FINANCIAL AND SPORTING EFFICIENCY AND PRODUCTIVITY IN BRAZILIAN FOOTBALL CLUBS

Marke Geisy da Silva Dantas[a], Thadeu Gasparetto[b*], Alexandro Barbosa[c] & Luciano Menezes Bezerra Sampaio[c]

[a]Instituto Federal de Educação, Ciência e Tecnologia do Rio Grande do Norte, Natal, Brazil. markegeisy@hotmail.com

[b]Leeds Beckett University, Leeds, United Kingdom. t.miranda-gasparetto@leedsbeckett.ac.uk

[c]Universidade Federal do Rio Grande do Norte, Natal, Brazil. alexufrnet@gmail.com

[c]Universidade Federal do Rio Grande do Norte, Natal, Brazil. lucianombsampaio@gmail.com

*__Corresponding Author__:

Thadeu Gasparetto

Leeds Beckett University.

Carnegie School of Sport.

Headingley Campus

LS6 3QU

Leeds, United Kingdom

Email: t.miranda-gasparetto@leedsbeckett.ac.uk

Funding details

This paper did not receive any funding.

Disclosure statement

The authors report there are no competing interests to declare.

Data availability statement

The data that support the findings of this study are available from the corresponding author upon reasonable request.

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Abstract

Purpose

This paper analyses the efficiency and productivity of Brazilian football clubs in the post-World Cup 2014 period (2014 to 2022) using a Network Dynamic DEA-Malmquist model.

Design/methodology/approach

Efficiency and productivity are categorised into two dimensions: sporting performance and financial performance. These indices are used as dependent variables in regression models employing generalised estimating equations (GEE).

Findings

The financial division's average efficiency is higher than that of the sporting division and overall efficiency from 2014 to 2022. Fourteen clubs exhibited increased productivity during this period. Regression models revealed a statistically significant positive relationship between the Debt Ratio and DEA Dependent Variable Models at a 1% significance level and a significant negative relationship with the three Malmquist Dependent Variable Models. Additionally, the models identified a statistically significant relationship with the "Covid" (2020 year) variable across all models.

Practical implications

Our findings suggest that increased expenditures can lead to higher liabilities, reducing the ability to afford high-quality players and thus diminishing overall club value. Additionally, the inefficiencies observed among some of the largest football clubs reveal room for improvement in both financial and sportive aspects.

Originality/value

This is the first study to investigate efficiency and productivity in two dimensions for Brazilian football clubs, incorporating an analysis of productivity over an extended period and examining the impact of debt and other determinants on club performance

Keywords Sporting Efficiency; Financial Efficiency; Network Dynamic DEA; Malmquist Index; Debt Ratio.

1 Introduction

Sloane (1971) and Dietl, Grossmann, and Lang (2011) have posited that maximising wins, attendance, and profit are crucial objectives for sports organisations. Research demonstrated a correlation between sports performance, attendance (Buraimo, Tena, and De La Piedra, 2018), and revenue (Késenne and Pauwels, 2006). Furthermore, investing in high-quality players is often considered a means of enhancing on-field performance (Gerhards and Mutz, 2017; Bradley, Lago-Peñas, and Sampaio, 2014). Therefore, it is important to evaluate the efficiency of these three aspects: wins, attendance, and profit, from the investments made.

The sports industry, particularly football, has been the subject of extensive economics academic research. This literature has focused on assessing on-field performance (Pícazo-Tadeo & González-Gómez, 2010; González-Gómez & Pícazo-Tadeo, 2010; Roboredo, Aizemberg & Meza, 2015) and off-field efficiency (Özaydin & Donduran, 2020; Barros & García-Del-Barrio, 2011). There remains ongoing debate among scholars regarding the goals of sports organisations, particularly whether they focus on winning or profit maximisation (Garcia-Del-Barrio & Szymanski, 2009; Dielt, Lang & Werner, 2009). Several papers proposed the creation of efficiency indices that take into account both objectives (Barros and Leach, 2006; Barros, Assaf, and Sá-Earp, 2010; Kern, Schwarzmann, and Wiedenegger, 2012; Roboredo, Aizemberg, and Meza, 2015).

