Navigating Challenges in the Fast-Food Sector:
A Benchmarking Study Using Data Envelopment Analysis

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The research evaluates efficiency levels of nineteen major U.S. fast-food chains between 2020 and 2024 using Data Envelopment Analysis (DEA). This study evaluates how fast-food chain companies managed operational challenges during the pandemic and post-COVID-19 recovery by studying return on assets, EBITDA margin, capital utilization, and revenue growth metrics. Our findings show sharp differences in the performance of fast-food restaurant chains. DEA analysis reveals which companies demonstrate operational efficiency while pinpointing areas where others struggle such as capital management and revenue growth. The insights assist investors evaluate company performance and let management concentrate their efforts toward improvement. Particularly in sectors with low profit margins and changing consumer behavior, the DEA benchmarking methodology seems to be a good way to track operational efficiency and provide strategic direction.

Keywords: data envelopment analysis (DEA), fast-food industry, operational efficiency, financial performance, benchmarking

INTRODUCTION

The fast-food industry in the United States stands as a major force in the food and beverage sector, providing cost-effective meals that are conveniently available to diverse customers. The industry underwent significant transformations during the last five years because of the COVID-19 pandemic, alongside fast-paced technological advancements and evolving consumer habits (Lee & Ham, 2021).

The years between 2020 and 2024 are crucial for scrutinizing the financial and operational performance of fast-food restaurant chains, because the pandemic in 2020 and subsequent lockdowns and social distancing measures caused extensive disruption, resulting in the temporary closure of dine-in restaurant services. Restaurants quickly adjusted their business models by implementing online ordering systems and enhancing their drive-through and takeout services, while investing in delivery platforms to satisfy evolving customer needs.

During this period, consumer demand for budget-friendly and convenient eating options grew as people changed their daily routines. The transformation led many restaurant chains to optimize operations, automate services, and boost digital enhancements to deliver value-based service offerings (National Restaurant Association, 2023). The impact of labor shortages combined with inflationary pressures and supply chain volatility highlighted restaurants' requirements for operational efficiency and strategic flexibility.

The purpose of this study is to evaluate the economic and functional performance of top fast-food restaurants across the United States throughout the years 2020 to 2024. The primary performance indicators consist of Return on Assets (ROA), Earnings Before Interest, Taxes, Depreciation, and Amortization (EBITDA) margin, alongside capital utilization and total revenue expansion. Studying these metrics will reveal important information about how competitive the industry is, as well as the strengths and weaknesses of each player, and how strategic choices affect future growth and profit potential.

PREVIOUS STUDIES

Charnes et al. (1978) introduced the development of Data Envelopment Analysis (DEA) as a method to evaluate decision-making unit (DMU) efficiency through input-output ratio assessment, enabling quantitative comparison of entities pursuing similar objectives. Banker et al. (1984) built on Charnes et al.'s (1978) model and extended the model by incorporating variable returns to scale (VRS), allowing for a more realistic assessment of scale inefficiencies in addition to technical inefficiencies. These enhancements laid the groundwork for DEA to evolve into a potent non-parametric technique for identifying efficient entities that can be used as performance benchmarks. The method determines which DMUs operate at the efficiency frontier by optimizing input-output ratios and incorporates a weighting system to reflect the varying importance of different inputs and outputs. A DMU that achieves optimal efficiency receives a score of 100 percent, while others scoring below that threshold are considered inefficient relative to the benchmark (Banker et al., 1984; Malhotra & Malhotra, 2024).

DEA has been widely applied across service industry sectors such as banking, healthcare, and education, demonstrating its adaptability to various operational environments. Studies by Ghimire et al. (2021) applied DEA to assess institutional performance in higher education, while Cruz and Tumibay (2019) evaluated service delivery outcomes in public health. In the banking sector, Li et al. (2022) used DEA to explore profit and risk inefficiencies. These studies confirm DEA's ability to detect performance gaps and recommend specific improvements, making it an essential tool for strategic decision-making.

While DEA has been widely applied in other service sectors, performance evaluation in hospitality has traditionally relied on broader benchmarking tools, with a focus on customer satisfaction and service quality due to the industry's service-oriented nature. DiPietro (2017) reviewed literature highlighting the integration of financial, customer, and organizational elements in restaurant performance assessments. In addition, cross-national benchmarking systems have been developed to reflect regional variations in consumer expectations, as demonstrated in studies by Min and Min (2011; 2013). Their findings indicate that while U.S. consumers prioritize the taste of food, Korean consumers place greater importance on cleanliness and staff politeness. These cultural nuances influence internal performance goals and strategic positioning, reinforcing the need for flexible benchmarking frameworks.

Gomes et al. (2025) further emphasized that financial sustainability is directly influenced by menu performance analysis, focusing on contribution margins, item-level profitability, and popularity indices. Such research provides practical insights for restaurant management when combined with broader operational criteria like capital utilization and revenue growth. A bibliometric study by Cao et al. (2025) revealed that, despite being under-researched, financial performance is a critical topic often overshadowed by studies on customer behavior. Their work supports the integration of finance-based performance models into restaurant benchmarking strategies.

DEA has been effectively utilized in restaurant and food service research to evaluate efficiency at the outlet or firm level, including fast-food chains and coffee shops. For example, Donthu and Yoo (1998) presented an early DEA application in the fast-food sector, evaluating outlet-level performance using multiple inputs and outputs. Their study demonstrated how DEA can benchmark retail productivity by enabling relative efficiency comparisons across store units, including behavioral and financial measures. Joo et al. (2009) applied DEA to assess operational efficiency across stores within a specialty coffee company, identifying inefficiencies related to occupancy expenses and non-coffee item sales, and highlighting performance differences by location. Roh and Choi (2010) advanced DEA applications by evaluating multiple brands under a single franchisor using a multi-output framework. Their study showed how DEA captures differences in input use and output generation across brands within the same franchise system, offering a diagnostic tool for internal benchmarking. Assaf et al. (2010) employed bootstrapped DEA to evaluate scale efficiency in Australian restaurants, finding widespread inefficiencies and that larger firms were more efficient due to economies of scale. Joo et al. (2012) applied DEA to labor management in a family gourmet restaurant, analyzing hourly staffing efficiency during peak hours and offering insights into reallocating staff to improve performance. Choi et al. (2007) applied DEA to evaluate productivity across franchised units of a restaurant chain operating in the Pacific Rim region. Using factor analysis to identify key input variables, the study revealed efficiency disparities and provided a framework for internal benchmarking and resource optimization.

