Evaluating the Economic and Financial Efficiency of Sugar-Energy Companies Using Financial Ratios and Data Envelopment Analysis

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Abstract - **The sugar-energy sector is highly relevant to Brazilian agribusiness, particularly in São Paulo, which hosts most of the country's operational plants. This study compared the economic-financial performance of ten sugar-energy companies in São Paulo between 2018 and 2024 using two complementary methods: financial indicator analysis and Data Envelopment Analysis (DEA). The descriptive, quantitative research drew from financial statements. Initially, capital structure, liquidity, and profitability indicators were calculated to estimate the sector's standard index. Subsequently, output-oriented DEA CCR and BCC models were applied, using accounting variables as inputs and outputs. The results revealed significant differences in relative performance: some firms operated near the efficient frontier, while others showed opportunities to improve resource utilization and economic results.**

Keywords - **Data Envelopment Analysis (DEA), Operational Research, Production Engineering, Economic and Financial Indicators.**

I. INTRODUCTION

Brazilian agribusiness plays an important role in the country´s economy. In 2024, Brazil's GDP reached approximately US$ 2.33 trillion, while the GDP of agribusiness was estimated at around US$ 540 billion, corresponding to 23.2% of the national GDP [1] [2]. In this context, the sugar-energy sector stands out, as its production chain integrates agricultural, industrial, and energy activities, consolidating Brazil as the world's leading producer and exporter of sugar and one of the largest global producers of ethanol [2][3]. In 2024, the sugar-alcohol sector generated approximately US$ 63 billion, about 11.6% of Brazil's agribusiness GDP, evidencing its strategic importance [1][3]. The sector comprises approximately 368 plants in operation, responsible for processing sugarcane into sugar, ethanol, bioelectricity, and industrial byproducts, contributing to the diversification of the Brazilian energy matrix and reduction of greenhouse gas emissions [2][3].

In the regional context, the state of São Paulo stands out as Brazil's main sugar-energy hub, concentrating approximately 160 plants in 2024 [1]. São Paulo accounted for about 54% of national sugar production and 44% of Brazilian ethanol production [5][3]. This prominence is associated with consolidated logistics infrastructure, favorable edaphoclimatic conditions, and a high level of mechanization. The economic, energy, and environmental relevance of the sector reinforces its importance as an object of study in research focused on sustainability, competitiveness, and innovation in Brazilian agribusiness.

The economics of the Brazilian sugar-energy sector have reinforced the need for analytical instruments capable of evaluating firm performance. Accounting and financial information are essential for understanding operational efficiency, cost structure, and economic sustainability. Indicators derived from financial statements help measure companies' ability to generate results, manage resources, and face agribusiness volatility cycles, while reducing information asymmetry among managers, investors, and market agents [9][7]. The systematic analysis of these data is crucial for understanding economic performance in capital-intensive sectors dependent on market and climatic factors [6][7][8]. Thus, this study aimed to compare the economic-financial performance of sugar-energy companies in São Paulo between 2018 and 2024 through two analytical models: i) analysis of economic-financial indicators; and ii) Data Envelopment Analysis (DEA).

Although financial indicator analysis and DEA are well-established techniques, the study's innovative elements include: (i) systematic comparison between rankings generated by both methods over seven consecutive years, identifying convergences and divergences between financial and productive efficiency; (ii) empirical demonstration of how different DEA model specifications (3x3, 3x4, 3x5) affect company classifications, providing practical warnings about the method's interpretative limits; and (iii) an integrated diagnosis associating efficiency scores with specific financial variables (leverage, liquidity, asset immobilization). Thus, the study advances beyond standard tool application by translating findings into actionable managerial recommendations [6][7].

II. METHODOLOGY

This research can be characterized as descriptive and quantitative, seeking, through the application of economic-financial indicator calculations and Data Envelopment Analysis (DEA), to comparatively identify the performance of the firms that make up the sample. Thus, the methodology of this study was divided into two parts: i) the first refers to the procedures necessary for calculating liquidity, profitability, and indebtedness indicators of the 10 firms that compose the sample, as well as the sector standard

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index; ii) the application of Data Envelopment Analysis (DEA) to perform the relative analysis of the selected firms.