A consideration when analysing efficiency is the inclusion of dynamic factors. Villa and Lozano (2016) and Barbosa, Dantas, Azevedo, and Holanda (2017) have employed Dynamic Data Envelopment Analysis (DEA) in the calculation of efficiency indicators. This method utilises a proxy known as "carry-over," which is transferred to the next period for the same Decision-Making Unit (DMU). It is crucial to highlight the relevant factors that are carried over time in the calculation of efficiency. For instance, in the case of football, a club's previous season can influence subsequent seasons due to factors such as winning championships, promotion, or relegation.

In Brazil, one of the leading football countries worldwide, several changes have occurred in recent years that have changed clubs' management, such as the hosting of the 2014 FIFA World Cup, and some legislative changes imposed by the federal government. The implementation by the Brazilian government of the Program for Modernization of Management and Fiscal Responsibility in Brazilian Football (Profut) through Law 13.155/15 aims to promote accountability, democratic management, and financial balance in professional football entities. Additionally, another change in legislation in the Brazilian environment was the promulgation of Law nº 14,193/21, which created a particular corporate model for football clubs in Brazil

(Sociedade Anônima do Futebol – SAF, in Portuguese). This law allows clubs to shift from the standard associative model of Brazilian football (associations) to public limited football companies.

This paper employs a Network Dynamic DEA-Malmquist model (Tone & Tsutsui, 2014) to analyse the efficiency and productivity of Brazilian football clubs in the post-World Cup 2014 period. This model considers not only sporting performance – as in previous research – but also financial performance, incorporating the relationship between them. Regression models explore the impact of period-specific characteristics. Variables of interest include sporting performance, club indebtedness—an important factor in Brazilian football—and the construction and use of new stadiums.

This study aims to contribute to the specific literature on the efficiency of football clubs by presenting a comprehensive model that identifies dynamic factors and categorises variables into distinct dimensions. Unlike previous research, which treated these aspects in isolation, our approach offers a more integrated and holistic understanding. Additionally, this study seeks to enhance existing knowledge regarding the efficiency assessment of Brazilian football clubs, focusing on a specific period following a major national sporting event. This time frame is crucial as it may have influenced clubs' perceived efficiency. Notably, most of the previous research used smaller sample sizes and shorter observation periods compared to our study.

The rest of the paper is structured into four parts. The following section presents a literature review on football efficiency research, focusing on utility maximization, primarily involving sports results, financial outcomes, and stadium attendance. The Methods section defines the methodology used in this work, highlighting the Network Dynamic DEA-Malmquist model as the primary method for efficiency calculation. It also describes the variables used and establishes GEE as the regression model to identify the influence of independent variables on the efficiency and productivity of the clubs. Our key findings are presented and discussed in the Results section, showing the correlations between variables, efficiency and productivity indicators through clusters formed by the clubs, and the regression models outlining the relationships between independent and dependent variables. Finally, the paper concludes with final considerations.

2 Literature Review

The efficiency of football clubs has been widely studied using both Data Envelopment Analysis (DEA) and stochastic frontier models. According to the literature, professional football clubs try to maximise wins, profit, revenue, and attendance. Specifically, we assume in this work that professional football clubs preach for the maximisation of utility as suggested by Sloane (1971) and several recent empirical papers. Therefore, in this review, we discuss research that included one to all three aspects (i.e., sporting performance, attendance, and revenues) in their modelling.

González-Gómez & Pícazo-Tadeo (2010), Pícazo-Tadeo & González-Gómez (2010), Roboredo, Aizemberg & Meza (2015), and Guzmán-Raja & Guzmán-Raja (2021), for instance, based their research on models with sporting outputs, focusing on win maximization. On the other hand, Haas (2003a), Haas (2003b), Haas, Kocher & Sutter (2004), Barros & Leach (2006), García-Sánchez (2007), Barros, Assaf & Sá-Earp (2010), Kern, Schwarzmann & Wiedenegger (2012), Özaydin & Donduran (2020), Terrien & Andreff (2020), Cifuentes-Faura (2022) and Fan, Liu, Yi & Gong (2023) included other outputs to their models, such as attendance, sporting performance, revenue, attendance revenue, among others.