The restaurant sector, particularly fast food, is dynamic, marked by thin profit margins, intense rivalry, and evolving customer expectations. Recent external shocks, such as the COVID-19 pandemic, have disrupted operational continuity, highlighting the need for robust tools for strategic benchmarking and efficiency evaluation. The pandemic exposed significant operational vulnerabilities across the restaurant industry. Studies have highlighted how lockdowns, supply chain disruptions, labor shortages, and shifting customer behaviors have impacted restaurant survival. Dhillon et al. (2025) found that in the Indian context, factors like turnover, financial flexibility, and external environment were critical for an eatery's survival during COVID-19, with traditional marketing elements losing predictive effectiveness. Ndhlovu (2025) argued that restaurant recovery is intertwined with ongoing global challenges, including rising labor and energy costs, political conflicts, and climate-related disturbances, that delay full post-pandemic stability. Mandal et al. (2024) emphasized the need for a multilayered capacity framework in informal dining to ensure business continuity. Their interpretative structural modeling identified financial resilience, labor stability, and digital engagement as fundamental drivers enabling scalability, process control, and customer value delivery in the new normal.

Previous studies highlight the value of applying DEA to benchmark efficiency in the restaurant industry. The fast-food sector, in particular, is well-suited for DEA due to its standardized operations, cost-driven strategies, and emphasis on customer satisfaction and performance optimization. Despite its relevance, DEA applications in fast-food chains remain limited, especially during the critical period of pandemic disruption and post-pandemic recovery, when benchmarking tools were most needed. This study addresses that gap by applying DEA to the fast-food segment, incorporating financial performance indicators such as return on assets (ROA), EBITDA margin, capital utilization, and total revenue growth. By extending beyond traditional customer-centric metrics, it provides a more comprehensive and strategically focused assessment of operational efficiency in the fast-food sector.

MODEL

Originally developed by Charnes et al. (1978), data envelopment analysis (DEA) has grown to be a well-known non-parametric technique in operations research and economics for evaluating the efficiency of decision-making units (DMUs), which can span companies, government agencies, and service providers. Providing a complete substitute for conventional ratio-based performance analysis, DEA evaluates how successfully these entities transform several inputs into outputs using linear programming. It creates a production possibility frontier shaped by the most successful companies, which act as standards for others.

Unlike methods based on a single measure, DEA allows several inputs and outputs—each of which may be quantified in various units—without imposing preconceived functional relationships. It is well suited for service industries, such as fast-food, because managerial quality and customer satisfaction equally affect operational efficiency depending on technology and capital. By means of its ability to successfully convert resources like labor, capital, and technology into desired outputs such as profitability, market expansion, and operational efficiency, DEA facilitates benchmarking.

We assess nineteen prominent fast-food chains in the United States in this paper. Every restaurant is considered a DMU. Traditional ratio analysis looks at individual financial indicators, but DEA enables simultaneous evaluation of various performance aspects. The service industry, including fast-food chains gains advantages through this approach since their financial success depends on management practices combined with technology investments and external market conditions.

The DEA methodology assesses relative efficiency through comparisons of firms' abilities to transform limited resources into desired performance results. The model treats capital utilization as the input variable by calculating it through total assets divided by revenue, with lower values demonstrating superior capital utilization. The model maximizes return on assets (ROA) as a profitability metric and EBITDA margin, along with total revenue growth, because they represent operational strength and market expansion alongside profitability. We want to find which companies fall short and which stand on the efficiency frontier.

Under assumptions of variable returns to scale (VRS), we implement an output-oriented DEA model. When inputs are relatively fixed and the main administrative objective is to maximize outputs, this orientation is suitable. In order to more faithfully depict their operational reality, the VRS framework also catches the variation in size and scale among fast-food companies (Gökşen et al., 2015; Cruz & Tumibay, 2019). The orientation demonstrates management's strategy to enhance revenue growth and financial performance while avoiding additional resource allocation.

The efficiency scores for each firm come from benchmarking against a performance standard created by the most efficient DMUs within the sample. The benchmark of 100% efficiency corresponds to a score of 1.0, whereas any score below this represents how far a firm is from full efficiency. DEA creates theoretical composite firms from efficient entities to provide attainable performance goals for less efficient businesses.

At the core of DEA is the formulation of an optimization problem where each DMU selects its most favorable set of weights for inputs and outputs to showcase its efficiency. We define the following variables and take n decision-making units (DMUs) into account to build the DEA model.

$j = 1, 2…n$ (DMU variable).

$i = 1, 2,…,m$ (inputs variable).

$r = 1, 2,…,s$ (outputs variable).

Therefore, each DMU_j, $j = 1, 2,…, n$, uses the following variable factors:

x_{ij} – amount of input i for the unit j, $i =1,2,……,m$ and $j =1,2,….,n$.

y_{rj} – amount of output r for the unit j, $r = 1, 2,….., s$ and $j = 1, 2,….,n$.

u_r – weight assigned to the output r, $r = 1,2,…..,s$

v_i – weight assigned to the input i, $i =1,2,……,m$.

Further, for each DMU, we form the virtual input and output using the weights (to be determined) v_i and u_r:

Virtual input = $\sum_{i=1}^{m} v_i x_{ij}$

Virtual output = $\sum_{r=1}^{s} u_r\, y_{rj}$

where j= 1,2, …., n (DMU variable). We want to determine the weights, using linear programming so as to maximize the ratio as

$$\frac{Virtual\ Output}{Virtual\ Input}$$

Data envelopment analysis (DEA) establishes efficiency through the division of weighted output totals by weighted input totals. The primary difficulty in utilizing DEA involves figuring out the correct method for assigning relevant weights. DEA provides flexibility in weight selection because it was designed by Charnes et al. (1978) not to depend on fixed values. The DEA model permits every decision-making unit

(DMU) to choose the optimal weight set that highlights its best performance results. The ability to choose optimal weights lets different units express their unique operational strengths since these weights can differ between units. A DMU is deemed inefficient with any weighting scheme if it shows inefficiency with its optimal set of weights. DEA provides a structure where individual units get specific evaluation criteria but remain within a universal benchmarking system, which enables detailed yet stringent performance comparisons between comparable units.