The sample definition followed a non-probabilistic purposive sampling, based on the availability and consistency of financial statements published by sugar-energy plants located in the state of São Paulo. The literature highlights that, for the application of Data Envelopment Analysis (DEA), it is essential that the decision-making units (DMUs) present structural and operational homogeneity in order to ensure technical comparability among them [12]. The ten companies analyzed (identified as FA, FB, FC, FD, FE, FF, FG, FH, FI, and FJ for confidentiality purposes) are sugar-energy plants in operation in the state of São Paulo. All have an annual crushing capacity exceeding 2 million tons of sugarcane, operate in both sugar and ethanol production, and have been in continuous operation for at least 15 years, being located in the main producing regions of the state, including the mesoregions of Ribeirão Preto, São José do Rio Preto, Piracicaba, and Araçatuba [8]. The accounting data were extracted from audited financial statements published annually in management reports and official corporate disclosure systems, covering the period from 2018 to 2024.

Data collection was performed directly from the financial statements published in annual reports and official corporate information disclosure systems of the selected firms. Accounting standardization, reclassification, and harmonization of balance sheet and income statement accounts were carried out to ensure conceptual uniformity among the analyzed companies [13].

A. Calculation of economic-financial indicators

The calculations of economic-financial indicators were performed based on the equations in TABLE I. These indices establish classical relationships between balance sheet and income statement accounts, allowing the assessment of payment capacity, capital structure, and results generation of the sample. After calculating the indicators for each company and year, the standard index was calculated. In this step, the indicators calculated for each firm were organized into a single set representing the analyzed sugar-energy sector. The standard index must be calculated based on a set of comparable firms belonging to the same economic sector [14]. For each calculated financial indicator, the values observed in the companies must be placed in ascending or descending order, depending on the economic interpretation of the indicator.

Then, the distribution of indicators was divided into 10 equal parts (deciles), each containing 10% of the observations. The sector standard index is represented by the central value of the distribution (median or fifth decile). This value serves as a reference for evaluating the performance of the analyzed companies, where each range represents a level of relative performance within the sector: very low; low; medium; high; very high. This approach allows comparing a company's financial performance with the standard observed in the sector [14].

TABLE I: FORMULAS FOR CALCULATING THE INDICATORS.

Financial Ratios	Equations
Capital Structure	
Debt-to-Equity Ratio	Total Liabilities / Equity
Debt Composition Ratio	Current Liabilities / Total Liabilities
Equity Immobilization Ratio	(Non-Current Assets) / Equity
Non-Current Resources Immobilization Ratio	(Non-Current Assets) / (Equity + Non-Current Liabilities)
Liquidity	
General Liquidity Ratio	(Current Assets + Long Term Receivables) / Total Liabilities
Current Ratio	Current Assets / Current Liabilities
Quick Ratio	(Current Assets – Inventory – Prepaid Expenses) / Current Liabilities
Profitability	
Total Asset Turnover	Net Revenue / Total Assets
Net Profit Margin	Net Income / Net Sales
Return on Assets (ROA)	Net Income / Total Assets
Return on Equity (ROE)	Net Income / Equity

Source: Authors based on [14].

B. Data Envelopment Analysis (DEA)

DEA was conducted based on the CCR (Charnes, Cooper, and Rhodes) and BCC (Banker, Charnes, and Cooper) models, both oriented towards output maximization. The objective is to evaluate the companies' ability to maximize their results from a given level of resources used. This type of approach is particularly suitable in economic-financial performance studies because it allows identifying the potential for expanding companies' results without necessarily changing the volume of resources employed [16].

The CCR model assumes constant returns to scale, while the BCC model incorporates variable returns to scale through the convexity constraint [12]. The joint use of the CCR and BCC models allows decomposing total technical efficiency into pure efficiency and scale efficiency. This decomposition is fundamental to identify whether inefficiency stems from poor resource allocation or inadequate operational size [16].

The first step consists of determining the decision-making units (DMUs) to be evaluated by the DEA model, in this case, the 10 sugar-energy plants in the sample. Then, the accounting data of each firm were collected, processed, and normalized, which are important for constructing the input and output variables of the DEA model.

Based on a literature review, the following variables were initially considered for the model: i) inputs: Current Liabilities, Long-Term Debt, Third-Party Capital, Equity, Total Liabilities, Net Revenue; ii) outputs: Current Assets, Long-Term Receivables, Fixed Assets, Net Income for the Year, Total Assets [16], [13].

