sensitive to external economic changes. Interestingly, companies aged 5-10 years demonstrate outstanding efficiency (0.7421), indicating that they have surpassed the initial learning phase but have not yet reached a plateau in growth. Overall, the age-related trends suggest that technical efficiency does not increase linearly with experience but rather follows an inverted U-shaped curve: the youngest and oldest companies perform best, while mid-aged segments are more prone to technical lag. In the 2023 data, a decline is observable across all age categories; however, the oldest companies experienced the smallest decrease (0.7067), while the lowest annual DEA score was recorded among companies aged 10-20 years (0.3707). This suggests that economic shocks—such as inflation, rising interest rates, and energy costs —have had the most significant impact on companies with moderate levels of experience, while companies in the extreme age categories have been better able to adapt. Overall, the results suggest that while company age is a significant factor in technical efficiency, it is not the sole determinant; innovation capacity, strategic flexibility, and capital resources collectively influence how companies perform in the DEA model.

7. Conclusions

The results of the study reveal that the technical efficiency of Hungarian food industry companies has exhibited significant structural differences in recent years - by region, industry sector, company size, and age. The application of the DEA method enabled an objective evaluation of firms' relative performance across multiple dimensions. The analysis indicates that technical efficiency remained generally stable between 2018 and 2022; however, in 2023, a marked decline was observed, primarily due to unfavorable macroeconomic conditions - most notably inflation, rising energy prices, and increasing interest costs - which disproportionately affected smaller and less capital-intensive enterprises.

It can also be observed that there are significant regional differences in the efficiency of Hungarian food industry companies, which intensified dramatically in 2023. While Budapest and Dél-Alföld consistently performed well, Észak-Magyarország and Észak-Alföld produced persistently low efficiency scores. In 2023, all regions experienced a substantial decline, clearly illustrated by the dominance of red color codes, indicating the negative impact of economic shocks - particularly inflation and rising interest costs - on the sector's performance.

In terms of industry sub-sectors, firms engaged in dairy production, feed manufacturing, and animal slaughtering and processing achieved the highest DEA scores. In contrast, companies operating in sugar and confectionery manufacturing, as well as in fruit and vegetable processing, showed lower efficiency - likely due to differences in technological advancement and input structures.

The analysis by company size revealed a strong positive correlation between technical efficiency and firm size. Enterprises employing more than 250 people performed significantly better than smaller firms, underscoring the role of economies of scale in improving operational performance.

Concerning company age, the youngest (0-5 years) and oldest (over 50 years) firms achieved the highest efficiency scores, while mid-aged companies tended to perform less efficiently. This pattern suggests that both the dynamic growth phase and the accumulated stability of mature firms are more conducive to efficient operations than the plateau often experienced by middle-aged enterprises.

Overall, the findings demonstrate that corporate performance in the Hungarian food industry is strongly influenced by regional, sectoral, size-related, and age-related factors. Accordingly, future development strategies should take these dimensions into account. The practical application of DEA-based benchmarking can help define company-level development pathways, enhance competitiveness, and inform more effectively economic policy decisions within the food industry.

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