Efficiency in data envelopment analysis (DEA) is calculated as the ratio of a weighted sum of outputs to a weighted sum of inputs as shown in Equation 1.

$$\text{Efficiency} = \frac{\sum_{r=1}^{s} u_r y_{rj}}{\sum_{i=1}^{m} v_i x_{ij}} \tag{1}$$

One of the key challenges in applying DEA is deciding how these weights should be assigned. Instead of using fixed or predetermined values, DEA, as outlined by Charnes and colleagues, lets each decision-making unit (DMU) choose the set of weights that best highlights its performance. Naturally, this means the weights may differ across units, reflecting their individual operational strengths. Still, if a DMU turns out to be inefficient even when evaluated using its most favorable set of weights, it is deemed inefficient under any weighting scenario. At its core, DEA defines DMU's efficiency as the proportion of weighted outputs it generates relative to its weighted inputs, offering a flexible yet consistent way to evaluate performance across comparable entities (Equation 2).

$$\max E_o = \frac{\sum_{r=1}^{s} u_r y_{ro}}{\sum_{i=1}^{m} v_i x_{io}} \tag{2}$$

subject to

$$\frac{\sum_{r=1}^{s} u_r y_{rj}}{\sum_{i=1}^{m} v_i x_{ij}} \leq 1, \ j = 1,..,n$$

$u_r \geq \varepsilon$, r = 1,…,s
$v_i \geq \varepsilon$, i = 1,….,m

where ε is an infinitesimal or non-Archimedean constant that prevents the weights from vanishing (Charnes et al., 1994). When the above mathematical program is solved, it yields the optimal objective value representing the efficiency score of the DMU under evaluation, referred to as DMU_o. If the efficiency score equals one, the unit is considered efficient and lies on the efficiency frontier. Otherwise, the DMU is classified as relatively inefficient. To determine the efficiency of each DMU in the data set, the mathematical program must be solved repeatedly, treating each unit in turn as the reference DMU. In doing so, we obtain a set of Pareto efficiency measures, where the efficient units form the efficiency frontier (Thanassoulis, 2001). Because fractional mathematical programs are often challenging to solve directly, it is standard practice to convert them into equivalent linear programming formulations to simplify computation. The fractional program (Equation 1 and 2) can be conveniently converted into an equivalent linear program by normalizing the denominator using the constraint = 1, as the weighted sum of inputs is constrained to be unity and the objective function is the weighted sum of outputs that has to be maximized (Equation 3).

$$\max \sum_{r=1}^{s} u_r y_{ro} \tag{3}$$

subject to

$$\sum_{i=1}^{m} v_i x_{io} = 1,$$

$$\sum_{r=1}^{s} u_r y_{rj} - \sum_{i=1}^{m} v_i x_{ij} \leq 0,\ j = 1,..,n,$$

$u_r \geq \varepsilon$, r = 1,…,s
$v_i \geq \varepsilon$, i = 1,….,m

This model is the CCR (Charnes, Cooper, and Rhodes) model. Similarly, a general input minimization CCR model can be represented as Equation 4.

$$\min \sum_{i=1}^{m} v'_i x_{io} \tag{4}$$

subject to

$$\sum_{r=1}^{s} u'_r y_{ro} = 1$$

$$\sum_{r=1}^{s} u'_r y_{rj} - \sum_{i=1}^{m} v'_i x_{ij} \leq 0,\ j = 1,..,n,$$

$u_r \geq \varepsilon$, r = 1,…,s
$v_i \geq \varepsilon$, i = 1,….,m

According to basic linear programming, every linear programming problem (usually called the primal problem) has another closely related linear program, called its dual. Therefore, the dual of the output maximizing DEA program is as follows in Equation 5.

$$\theta^* = \min \theta \tag{5}$$

subject to

$$\sum_{j=1}^{n} \lambda_j x_{ij} \leq \theta x_{io},\ i = 1,….,m$$

$$\sum_{j=1}^{n} \lambda_j y_{rj} \geq y_{ro},\ r = 1,\ldots,s$$

$\lambda_j \geq 0$, θ unrestricted.

If $\theta^* = 1$, then the current input levels cannot be reduced, indicating that DMU_o is on the frontier. Otherwise, if $\theta^* < 1$, then DMU_o is dominated by the frontier. θ^* represents the input-oriented efficiency score of DMU_o. The individual input reduction is called slack. In fact, both input and output slack values may exist in models (Equations 6 and 7).

$$s_i^- = \theta^* x_{io} - \sum_{j=1}^{n} \lambda_j x_{ij}\ i = 1,\ldots,m \qquad (6)$$

$$s_r^+ = \sum_{j=1}^{n} \lambda_j y_{rj} - y_{ro},\ r = 1,\ldots,s \qquad (7)$$

To determine the possible non-zero slacks after solving the linear program (8), we should solve the following linear program:

$$\max \sum_{i=1}^{m} s_i^- + \sum_{r=1}^{s} s_r^+ \qquad (8)$$

subject to

$$\sum_{j=1}^{n} \lambda_j x_{ij} + s_i^- = \theta^* x_{io},\ i = 1,\ldots,m$$

$$\sum_{j=1}^{n} \lambda_j y_{rj} - s_r^+ = y_{ro},\ r = 1,\ldots,s$$

$\lambda_j \geq 0$, θ unrestricted.

DMU_o is efficient if and only if $\theta^* = 1$ and $s_i^{-*} = s_r^{+*} = 0$ for all i and r. DMU_o is weakly efficient if and only if $\theta^* = 1$ and $s_i^{-*} \neq 0$ and (or) $s_r^{+*} \neq 0$ for some i and r. In fact, models (7) and (8) represent a two-stage DEA process that can be summarized in the following DEA model (Equation 9):

$$\min \theta - \varepsilon\left(\sum_{i=1}^{m} s_i^- + \sum_{r=1}^{s} s_r^+\right) \qquad (9)$$

subject to

$$\sum_{j=1}^{n} \lambda_j x_{ij} + s_i^- = \theta x_{io},\ i = 1,\ldots,m$$

$$\sum_{j=1}^{n} \lambda_j y_{rj} - s_r^{+} = y_{ro}, \; r = 1,\ldots,s$$

$\lambda_j \geq 0$, θ unrestricted.

DATA AND METHODOLOGY

The data for this study was sourced from Standard & Poor's NetAdvantage, a comprehensive database offering financial and operational information across a wide range of companies. The framework for evaluating performance includes return on assets (ROA), EBITDA margin, capital utilization, and total revenue growth. These metrics provide a comprehensive perspective on each firm's ability to generate profit and maintain operational efficiency, while also indicating future growth potential, which is essential in evaluating long-term competitive strength and sustainable operations.

Return on assets (ROA) serves as a critical measure in this assessment, providing insights into a firm's ability to generate profit from its asset base (De Souza et al., 2014; Malhotra & Malhotra, 2024). In the context of the fast-food industry, which is characterized by substantial investments in infrastructure, digital platforms, and supply chain systems, ROA captures how efficiently these resources are converted into net income. This metric is particularly salient due to its integration of operational efficiency and asset management, both of which are vital for sustained performance in a competitive landscape. ROA reveals the return on invested funds and reflects a company's resource utilization. It helps identify operational performance, competence, and efficiency. A high ROA indicates effective asset management in generating profits, whereas a low ROA signals inefficiencies or underutilization. Additionally, ROA is influenced by factors such as company size (Rapposelli et al., 2024), which should be considered when comparing fast-food chains of varying scales.