The chosen variables were collected from the DMUs' financial statements, analyzed based on the median of each year, and the correlations between different inputs and outputs were determined. The objective was to verify the Pearson correlation coefficient for the set of variables, selecting those with the highest correlation, i.e., the most linearly related variables. Based on the results obtained from the Pearson coefficient, the following variables were chosen for the efficiency analysis of the DMUs: i) inputs: Current Liabilities, Long-Term Debt, and Net Revenue; ii) outputs: Current Assets, Fixed Assets, Total Assets, Long-Term Receivables, and Net Income.

After defining the variables and the model orientation, the CCR model was applied [17], which allows estimating the global technical efficiency of the DMUs, considering the relationship between resources used and results obtained. Thus, it is possible to identify which companies operate on the efficient production frontier and which present levels of relative inefficiency [13].

$$\max w_0 = \sum_{r=1}^{s} u_r Y_{r0} \;\; / \;\; \sum_{i=1}^{m} v_i X_{i0} \tag{1}$$
subject to: $\sum_{r=1}^{s} u_r Y_{rj} \;\; / \;\; \sum_{i=1}^{m} v_i X_{ij} \leq 1, j = 1, 2 \ldots . n$
$u_r, \geq 0,\; r = 1, 2,..., s$
$v_i\,, \geq 0,\; i = 1, 2,..., m$

Where: w_0 = efficiency of DMU_0 (zero); Y_{rj} = quantity of outputs j for DMU j; X_{ij} = quantity of inputs i for DMU j; u_r = weight referring to the outputs; v_i weight referring to the inputs; Y_{r0} = quantity of outputs for observed of DMU; X_{i0} = quantity of inputs for observed of DMU; s = total quantity of outputs; m = total quantity of inputs; n = total quantity of DMU.

The model of equation (1) is non-linear, but the model can be linearized, resulting in equation (2). This model is better known as the multiplier model:

$$\max wo = \sum_{r=1}^{s} u_r Y_{r0} \tag{2}$$
subject to: $\sum_{i=1}^{s} v_i X_{i0} = 1$
$\sum_{r=1}^{m} u_r\, y_{rj} - \sum_{i=1}^{m} v_i\, x_{ij} \;\leq\; 0\,, j = 1{,}2 \ldots .\,, n$
$u_r \geq 0\,,\; r = 1, 2,..., s$
$v_i \geq 0,\; i = 1, 2,..., m$

From equation (2), the Data Envelopment Analysis (DEA) model called BCC [17] was developed, as presented in equation (3).

$$\max wo = \sum_{r=1}^{s} u_r Y_{r0} + c0 \tag{3}$$
subject to: $\sum_{i=1}^{s} v_i X_{i0} = 1$
$\sum_{r=1}^{s} u_r\, y_{rj} - \sum_{i=1}^{m} v_i\, x_{ij} +\; c0 \leq\; 0\,, j = 1{,}2 \ldots .\,, n$
$u_r \geq 0\,,\; r = 1, 2,..., s$
$v_i \geq 0,\; r = 1, 2,...,$ m
$c0$ unrestricted.

The scores calculated by the CCR and BCC models have the following interpretations: i) CCR model: assumes constant returns to scale and provides a measure of global technical efficiency, also referred to as productive efficiency; ii) BCC model: assumes variable returns to scale and provides a measure of pure technical efficiency, isolating scale effects [18].

Considering an output-oriented approach, the scale efficiency indicator will be the ratio between the productive efficiency indicator and the technical efficiency indicator. The productive efficiency analyses can be described as follows: i) if the result equals 1, the operation is productively efficient, and the scale and technical efficiency indicators will also equal 1; ii) if the result is greater than 1, the operation is inefficient in terms of productivity, due to technical or scale inefficiency [19].

The technical efficiency analyses behave as follows: i) if the result equals 1, the productive inefficiency is a consequence of an inappropriate production scale; ii) if the result is greater than 1, technical inefficiency exists, and it is necessary to calculate the index that demonstrates whether the operation is efficient in scale [19].

Finally, the scale efficiency analysis is described as: i) if the result equals 1, the inefficiency comes from technical factors; ii) if the result is greater than 1, there is both technical and scale inefficiency [18].

When applying a DEA model, it is possible to identify inefficient companies and categorize them as inefficient in terms of scale or inefficient in terms of the technology used. With this information, it is possible to identify the reason for the company's inefficiency, which may be related to its production scale or to misguided managerial decisions.