Research by Haas (2003a), Haas (2003b), Haas, Kocher & Sutter (2004), Barros & Leach (2006), García-Sánchez (2007), Barros, Assaf & Sá-Earp (2010), Kern, Schwarzmann & Wiedenegger (2012), Terrien & Andreff (2020), Pérez-González, Carlos & Alén (2022) and Fan, Liu, Yi & Gong (2023), implemented DEA, using as outputs some proxy for the number of fans (or average) during the season, alongside other sportive and financial variables.

Regarding the stochastic frontier papers shown in Table 1, they all work from the perspective of cost efficiency, which is the dependent variable of the three models. The three papers assign as independent variables, among others, the number of fans, total revenues, and some variables related to sports performance, corroborating the issue of maximising utilities.

The literature indicates that aspects related to football games, such as the number of fans and ticket revenue, are often addressed, but typically not in an isolated manner. These factors are often examined as complements of other variables, such as attendance influencing match-day revenue. Only the most recent studies discuss "social" efficiency, a dimension related specifically to football club attendance. Özaydin and Donduran (2020) note that social efficiency, referring to attendance, is often included in general efficiency models rather than being analysed separately. In this context, García-Sánchez (2007) is noteworthy for dividing efficiency into three groups, including the number of spectators as one of them. The authors applied a three-stage DEA model to the Spanish Professional Football League during the 2004-2005 season, separating the economic behaviour of the teams into operational efficiency (offensive and defensive), athletic efficiency, and social efficiency.

Considering the exposed papers, we can see that most of them value the maximisation of utility. However, even with the evolution of efficiency models, none of them divided efficiency into groups of outputs, considering sports, financial, and social dimensions in the same model. Haas (2003), Haas, Kocher & Sutter (2004), Barros, Assaf & Sá-Earp (2010), and Kern, Schwarzmann & Wiedenegger (2012), for example, add these three variables as the output of their models. The last three authors make two models where the output of the first model is the input of the second, but they are different models anyway. Considering Brazilian football as a sample, three articles also presented utility maximization in their models, cases of Barros, Assaf & Sá-Earp (2010), Barros, Assaf & Araújo Júnior (2011), and Barros, Wanke, and Figueiredo (2015). Robored, Aizemberg & Meza (2015) uses only one sports performance variable as the output. However, Pérez-González, Carlos & Alén (2022) introduced an additional dimension focused on Social Activities, alongside the existing Sports Activities dimension, in the Network DEA model. This novel inclusion significantly influenced the revenue generation of La Liga clubs during the 2016/17 season.

Despite the advancements in efficiency models and the inclusion of various dimensions such as sporting, financial, and social performance, the literature reveals significant gaps. Many studies do not comprehensively integrate these dimensions within a single, cohesive model. Additionally, research often focuses on limited periods, thereby restricting the generalizability of their findings. In this paper, we address these gaps by employing a network dynamic DEA model that distinctly separates efficiency into sports and financial dimensions, with attendance serving as the linking output. This approach not only bridges the identified gap in the existing literature but also offers a more robust and holistic analysis of football club efficiency over an extended period. By incorporating multiple years of data, we aim to provide more reliable and insightful conclusions that can inform both academic research and practical applications in football management.

[INSERT TABLE 1 HERE]

3 Methods

3.1 Dynamic Network DEA

The method employed to calculate efficiency indicators is the SBM Dynamic Network DEA (Tone & Tsutsui, 2014), which considers the efficiency of DMUs separated into divisions, each with its inputs and outputs, and includes continuous factors over time. Carry-over is a variable that links the same efficiency split between different periods (into four categories: “good”, “bad”, “free” and “fixed”), while the link variable (Free, Fixed, Input, and Output) connects different divisions of efficiency in the same period. The formulation of the SBM Dynamic Network DEA is presented in Tone and Tsutsui (2014). We used the DEA Solver Pro software, which also calculated the DEA-Malmquist indicators.