Earnings before interest, taxes, depreciation, and amortization (EBITDA) margin further refines the evaluation process by isolating operating profitability, excluding the influence of financing and accounting decisions. Calculated as earnings before interest, taxes, depreciation, and amortization divided by total revenue, this metric is especially relevant in the fast-food sector, where differences in capital structure and depreciation schedules arise from franchise models, lease arrangements, and equipment investments. By focusing on core earnings, EBITDA offers a standardized perspective on a company's ability to manage costs and improve operational performance, enabling meaningful comparisons across chains. It is frequently used by analysts and investors to assess financial performance (De Souza et al., 2014), offering a clearer picture of profitability by excluding variables that differ significantly across firms. As a result, EBITDA margin provides a more accurate view of a company's ability to generate cash flow from core operations.

Capital utilization ratio offers insight into how efficiently a company uses its capital to generate revenue. This ratio, calculated as total assets divided by total revenue, is especially meaningful in an industry known for thin margins and high fixed costs (Malhotra et al., 2023). A lower capital utilization ratio signifies more efficient capital deployment, indicating that the company use less capital per unit of revenue. This efficiency is especially critical in capital-intensive industries, where maximizing returns from a given capital base is key to maintaining competitive advantage and long-term success. Conversely, a high ratio signals underperformance in capital allocation.

Total revenue growth over the previous year is also a critical indicator in the fast-food industry, reflecting a company's ability to increase sales and expand its customer base. This measure helps identify market trends, assess performance, and benchmark against competitors, thereby supporting strategic decision-making and resource allocation (Lim et al, 2024; Malhotra & Malhotra, 2024).

Table 1 presents an overview of the financial performance of nineteen fast-food restaurant chains in the United States over the period from 2020 to 2024. During this period, the ROA steadily improved. In 2020, the mean ROA was 4.59 percent, rising to 8.73 percent by 2024. This indicates that, on average, restaurant chains became more efficient at generating profits from their assets. The standard deviation of ROA also declined slightly, from 8.56 percent in 2020 to 8.12 percent in 2024, suggesting increased consistency in asset utilization across the chains over time.

TABLE 1
SUMMARY STATISTICS OF THE VARIABLES USED IN THIS STUDY FOR THE PERIOD 2020-2024

	Return on Assets (%)	EBITDA Margin (%)	Capital Utilization Ratio	Total Revenue Growth over previous year (%)
2020				
Mean	4.59%	11.80%	1.59	-8.15%
Std. Dev.	8.56%	14.61%	1.20	21.92%
2021				
Mean	7.72%	17.87%	1.23	31.96%
Std. Dev.	7.34%	11.26%	0.67	42.10%
2022				
Mean	7.29%	16.39%	1.15	12.95%
Std. Dev.	7.01%	11.40%	0.64	12.29%
2023				
Mean	8.27%	17.47%	1.12	8.21%
Std. Dev.	7.43%	11.37%	0.64	8.68%
2024				
Mean	8.73%	17.73%	1.10	5.31%
Std. Dev.	8.12%	11.25%	0.62	9.44%

The EBITDA margin, which reflects the operating profitability of the chains, also showed significant improvement. The mean EBITDA margin increased from 11.80 percent in 2020 to 17.73 percent in 2024, highlighting a general trend of improved profitability relative to total revenue. However, the standard deviation remained relatively stable, fluctuating between 11.25 percent and 14.61 percent, indicating that while the overall margin improved, the variation among chains did not change significantly.

The capital utilization ratio, which measures revenue with the use of capital, also improved. In 2020, the mean ratio was 1.59, meaning that 1.59 dollars of capital were required to generate each dollar of sales revenue. By 2024, this figure had decreased to 1.10, indicating improved profitability through more efficient use of capital over the sample period. The stable standard deviation implies that the variation in capital utilization across the chains remained consistent, reflecting a general trend of improved capital efficiency with relatively steady gains across firms.

Total revenue growth showed a dramatic recovery following the COVID-19 pandemic. In 2020, the chains experienced a mean revenue decline of -8.15 percent. However, in 2021, mean growth surged to 31.96 percent, likely due to the easing of pandemic restrictions and the return of more normal consumer behavior. By 2024, the growth rate had moderated to 5.31 percent, indicating that while the chains continued to grow, the pace of the recovery had slowed. The standard deviation in revenue growth also decreased from 21.92 percent in 2020 to 9.44 percent in 2024, pointing to a stabilization of revenue trends across the chains as the market recovered and the pandemic's impact faded.

Overall, the data reveal a clear trend of improving profitability and revenue recovery over the period from 2020 to 2024. Fast-food restaurant chains became more efficient at generating profits, as reflected in rising ROA and EBITDA margins. Capital was used more efficiently, and revenue growth, though initially volatile, had stabilized by 2024, reflecting a return to normalcy after the pandemic's impact. These trends provide valuable insights into the industry's operational efficiency and its ability to recover and adapt to changing market conditions.

EMPIRICAL ANALYSIS

This section displays the data envelopment analysis (DEA) findings for major fast-food companies spanning the years 2020 to 2024. We provide a comparative analysis of the firm-level efficiency scores, along with benchmarking analysis and slack variables, to evaluate how these firms transformed inputs into outputs during times of economic instability and operational challenges.

Furthermore, we identify leading firms by monitoring their efficiency progress over time and apply slack diagnostics to identify weak performers and their sources of inefficiency. The findings deliver an extensive assessment of performance differences throughout the fast-food industry and propose actionable steps to boost operational effectiveness.

Empirical Analysis of Efficiency Scores at the Firm Level

Table 2 presents a five-year portrait of efficiency scores for major fast-food companies, measured from 2020 to 2024 using DEA. The table tells a story of resilience, stagnation, and fluctuation across the sector.