III. RESULTS AND DISCUSSION

Table II presents the evolution of the standard indices of the sugar-energy sector calculated from the sample of ten companies between 2018 and 2024. Regarding capital structure indicators, it is observed that the Debt-to-Equity Ratio remained high throughout the series, indicating a predominance of third-party capital in the companies' financing structure. The index decreased from 168.9% in 2018 to 146.4% in 2020, representing a drop of approximately 13.3% in the leverage level. However, from 2021 onwards, a new increase is observed, reaching 160.8% in 2024, suggesting a return to dependence on third-party resources. Regarding the Debt Composition Ratio, a reduction from 38.3% in 2018 to 31.9% in 2021 (a decrease of about 16.7%) is verified, followed by a slight increase to 36.8% in 2024, indicating a higher share of short-term debt in the final period of the series.

TABLE II. INDICES CALCULATED FROM THE SAMPLE OF 10 FIRMS FOR THE SUGAR-ALCOHOL SECTOR FOR THE PERIOD BETWEEN 2019 - 2024

	2019	2020	2021	2022	2023	2024
Debt to Equity Ratio	148.6	146.4	166.9	153.9	161	160.8
Debt Composition Ratio	34.1	34.3	31.9	32.6	32.8	36.8
Equity Immobilization Ratio	152.8	135.7	138.3	138.5	142.3	136.1
Non Current Resources Immobilization Ratio	75.7	75.8	76.6	76.3	72.6	64.3
General Liquidity Ratio	0.6	0.7	0.7	0.7	0.6	0.7
Current Ratio	1.6	1.7	0.7	1.3	1.4	1.8
Quick Ratio	1.2	1.2	1.2	0.9	1	1.3
Total Asset Turnover	0.5	0.6	0.5	0.6	0.6	0.6
Net Profit Margin	9.3	6	4.6	4.3	5	8.2
Return on Assets (ROA)	3.6	2.8	1.6	2.2	2.6	3.9
Return on Equity (ROE)	10.5	5.8	4.2	5.8	9.5	13.3

Source: Research results.

The indicators related to capital immobilization show relative stability throughout the analyzed period. The Equity Immobilization Ratio remained above 130% in all years, indicating that fixed assets exceed the companies' equity volume. The index reached 152.8% in 2019, a value approximately 11.8% higher than that recorded in 2018 (136.7%), gradually reducing to 136.1% in 2024. The Non-Current Resources Immobilization Ratio showed a decreasing trend throughout the series, from 69.2% in 2018 to 64.3% in 2024, an approximate reduction of 7.1%, suggesting less commitment of permanent resources to fixed assets over the period.

In the group of liquidity and profitability indicators, greater variability is observed throughout the series. The Current Ratio remained relatively stable between 1.6 and 1.7 from 2018 to 2020, but showed a significant drop in 2021 (0.7), corresponding to a reduction of approximately 58.8% compared to the previous year. In subsequent years, a gradual recovery is observed up to 1.8 in 2024, a value about 157% higher than that observed in 2021. In terms of profitability, the Net Profit Margin decreased from 9.3% in 2019 to 4.3% in 2022, a drop of approximately 53.8%, followed by a recovery in the final years of the series, reaching 8.2% in 2024. A similar trend is observed in ROA and ROE, which show a reduction until 2021 and partial recovery in subsequent years.

Table III presents the classification of the sample companies based on the weighting of scores obtained from the sector standard indices. It is observed that some companies maintained relatively stable positions in the top rankings throughout the analyzed period. Company FA, for example, occupied the first position between 2018 and 2021, indicating superior economic-financial performance compared to the other firms in this period. From 2022 onwards, however, a change in leadership is observed, with company FB assuming the first position in 2022 and 2023, while FC takes this position in 2024, evidencing relative changes in the performance of the sample companies.

Among the companies occupying intermediate positions in the ranking, greater variation is observed throughout the series. Company FC, for example, remained in the second position between 2018 and 2020, fell to the fourth position in 2021, and later improved its classification in subsequent years. Similarly, companies such as FD, FE, and FG alternated positions between third and sixth place throughout the analyzed series. This behavior suggests that the differences between the indicators of these companies are relatively small, so that specific variations in financial indices can result in changes in the relative classification of the firms.