We use a non-oriented model with variable returns to scale (BCC) because we acknowledge significant differences in the sizes of the clubs, requiring both input reduction and output increase. Additionally, we conducted the Wilcoxon test for paired samples to compare the results of the CCR and BCC models, as proposed by Zhu (2000). Since the null hypothesis of equal means was rejected, we opted to use the BCC model.

3.2 Data and Sample

The research sample consisted of 23 Brazilian football clubs that participated in the Campeonato Brasileiro Série A and Série B between 2014 and 2022. To obtain a representative sample, clubs that did not participate in either Série A or Série B during the entire period of study were excluded. The final sample included: América-MG, Athletico-PR, Atlético-GO, Atlético-MG, Avaí, Bahia, Botafogo, Ceará, Chapecoense, Corinthians, Coritiba, Cruzeiro, Flamengo, Fluminense, Goiás, Grêmio, Internacional, Palmeiras, Ponte Preta, Santos, São Paulo, Sport Recife and Vasco, resulting in a total of 207 observations.

The present paper employs a two-category approach to efficiency measurement. We define sporting efficiency as the ability of a club to maximise its performance on the field, as measured by its win-loss record during a given season. Financial efficiency is defined as the ability of a club to maximise revenues during a given season. Ticket sales are used as the link between the sporting and financial dimensions of efficiency.

[INSERT TABLE 2 HERE]

In the sporting dimension, the input used was team value in euros (€), obtained from the Transfermarkt website (Kern, Schwarzmann & Wiedenegger, 2012; Carmichael, Rossi & Thomas, 2017). The carry-over of this division was the clubs' total assets (Barros & Leach, 2006; Barros, Assaf & Sá-Earp, 2010; Barros & García-del-Barrio, 2011), which are a measure of club size and can indirectly affect efficiency calculation. The output of this dimension was Ranking CBF, a variable calculated by the national confederation that reflects the results of national championships over the last five years. Additionally, we considered that the sporting factor plays a crucial role in attracting fans to the stadium. Therefore, the number of tickets sold in the league (Haas, 2003a; Haas, 2003b; García-Sánchez, 2007; Kern, Schwarzmann & Wiedenegger, 2012; Özaydin & Donduran, 2020) was used as the link output variable of this division. Data on ticket sales were extracted from the Transfermarkt website and *the Confederação Brasileira de Futebol* website (CBF). In 2020, the Brazilian Football League was played under closed gates due to the COVID-19 pandemic, resulting in no attendance data. In this sense, we controlled for that employing a dummy for COVID.

In the financial dimension, the input used was the clubs' operational costs/expenses (Barros, Assaf & Sá-Earp, 2010; Barros & García-del-Barrio, 2011; Barros, Wanke & Figueiredo, 2015). The Carry-over of this dimension was Total Liabilities. The purpose of choosing this variable is to demonstrate that a larger amount of liabilities hinders teams in their search for better players (affecting the Value of Players), making them unable to achieve better positions in national championships (Ranking CBF), decreasing attendance (tickets sold), and ultimately, revenue. Therefore, it is a"bad" type of carry-over. The carry-over from the year before the sample, 2013, had already been used to calculate the efficiency of the year 2014. The output of the financial division was the clubs' net revenue (Barros & Garcia-Del-Barrio, 2011).

3.3 Generalised equation estimates (GEE) models

We used regression models to examine the impact of various factors on the efficiency and productivity of DMUs in the sporting and financial divisions, as measured by the DEA index and the Malmquist and Cumulative Malmquist indices, respectively. Two hundred and seven observations were used in the DEA analysis. One hundred and eighty-four observations were used in the Malmquist analysis, with one sample year being lost (2014), once the Malmquist index represents a productivity change from period t compared to period t_{-1}. Therefore, the number of observations is smaller than the number of DMUs.