TABLE 2
DEA EFFICIENCY SCORE FOR FAST-FOOD COMPANIES FOR THE PERIOD 2020-2024

Company	2020	2021	2022	2023	2024	Average Efficiency Score for the period 2020 to 2024
BJ's Restaurants, Inc.	100%	100%	100%	100%	100%	100%
Brinker International, Inc. (Chili's Grill & Bar, Maggiano's Little Italy)	73%	72%	64%	71%	69%	70%
Chipotle Mexican Grill, Inc.	81%	59%	71%	75%	73%	72%
Chuy's Holdings, Inc. (Tex-Mex Restaurant chain)	71%	57%	50%	51%	51%	56%
Cracker Barrel Old Country Store, Inc.	100%	100%	100%	100%	100%	100%
Darden Restaurants, Inc. (Olive Garden, Longhorn, Yard House, Bahama Breeze)	100%	100%	100%	100%	100%	100%
Dave & Buster's Entertainment, Inc.	62%	88%	100%	100%	88%	87%
Dine Brands Global, Inc. (Applebee's, IHOP)	61%	23%	44%	79%	57%	53%
Domino's Pizza, Inc.	86%	47%	55%	53%	50%	58%
El Pollo Loco Holdings, Inc. (Mexican-style grilled chicken chain)	84%	44%	62%	69%	66%	65%
Jack in the Box Inc.	95%	100%	52%	96%	57%	80%
McDonald's Corporation	3%	100%	100%	67%	52%	64%
Papa John's International, Inc.	88%	71%	74%	66%	43%	68%
Red Robin Gourmet Burgers, Inc.	86%	36%	38%	38%	35%	47%
Shake Shack Inc.	46%	46%	81%	39%	25%	47%
Starbucks Corporation	61%	48%	33%	49%	39%	46%
Texas Roadhouse, Inc.	67%	58%	50%	50%	54%	56%
The Wendy's Company	73%	37%	28%	30%	31%	40%
Wingstop Inc.	40%	50%	52%	48%	27%	43%

BJ's Restaurants, Cracker Barrel Old Country Store, and Darden Restaurants demonstrate outstanding reliability in performance. Over the five-year span, these companies achieved perfect efficiency with a score of 100 percent. These organizations demonstrate effective resource conversion through stable business operations that remained largely unaffected by fluctuations in the industry or economy.

Dave & Buster's Entertainment showed considerable improvement over the period. The company began with a 62 percent efficiency score in 2020 and achieved full efficiency by 2022, which it maintained through 2023. Although its score declined to 88 percent in 2024, the company maintained a strong five-year average of 87 percent. This performance trajectory suggests effective strategic or operational adjustments during the post-pandemic period.

Other firms showed more variable paths. Chipotle Mexican Grill started with an 81 percent score in 2020, which dropped to 59 percent in 2021, before steadily rising to 73 percent by 2024, resulting in an overall five-year average of 72 percent. This pattern reflects volatility, possibly due to supply chain disruptions or shifting consumer trends.

McDonald's followed one of the most unusual and noteworthy trajectories. Despite its status as a global industry leader, it recorded a surprisingly low efficiency score of only 3 percent in 2020. Although it rebounded quickly to full efficiency in 2021 and 2022, McDonald's experienced another decline in subsequent years, resulting in an average efficiency of 64 percent over the five-year period. This inconsistent performance during the early pandemic period may reflect temporary operational inefficiencies or shifting strategic priorities.

Some chains consistently struggled. Red Robin Gourmet Burgers and Wendy's averaged 47 percent and 40 percent in efficiency scores, respectively, driven by temporary gains in 2020 followed by weaker performance in subsequent years. Shake Shack followed a similar pattern, with a brief performance enhancement offset by low scores in other years, resulting in a 47 percent average. Starbucks and Wingstop operated at 50 percent efficiency or less in most years.

Overall, Table 2 demonstrates significant variation in operational efficiency across the fast-food industry, including among prominent brands. The data suggest that successful navigation through a turbulent five-year period depended heavily on companies' adaptability, innovation, and cost-control capabilities.

Figures 1, 2, and 3 illustrate the relative operational efficiency of leading fast-food companies across three distinct views. This analysis presents operational efficiency data for 2020 and 2024 separately, alongside a five-year average calculation for the period between 2020 and 2024. The graphs highlight both short-term performance changes and long-term efficiency patterns over time.