In the lower positions of the ranking, greater persistence of the same companies is observed throughout the analyzed period. Company FI, for example, remained predominantly in ninth position between 2018 and 2022, showing slight improvement only in 2023, when it moved to a higher position in the ranking. A similar situation occurs with company FF, which occupied the tenth position between 2018 and 2022, showing improvement only in the final years of the series. These results indicate that these companies presented economic-financial indicators systematically below the average standard observed in the sample set.

TABLE III. COMPANY RANKINGS BY STANDARD INDEX SCORES (2018-2024)

	2018	2019	2020	2021	2022	2023	2024
1	FA	FA	FA	FA	FB	FB	FB
2	FC	FC	FC	FB	FA	FC	FC
3	FB	FB	FE	FD	FG	FA	FA
4	FD	FE	FB	FC	FC	FE	FH
5	FE	FD	FH	FE	FE	FH	FE
6	FG	FG	FD	FG	FH	FF	FF
7	FH	FH	FJ	FJ	FJ	FG	FD
8	FJ	FJ	FG	FH	FD	FJ	FJ
9	FI	FI	FI	FI	FI	FD	FI
10	FF	FF	FF	FF	FF	FI	FG

Source: Research results.

The joint analysis of Tables II and III allows us to observe that variations in the sector's standard indices directly influence the relative classification of the sample companies throughout the analyzed period. The reduction observed in profitability indicators between 2019 and 2022, especially in Net Profit Margin, ROA, and ROE, coincides with greater instability in the companies' ranking positions during this interval. This behavior suggests that the deterioration of the sector's economic-financial performance contributed to changes in the relative position of firms in the annual ranking.

On the other hand, the gradual recovery of liquidity and profitability indicators observed from 2023 onwards is also reflected in the improvement of some companies' positions in the overall classification. The increase in Net Profit Margin from 5.0% in 2023 to 8.2% in 2024, as well as the increase in ROE from 9.5% to 13.3% in the same period, indicates an improvement in the sector's economic conditions. In this context, the results demonstrate that the use of sector standard indices constitutes a relevant instrument for evaluating the relative performance of companies, allowing the identification of differences in economic-financial efficiency among firms over time.

TABLE IV. DATA ENVELOPMENT ANALYSIS RESULTS BETWEEN 2018 AND 2024 - CCR MODEL

DMUs	Efficiency	Factor
FE	96.72%	1.0339139
FD	100.00%	1.0000000
FB	100.00%	1.0000000
FC	94.32%	1.0602662
FG	92.32%	1.0831314
FH	100.00%	1.0000000
FF	100.00%	1.0000000
FI	100.00%	1.0000000
FA	89.17%	1.1214893
FJ	98.02%	1.0201697

Source: Research results.

The ranking used in the financial analysis column of Tables IV, V, VI, and VII was derived from the weighted scores of the sector standard indices presented in Table III. The companies were classified annually based on their relative position in the distribution of capital structure, liquidity, and profitability indicators. Table IV presents the results of the application of the Data Envelopment Analysis (DEA) model with constant returns to scale (CCR) for the period from 2018 to 2024.

Table IV presents the results of the application of the Data Envelopment Analysis (DEA) model with constant returns to scale (CCR) for the period from 2018 to 2024. It is observed that five companies were classified as efficient, presenting an efficiency score equal to 100%: FD, FB, FH, FF, and FI. These companies compose the efficient frontier of the model, indicating that, considering the set of inputs and outputs used, they were able to transform their financial resources into economic results in a relatively superior manner compared to the other firms in the sample. Among the efficient companies, FB stands out, which also occupies the first position in the economic-financial analysis classification, suggesting consistency between the two performance evaluation methods.

On the other hand, five companies presented efficiency levels below 100%, being considered relatively inefficient in the CCR model. Among these, company FA presented the lowest efficiency score (89.17%), indicating a potential need for improvement of approximately 12.1% in the relationship between outputs and inputs to reach the efficient frontier. Companies FG (92.32%), FC (94.32%), FE (96.72%), and FJ (98.02%) also presented efficiency levels below the maximum limit. These results indicate that, although some of these company's present performance relatively close to the efficient frontier, there are still margins for improvement in the use of financial and operational resources.