The generalised estimating equations (GEE) method was utilised. First proposed by Liang & Zeger (1986), GEE is a well-established extension of generalised linear models (GLM) (CUI, 2007). The coefficients are estimated using maximum likelihood, and the variance is calculated using a link function, which transforms the dependent variable into an equation of parameter estimates in the form of an additive model (Guimarães & Hirakata, 2012). GEE requires specifying the following: a) link function, b) distribution of the dependent variable, and c) correlation structure. In this study, the "Gaussian" family was found to have the lowest QIC values. Within this family, only an "identity" link is allowed. Therefore, a thorough examination of the possibilities between the family, link, and correlation matrix was conducted to obtain the results and proposed models.

The selection of this model is attributed to several reasons, including its ability to accommodate non-normally distributed residuals when applied to panel data (Barbosa, Lima & Brusca, 2016; Dohmen, Ineveld, Markus, Hagen & Klundert, 2022), the capability to handle correlated data over time, and the presence of heterogeneity among observations (Barbosa, Lima & Brusca, 2016). In preliminary analyses, the OLS model failed to meet the assumptions adequately, leading to the decision to opt for a model with more relaxed assumptions. Moreover, the choice of the Generalised Estimating Equations (GEE) model is justified as empirical evidence suggests that its application in the analysis of longitudinal repeated-measures data does not substantively differ from fixed and random effects models (Gardiner, Luo & Roman, 2008). Furthermore, GEE addresses the challenges posed by non-normally distributed residuals and correlated data over time, making it a suitable alternative to panel data fixed effects models.

The equations are the following:

$$\begin{aligned} SportDEA_{jt} = {} & \beta_0 + \beta_1 DebtRatio_{jt} + \beta_2 NewStadium_{jt} + \beta_3 Covid_{jt} + \beta_4 \text{Série}A_{jt} \\ & + \beta_5 Prom_{jt} + \beta_6 Prom_{jt-1} + \beta_7 LibertZone_{jt} + \beta_8 LibertPart_{jt} \\ & + \beta_9 Relegated_{jt} + \beta_{10} Relegated_{jt-1} + \varepsilon_{jt} \end{aligned}$$

$$\begin{aligned} & FinancialDEA_{jt} \\ & = \beta_0 + \beta_1 DebtRatio_{jt} + \beta_2 NewStadium_{jt} + \beta_3 Covid_{jt} + \beta_4 \text{Série}A_{jt} \\ & + \beta_5 Prom_{jt} + \beta_6 Prom_{jt-1} + \beta_7 LibertZone_{jt} + \beta_8 LibertPart_{jt} \\ & + \beta_9 Relegated_{jt} + \beta_{10} Relegated_{jt-1} \\ & + \beta_{11} Cluster1_{jt-1} + \beta_{12} Cluster3_{jt-1} + \varepsilon_{jt} \end{aligned}$$

$$\begin{aligned} TotalDEA_{jt} = {} & \beta_0 + \beta_1 DebtRatio_{jt} + \beta_2 NewStadium_{jt} + \beta_3 Covid_{jt} + \beta_4 \text{Série}A_{jt} \\ & + \beta_5 Prom_{jt} + \beta_6 Prom_{jt-1} + \beta_7 LibertZone_{jt} + \beta_8 LibertPart_{jt} \\ & + \beta_9 Relegated_{jt} + \beta_{10} Relegated_{jt-1} \\ & + \beta_{11} Cluster1_{jt-1} + \beta_{12} Cluster3_{jt-1} + \varepsilon_{jt} \end{aligned}$$

$$\begin{aligned} SportMalm_{jt} = {} & \beta_0 + \beta_1 DebtRatio_{jt} + \beta_2 NewStadium_{jt} + \beta_3 Covid_{jt} + \beta_4 \text{Série}A_{jt} \\ & + \beta_5 Prom_{jt} + \beta_6 Prom_{jt-1} + \beta_7 LibertZone_{jt} + \beta_8 LibertPart_{jt} \\ & + \beta_9 Relegated_{jt} + \beta_{10} Relegated_{jt-1} \\ & + \beta_{11} Cluster1_{jt-1} + \beta_{12} Cluster3_{jt-1} + \varepsilon_{jt} \end{aligned}$$