FIGURE 1
EFFICIENCY FRONTIER OF FAST FOOD COMPANIES FOR THE YEAR 2020

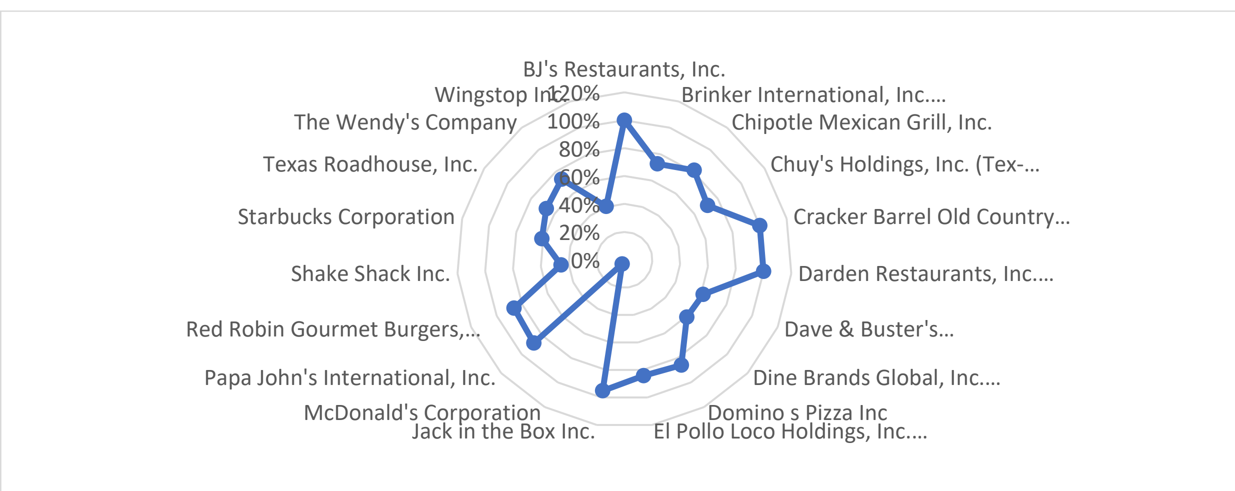


FIGURE 2
EFFICIENCY FRONTIER OF FAST FOOD COMPANIES FOR THE YEAR 2024

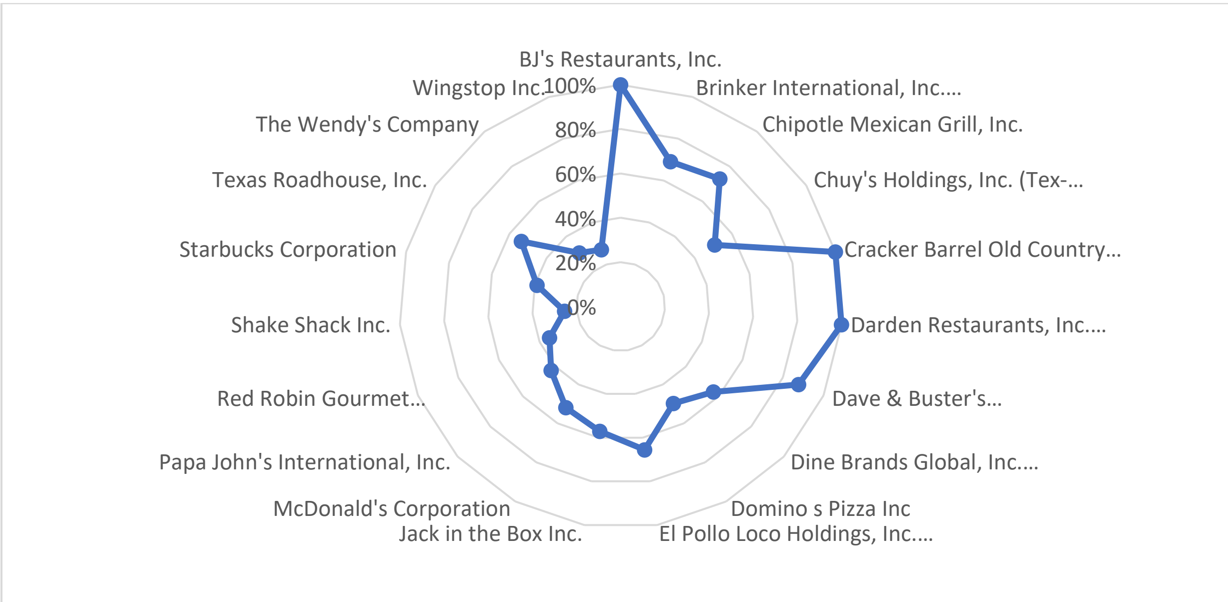
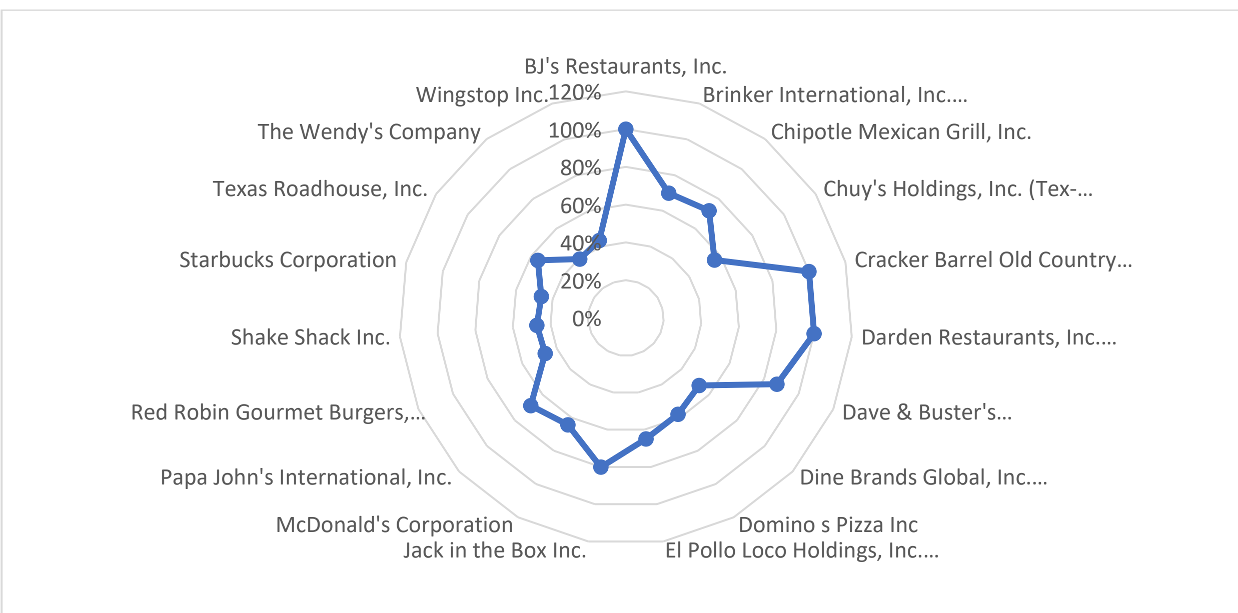


FIGURE 3
EFFICIENCY FRONTIER OF FAST FOOD COMPANIES BASED ON THE AVERAGE OF THE EFFICIENCY SCORES FROM 2020 TO 2024



During 2020, As shown in Figure 1, BJ's Restaurants, Cracker Barrel Old Country Store, and Darden Restaurants achieved perfect efficiency scores, demonstrating strong operational resilience and consistent resource utilization during the pandemic. In contrast, McDonald's (3%), Wingstop (40%), and Shake Shack (46%) underperformed, suggesting early challenges in maintaining profitability, managing asset efficiency, or adapting operations to a rapidly changing environment.

In 2024, as shown in Figure 2, a few chains maintained perfect efficiency scores, while others showed varied performance levels, reflecting uneven recovery and operational execution across the industry. BJ’s Restaurants, Cracker Barrel Old Country Store, and Darden Restaurants maintained flawless scores, while Dave & Buster’s Entertainment (88%) and Chipotle Mexican Grill (73%) posted strong gains, supported by streamlined operations and enhanced digital and delivery capabilities. In contrast, Shake Shack (25%), Wingstop (27%), and Wendy’s (31%) remained at the lower end of the efficiency spectrum. These results suggest that ongoing challenges, such as high urban operating costs, fluctuating input prices, and inconsistent execution across franchised locations, may have limited the effectiveness of their strategies in improving long-term efficiency.

Figure 3, which presents five-year average efficiency scores, offers a more comprehensive view of sustained performance. BJ’s Restaurants, Cracker Barrel Old Country Store, and Darden Restaurants led the sector with perfect averages, while Dave & Buster’s Entertainment (87%) and Chipotle Mexican Grill (72%) followed with consistently strong results. Jack in the Box posted a solid 80 percent average despite fluctuations across individual years. Meanwhile, Red Robin Gourmet Burgers, Shake Shack, Starbucks, Wendy's, and Wingstop averaged below 50 percent, highlighting persistent challenges in maintaining stable margins, scaling operations efficiently, or achieving consistent growth outcomes.

Taken together, the figures underscore the importance of translating operational strategies such as digital transformation, delivery integration, and resource optimization into consistent performance over time. While some firms have successfully embedded these approaches into scalable and resilient models, others appear to face persistent barriers. The contrasting outcomes emphasize that sustained efficiency requires not only innovation, but also effective alignment between strategy, execution, and market conditions.