Table V presents a comparative summary between the results of the economic-financial analysis based on accounting ratios and the results obtained by applying the DEA with the CCR model considering different variable specifications (3x3, 3x4, and 3x5). It is observed that, in the 3x3 model, five companies were considered efficient, a result similar to that observed in Table IV. When the number of outputs increases to four variables (3x4), six companies become classified as efficient, indicating that the expansion of output variables tends to increase the number of units positioned on the efficient frontier.

TABLE V. DEA VS. FINANCIAL RESULTS SUMMARY – CCR MODEL 2018-2024

DMUs	Financial Analysis Classification	Efficiency (3x3)	Efficiency (3x4)	Efficiency (3x5)
FE	8	96.72%	95.66%	100.00%
FD	3	100.00%	94.96%	100.00%
FB	1	100.00%	100.00%	100.00%
FC	2	94.32%	100,00%	100.00%
FG	6	92.32%	69.61%	100.00%
FH	9	100.00%	100.00%	100.00%
FF	4	100.00%	100.00%	100.00%
FI	10	100.00%	57.00%	57,88%
FA	5	89.17%	100.00%	100.00%
FJ	7	98.02%	100.00%	100.00%

Source: Research results.

In the 3x5 model, which considers a larger number of output variables, an even greater increase in the number of efficient companies is verified, with nine out of ten companies presenting an efficiency score equal to 100%, leaving only one company as inefficient. This behavior is expected in DEA applications, since increasing the number of outputs tends to expand the possibilities of efficient combinations among variables. The comparison between DEA results and financial analysis results indicates that approximately 70% of the results obtained with the CCR model are consistent with the classification obtained by the financial ratio analysis, suggesting partial convergence between the two performance evaluation methods.

TABLE VI. DATA ENVELOPMENT ANALYSIS RESULTS BETWEEN 2018 AND 2024 - BCC MODEL

DMUs	Efficiency	Factor
FE	96.72%	1.0339139
FD	100.00%	1.0000000
FB	100.00%	1.0000000
FC	94.32%	1.0602662
FG	92.32%	1.0831314
FH	100.00%	1.0000000
FF	100.00%	1.0000000
FI	100.00%	1.0000000
FA	100.00%	1.0000000
FJ	100.00%	1.0000000

Source: Research results.

Table VI presents the results of the application of the DEA BCC model, which considers variable returns to scale. In this model, an increase in the number of companies classified as efficient is observed compared to the CCR model. In total, seven companies were considered efficient, presenting a score equal to 100%, namely: FD, FB, FH, FF, FI, FA, and FJ. This result indicates that, when considering variations in the companies' scale of operation, some units previously classified as inefficient in the CCR model become considered efficient in the BCC model.

Among the companies classified as inefficient in the BCC model, FE (96.72%), FC (94.32%), and FG (92.32%) stand out, with the latter presenting the lowest efficiency score in the sample set. These results suggest that part of the inefficiencies observed in the CCR model may be associated with differences in the companies' scale of operation. Thus, the BCC model allows identifying situations in which companies are technically efficient but operate at production scales different from those considered optimal.

Table VII presents the comparison between the results of the economic-financial analysis and the efficiency scores obtained by the BCC model considering different combinations of variables. In the 3x3 model, it is observed that seven companies present maximum efficiency, a result consistent with the values presented in Table VI. When the number of outputs is expanded to four variables (3x4), the number of efficient companies increases to eight, indicating that the inclusion of new outputs expands the ability of companies to reach the efficient frontier.

In the 3x5 model, again eight companies were classified as efficient, while two remained with efficiency levels below 100%. Among the companies that maintained lower scores, FG stands out with an efficiency of 74.19%, and FD with 95.57%, depending on the model specification. The comparison with the economic-financial analysis results indicates that approximately 50% of the results coincide between the two methods, suggesting that the DEA BCC model captures additional dimensions of performance related to the companies' scale of operation.

TABLE VII. DEA VS. FINANCIAL RESULTS SUMMARY – BCC MODEL (2018-2024)

DMUs	Financial Analysis Classification	Efficiency (3x3)	Efficiency (3x4)	Efficiency (3x5)
FE	8	96.72%	100.00%	100.00%
FD	3	100.00%	94.96%	95.57%
FB	1	100.00%	100.00%	100.00%
FC	2	94.32%	100.00%	100.00%
FG	6	92.32%	71.25%	74.19%
FH	9	100.00%	100.00%	100.00%
FF	4	100.00%	100.00%	100.00%
FI	10	100.00%	100.00%	100.00%
FA	5	100.00%	100.00%	100.00%
FJ	7	100.00%	100.00%	100.00%

Source: Research results.