$$
\begin{aligned}
SportCumMalm_{jt} &= \beta_0 + \beta_1 DebtRatio_{jt} + \beta_2 NewStadium_{jt} + \beta_3 Covid_{jt} + \beta_4 \text{Série}A_{jt} \\
&+ \beta_5 Prom_{jt} + \beta_6 Prom_{jt-1} + \beta_7 LibertZone_{jt} + \beta_8 LibertPart_{jt} \\
&+ \beta_9 Relegated_{jt} + \beta_{10} Relegated_{jt-1} + \beta_{11} Cluster1_{jt-1} \\
&+ \beta_{12} Cluster3_{jt-1} + \varepsilon_{jt}
\end{aligned}
$$

$$
\begin{aligned}
FinanMalm_{jt} = \; &\beta_0 + \beta_1 DebtRatio_{jt} + \beta_2 NewStadium_{jt} + \beta_3 Covid_{jt} + \beta_4 \text{Série}A_{jt} \\
&+ \beta_5 Prom_{jt} + \beta_6 Prom_{jt-1} + \beta_7 LibertZone_{jt} + \beta_8 LibertPart_{jt} \\
&+ \beta_9 Relegated_{jt} + \beta_{10} Relegated_{jt-1} + \beta_{11} Cluster1_{jt-1} \\
&+ \beta_{12} Cluster3_{jt-1} + \varepsilon_{jt}
\end{aligned}
$$

$$
\begin{aligned}
FinanCumMalm_{jt} &= \beta_0 + \beta_1 DebtRatio_{jt} + \beta_2 NewStadium_{jt} + \beta_3 Covid_{jt} + \beta_4 \text{Série}A_{jt} \\
&+ \beta_5 Prom_{jt} + \beta_6 Prom_{jt-1} + \beta_7 LibertZone_{jt} + \beta_8 LibertPart_{jt} \\
&+ \beta_9 Relegated_{jt} + \beta_{10} Relegated_{jt-1} \\
&+ \beta_{11} Cluster1_{jt-1} + \beta_{12} Cluster3_{jt-1} + \varepsilon_{jt}
\end{aligned}
$$

Where j is the club in year t. $SportDEA_{jt}$, $FinancialDEA_{jt}$, $TotalDEA_{jt}$, $SportMalm_{jt}$, $SportCumMalm_{jt}$, $FinanMalm_{jt}$, and $FinanCumMalm_{jt}$ are the dependent variables of the seven proposed models. The independent variables are listed in Table 3.

The main variable of interest in the regression models was the Debt Ratio. Brazilian football is already known for the large debt of its clubs. Recent changes in Brazilian legislation, such as PROFUT and the SAF's Law, have as one of their key objectives reducing debt, as well as giving Brazilian football greater financial and governance responsibility. Therefore, the Debt Ratio was chosen as a variable of interest to present the debt dimension of the clubs. Acero, Serrano and Dimitropoulos (2017) used debt ratio in their financial performance model for the five major European football leagues from 2007-2008 to 2012-2013 but found no evidence of a relationship between debt and the return on assets (ROA) or return on sales (ROS) indicators.

The second variable of interest was the "New Stadium". Some clubs have built stadiums in recent years, many of them for the 2014 World Cup. Therefore, we assume that these clubs could increase their efficiency and productivity with new sources of revenue and the attraction that new stadiums have. We created a dummy to identify the following clubs: América-MG (stadium completed in 2012), Athletico-PR (2014), Corinthians (2014), Internacional (2014), Grêmio (2012), Palmeiras (2014). Gasparetto & Barajas (2020) used a similar variable in their study to identify the potential impact of new stadiums on the attendance figures of Brazilian football. Nowland and Sankara (2024) investigated the relationship between investments in stadiums and sports performance using data from the English Premier League (EPL) from 2012 to 2021. Lastly, a variable that identifies the COVID period (2020) is included, based on the study by Alabi and Urquart (2023).