Empirical Analysis of Peer Benchmarking and Reference Efficiency Patterns

Through slack analysis, precise input and output variables responsible for inefficiencies are identified. A company might display strong revenue growth yet demonstrate inadequate ROA or capital utilization performance. These findings help managers and investors focus their efforts on areas that yield the best potential for enhancing performance and to organize their corrective steps accordingly.

The DEA system functions to classify companies as either efficient or inefficient while pinpointing the fundamental reasons for their underperformance. Table 3 examines inefficiencies in the fast-food sector by identifying underperforming companies and their more efficient peers. It offers insight into how firms can use peer benchmarks to improve operations and uncover gaps that traditional performance metrics may not capture.

TABLE 3
INEFFICIENT FAST-FOOD COMPANIES AND THEIR PEERS

Company	Efficiency (%)	McDonald's Corporation	Domino’s Pizza, Inc	Wingstop Inc.	Sum
Starbucks Corporation	69%	0.248	0.744	0.007	1.00
Chipotle Mexican Grill, Inc.	73%	0.041	0.322	0.638	1.00
Darden Restaurants, Inc. (Olive Garden, Longhorn, Yard House, Bahama Breeze)	51%	0.189	0.307	0.504	1.00
Texas Roadhouse, Inc.	88%	0.000	0.588	0.412	1.00
Shake Shack Inc.	57%	0.000	0.000	1.000	1.00
The Wendy's Company	50%	0.751	0.000	0.249	1.00
Brinker International, Inc. (Chili's Grill & Bar, Maggiano’s Little Italy)	66%	0.000	0.586	0.414	1.00
Papa John's International, Inc.	57%	0.000	0.918	0.082	1.00

Dave & Buster's Entertainment, Inc.	52%	0.718	0.085	0.196	1.00
Jack in the Box Inc.	43%	0.780	0.220	0.000	1.00
Cracker Barrel Old Country Store, Inc.	35%	0.000	0.476	0.524	1.00
BJ's Restaurants, Inc.	25%	0.106	0.417	0.477	1.00
Chuy's Holdings, Inc. (Tex-Mex Restaurant chain)	39%	0.206	0.180	0.614	1.00
Dine Brands Global, Inc. (Applebee's, IHOP)	54%	0.901	0.099	0.000	1.00
El Pollo Loco Holdings, Inc. (Mexican-style grilled chicken chain)	31%	0.361	0.200	0.439	1.00
Red Robin Gourmet Burgers, Inc.	27%	0.000	0.529	0.471	1.00

Starbucks maintains a 69 percent efficiency level and is benchmarked primarily against McDonald’s and Domino’s Pizza in the DEA model. The operational model analysis of Starbucks shows 24.8 percent peer weight from McDonald’s, while 74.4 percent comes from Domino’s Pizza, with Wingstop receiving minimal weight, suggesting potential benefits from adopting Domino’s Pizza’s supply chain methods alongside McDonald’s global consistency standards.

Chipotle Mexican Grill demonstrates a higher efficiency score at 73 percent and is benchmarked primarily against Wingstop (63.8%), while assigning less weight to Domino’s Pizza and McDonald’s. This suggests that Chipotle Mexican Grill could benefit from certain efficiency traits seen in Wingstop’s model, although it maintains an upscale fast-casual brand image.

Darden Restaurants maintains an efficiency score of 51 percent while distributing its reference points across three peer companies, showing a moderate preference toward Wingstop. Darden Restaurants’ varied peer group represents its wide-ranging brand portfolio, which extends from casual dining to upscale experiences.

Texas Roadhouse, with a high efficiency score of 88 percent, looks exclusively toward Domino’s Pizza and Wingstop for operational insight while completely ignoring McDonald’s. The company’s DEA benchmark suggests potential efficiency gains from streamlined, delivery-focused models instead of following McDonald’s intricate global model.

Several chains with midrange efficiency scores show strong benchmarking alignment with McDonald’s. Dine Brands Global, with an efficiency score of 54 percent, benchmarks most heavily against McDonald’s (90.1%), reinforcing potential alignment with globally scaled operational models. Jack in the Box, with an efficiency score of 43 percent, also relies significantly on McDonald’s (78.0%), with a secondary reference to Domino’s (22.0%), suggesting partial alignment with both models.

Dave & Buster’s Entertainment, with an efficiency score of 52 percent, draws 71.8 percent of its peer reference from McDonald’s, but also shows moderate reliance on Wingstop (19.6%) and a small share from Domino’s (8.5%). This pattern suggests potential efficiency gains from standardized systems, though the firm operates in a distinct full-service entertainment format. Wendy’s, with an efficiency score of 50 percent, allocates 75.1 percent of its benchmark weight to McDonald’s and 24.9 percent to Wingstop, reflecting a hybrid reference structure. This indicates possible efficiency improvements from adopting elements of McDonald’s traditional quick-service model and Wingstop’s lean delivery-focused operations.

In contrast, Shake Shack, with an efficiency score of 57 percent, is benchmarked entirely against Wingstop, indicating efficiency similarities with this niche, streamlined brand. Papa John’s International, with an efficiency score of 57 percent, shows a strong reliance on Domino’s Pizza, with a benchmark weight of 91.8 percent, suggesting potential efficiency gains from operational practices such as delivery optimization, digital infrastructure, and capital deployment within a shared franchise-based model.

Cracker Barrel Old Country Store, BJ’s Restaurants, and Red Robin Gourmet Burgers represent underperforming chains, with efficiency scores of 35%, 25%, and 27%, respectively. All three operate in full-service, casual dining formats and distribute their DEA benchmark references nearly evenly between

Domino’s Pizza and Wingstop. Cracker Barrel assigns 47.6% of its peer weight to Domino’s and 52.4% to Wingstop. BJ’s benchmarks at 41.7% to Domino’s and 47.7% to Wingstop, while Red Robin assigns 52.9% to Domino’s and 47.1% to Wingstop. These dual-reference patterns suggest opportunities to improve performance by adopting delivery-driven efficiencies from Domino’s and streamlined operational practices from Wingstop.

Table 3 illustrates how efficiency benchmarking enables less efficient companies to identify and learn from more efficient peers. The data highlights which firms are underperforming and reveals the high-performing companies they reference as models for potential improvement.

Diagnostic Analysis of Slack Variables and Sources of Inefficiency

The analysis of Table 4 reveals inefficiency factors by examining slack variables in companies that did not reach full efficiency. The slack values provide clear insights into both the magnitude and location of necessary improvements to guide companies toward greater efficiency.