The joint analysis of the CCR and BCC models indicates that some companies present consistently high performance regardless of the model specification used. Companies such as FB, FH, and FF present maximum efficiency in practically all DEA specifications, suggesting a greater capacity to convert financial resources into economic results within the analyzed sample set. Furthermore, these companies also present favorable positions in the classification based on economic-financial indicators, reinforcing the consistency of the results.

On the other hand, companies such as FG, FC, and FE present lower efficiency scores in several models, indicating a greater distance from the efficient frontier. Considering the combined results of the CCR and BCC models, it is possible to establish an approximate ranking of the most efficient companies in the sample, highlighting FB, FH, FF, and FD as the units with relatively superior performance in the analyzed period. These results indicate that the application of DEA constitutes a relevant complementary tool to financial ratio analysis, allowing a more comprehensive evaluation of the economic-financial efficiency of companies in the sugar-energy sector.

The results indicate that companies such as FB, FH, and FF presented consistently high efficiency in both approaches (financial indicators and DEA). A possible explanation for this superior performance lies in the combination of operational and financial factors: (i) lower level of short-term debt, reducing pressure on cash flow; (ii) higher total asset turnover, indicating more efficient use of productive resources; and (iii) economies of scale, suggested by the fact that these companies have crushing capacity above the sample average. On the other hand, companies such as FG, FC, and FE, which consistently appeared among the least efficient, presented higher equity immobilization and lower current liquidity, suggesting difficulties in working capital management and fixed asset allocation. These findings indicate that relative inefficiency is associated not only with operational decisions but also with financing structure and asset management.

An inherent limitation of DEA application, evidenced in the results of Tables V and VII, is the sensitivity of the model to variable specification. It is observed that increasing the number of outputs (from 3x3 to 3x5) artificially raises the number of companies classified as efficient - from five to nine in the CCR model - reducing the discriminatory power of the analysis. This behavior, although expected in the DEA literature, suggests caution in the interpretation of efficiency scores, and it is recommended to use parsimonious criteria in the selection of inputs and outputs.

IV. CONCLUSION

This study compared the economic-financial performance of ten sugar-energy companies located in the state of São Paulo between 2018 and 2024 using two complementary methods: financial ratio analysis and Data Envelopment Analysis (DEA). The analysis of economic-financial indicators revealed that the sector presented relatively high levels of leverage throughout the analyzed period, along with fluctuations in liquidity and profitability indicators. A reduction in profitability levels was observed between 2019 and 2022, followed by a gradual recovery in the most recent years of the series, suggesting an influence of the sector's economic and operational conditions on the financial performance of the analyzed companies.

The DEA results indicated that some companies presented maximum efficiency across different model specifications, especially FB, FH, FF, and FD, which demonstrated a greater capacity to convert financial resources into economic results. Conversely, companies such as FG, FC, and FE presented lower efficiency levels in part of the analyses, showing a greater distance from the efficient frontier and indicating potential for improvement in the management of financial and operational resources. The comparison between methods revealed partial convergence: approximately 70% of the CCR model results were consistent with the financial ratio classification, reinforcing DEA as a complementary tool to traditional financial analysis.

A limitation of Data Envelopment Analysis refers to its sensitivity to the selection and number of variables employed in the model. The inclusion or exclusion of inputs and outputs can alter the efficient frontier and the efficiency scores of the DMUs. A second limitation is the reduced sample size (ten companies), which restricts the statistical robustness and generalizability of the findings to the entire sugar-energy sector of São Paulo. Future studies should expand the sample by including plants from other regions of Brazil, as well as employ bootstrap techniques to validate the efficiency scores obtained.

Overall, the results demonstrate that the combined use of economic-financial indicators and DEA constitutes a relevant analytical approach for the comparative evaluation of business performance. The integration of these methods allows not only analyzing the financial situation of companies but also identifying differences in relative efficiency among productive units within the same sector. Thus, this study contributes to managerial practice by offering an integrated diagnosis that links efficiency scores to specific financial variables (leverage, liquidity, and asset immobilization), supporting more informed strategic decisions in the sugar-energy sector.

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