TABLE 4
SLACK VARIABLES FOR INEFFICIENT COMPANIES

Company	efficiency	Capital Utilization Rate	Return on Assets (%)	EBITDA Margin %	Total Revenue Growth Over Previous Year (%)
McDonald's Corporation	100%	1.00	0.000	0.000	0.000
Starbucks Corporation	69%	1.45	0.000	0.105	0.000
Chipotle Mexican Grill, Inc.	73%	1.37	0.000	0.051	0.000
Darden Restaurants, Inc. (Olive Garden, Longhorn, Yard House, Bahama Breeze)	51%	1.97	0.000	0.063	0.000
Domino’s Pizza, Inc	100%	1.00	0.000	0.000	0.000
Wingstop Inc.	100%	1.00	0.000	0.000	0.000
Texas Roadhouse, Inc.	88%	1.14	0.000	0.157	0.107
Shake Shack Inc.	57%	1.76	0.562	0.189	0.117
The Wendy's Company	50%	2.01	0.661	0.041	0.000
Brinker International, Inc. (Chili's Grill & Bar, Maggiano’s Little Italy)	66%	1.53	0.000	0.148	0.079
Papa John's International, Inc.	57%	1.75	0.000	0.039	0.021
Dave & Buster's Entertainment, Inc.	52%	1.925	0.000	0.049	0.000
Jack in the Box Inc.	43%	2.346	0.039	0.000	0.000
Cracker Barrel Old Country Store, Inc.	35%	2.846	0.000	0.158	0.091
BJ's Restaurants, Inc.	25%	3.933	0.000	0.096	0.000
Chuy's Holdings, Inc. (Tex-Mex Restaurant chain)	39%	2.563	0.000	0.063	0.000

Dine Brands Global, Inc. (Applebee's, IHOP)	54%	1.868	0.259	0.000	0.000
El Pollo Loco Holdings, Inc. (Mexican-style grilled chicken chain)	31%	3.271	0.059	0.000	0.000
Red Robin Gourmet Burgers, Inc.	27%	3.706	0.000	0.271	0.050

The efficiency ratings in Table 4 indicate that McDonald's, Domino's Pizza, and Wingstop achieve complete operational efficiency, with zero slack across all measured input and output variables. Companies seeking improvement should view these businesses as ideal benchmarks to emulate.

Starbucks displays significant slack in its EBITDA margin by 10.5 percentage points, while maintaining consistent performance in other business aspects, despite an overall efficiency score of 69 percent. Starbucks generates substantial revenues but could improve efficiency by enhancing profitability margins.

Chipotle Mexican Grill shows a 5.1 percentage point slack in EBITDA margin while operating at 73 percent efficiency. While the company benefits from strong brand equity and broad popularity, it still has room to improve its operating profitability.

Darden Restaurants, owner of Olive Garden and Longhorn Steakhouse, shows a shortfall of 6.3 percentage points in EBITDA margin. In addition, its high capital utilization ratio slack of 1.97 suggests that the company either uses resources inefficiently or maintains excessive capital investments relative to output.

Texas Roadhouse exhibits moderate operational inefficiencies, with a 15.7 percentage point shortfall in EBITDA margin and 10.7 percentage point slack in revenue growth, along with a modest capital utilization ratio slack of 1.14. Profile analysis indicates that the company is approaching its potential efficiency but would benefit from stronger cost control and improved revenue generation.

Lower-scoring companies reveal more pronounced inefficiencies compared to their higher-performing peers. Shake Shack, for example, has slack across all three dimensions: a considerable 56.2 percentage point gap in return on assets, an EBITDA margin shortfall of nearly 19 percentage points, and more than 11 percentage points in revenue growth slack. A capital utilization ratio of 1.76 further highlights the company's struggle to optimize asset utilization and profitability, suggesting its business model may be misaligned with efficient large-scale operations.

Wendy's also faces significant challenges. It shows a 66.1 percentage point shortfall in return on assets, nearly 4.1 percentage points in EBITDA margin slack, and a high capital utilization ratio of 2.01 points. The data suggest deep-rooted inefficiencies spanning multiple operational dimensions.

Cracker Barrel Old Country Store, BJ's Restaurants, Red Robin Gourmet Burgers, and El Pollo Loco Holdings comprise the lower end of the efficiency spectrum, all demonstrating high capital utilization rate slack, ranging from 2.8 to 3.9, indicating an inability to effectively utilize capital assets to generate output. BJ's Restaurants and Red Robin Gourmet Burgers, in particular, have the highest capital utilization rates and face profitability challenges marked by high EBITDA margin slack. Red Robin Gourmet Burgers also suffers from significant deficits in revenue growth.

The diagnostic value of slack variables serves as a useful tool for identifying inefficiencies. These measures not only highlight the presence of performance gaps but also pinpoint specific weaknesses such as insufficient asset returns, low profit margins, or weak revenue growth despite substantial capital input. For both managers and investors, this deeper insight can guide strategic decisions, reveal cost-saving opportunities, and support the reallocation of resources to enhance overall efficiency.

SUMMARY AND CONCLUSIONS

Data Envelopment Analysis (DEA) evaluated operational efficiency across nineteen major fast-food chains in the United States during the period from 2020 to 2024. The study identified substantial disparities in financial and operational performance based on analysis of the capital utilization rate as the input, and compared it against outputs such as Return on assets (ROA), EBITDA margin, and total revenue growth.

Only BJ's Restaurants, Cracker Barrel Old Country Store, and Darden Restaurants achieved full efficiency throughout the five-year span, with their exceptional operational practices and resource management. Dave & Buster's Entertainment and Chipotle Mexican Grill showed major efficient gains as they successfully adjusted their business operations during the post-pandemic recovery period. In contrast, McDonald’s and Jack in the Box experienced inconsistent performance or efficiency declines, indicating potential structural or strategic challenges within their operations.

This paper identifies the fast-food industry as a valuable addition to efficiency research using DEA, despite its common exclusion from such studies, due to its economic significance and operational uniformity. While existing studies have primarily examined sectors such as banking, healthcare, and education, this research applied the DEA framework to a dynamic, consumer-driven sector to analyze performance differences among firms with similar business structures.

The outcomes of the study have several important implications. Executives gain precise insights into their companies’ inefficiencies in capital deployment, profitability, and sales growth, and identify future strategic directions by examining more successful peers. Investors benefit from numerical efficiency scores that allow them to evaluate managerial effectiveness and strategic adaptability. Researchers and policymakers are encouraged to apply DEA when assessing service sectors to discover opportunities for policy changes or management reforms aimed at improving overall performance.

The research highlights that stable operational performance is a critical factor for business survival during times of economic turbulence and shifting consumer behavior. Enterprises that swiftly adapt their operations and make sensible investments in technology and services tend to outperform their competition. The findings demonstrate that efficiency benchmarking remains an essential strategic tool for sustaining competitive advantage in fast-evolving industries.

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