[INSERT TABLE 3 HERE]

The dummy variable "Série A" was used to differentiate between clubs in two divisions. Barbosa et al. (2017) also included a variable to identify teams in Série A, but they did not find a statistically significant relationship with efficiency indicators. In addition, five sporting dummy variables were included in regression models: Promotion, Promotion t-1, Libertadores Zone, Libertadores Participation, Relegated, and Relegated t-1. We also added dummy variables to identify Cluster 1 and Cluster 3, formed by the largest and smallest clubs in the sample, respectively. Cluster analysis will be explained throughout the paper.

3.4 Robustness check

A Pearson correlation was conducted among the variables used in Data Envelopment Analysis (DEA) to determine if there is a proportional increase in inputs resulting in a proportional increase in outputs, as suggested by Tone, Kweh, Lu & Ting (2019) and Golany & Roll (1989), named “isotonicity”. Additionally, a cluster analysis was performed using the "Ward’s linkage" method, a hierarchical clustering method, to propose an optimal number of groups (k) for comparison. The DMUs were divided into clusters based on their size to facilitate a more accurate comparison between them. All variables used in the DEA model, in 2022, were included in clustering analysis using Stata 13 software.

4 Results

4.1 Descriptive statistics and general results

The results of correlations are shown in Table 4. All the relationships were statistically significant at a 1% level. The correlation level between the variables indicated that the choice of inputs, outputs, and carry-overs was appropriate and that the model was able to adjust for smaller values. Therefore, based on the criteria of isotonicity proposed by Tone et al. (2019), the model appears to be satisfactory.

[INSERT TABLE 4 HERE]

Table 5 presents descriptive statistics for these variables. The number of tickets sold on average increased by 48.36% between 2014 and 2022. Revenues also increased during this period by 169.35%. However, expenses showed an increase of 115.29%.

[INSERT TABLE 5 HERE]

The team value showed an increase of 85,26% between 2014 and 2022. However, there was a significant increase in the standard deviation in 2018, indicating an increase in inequality in team value among the clubs. The average value of liabilities increased by 65.79% between 2014 and 2019. Table 6 presents the average values of the continuous variables and the frequency of the dummy variables. The Debt Ratio had its highest average between 2020 and 2022.

[INSERT TABLE 6 HERE]

4.2 Cluster Analysis

Figure 1 presents a dendrogram, showing the clusters based on the data. From the visualization of the graph, it appears that the optimal number of DMU groups is 3. Atlético-MG, Athletico-PR, Corinthians, Flamengo, Internacional, Palmeiras and São Paulo belong to Cluster 1. Cluster 2 includes Botafogo Cruzeiro, Fluminense, Grêmio, Santos and Vasco. These first two groups are composed of clubs that are considered "big clubs" in Brazil. The last group includes the remaining clubs in the sample.

[INSERT FIGURE 1 HERE]

4.3 Efficiency Index

Figure 2 shows the efficiency indicators average. The financial division average is higher than the sporting division average overall between 2014 and 2022.

[INSERT FIGURE 2 HERE]

The sporting division has the highest efficiency average in 2018 (0.8977). In the same year, Overall efficiency also presented its highest average value (0.9082). The financial division had the highest average value in 2014 (0.8683), but the efficiency levels in other years were lower than in 2015. The lowest average value of the financial division series is in 2012 (0.7863). It is observed that in the pandemic years, all efficiency indicators are below the levels of other years. The Malmquist indicators show their highest values in 2022. As they are an indicator of the evolution of productivity over the years, it is understood that these values were also caused by the pandemic, precisely in the year in which there was a decrease in health restrictions.

Figure 3 shows the value and overall ranking of efficiency for all data in all years, separated by divisions. The line represents the overall ratings by the club and shows a decreasing trend in value. The points around the line represent the averages of efficiency in the other divisions.

[INSERT FIGURE 3 HERE]

Table 7 shows the efficiency indicators average for each cluster. Cluster 1 has the highest average efficiency levels across in sports division and overall, although Ceará is shown as the most efficient club in the whole sample. However, it is cluster 3 that has the highest averages. We can infer, considering the DEA-BCC methodology, that the club was the most efficient in the sample because of the clubs that are closest in terms of size to it. Cluster 2 had the highest average efficiency in the financial division.

[INSERT TABLE 7 HERE]

4.4 Malmquist Index

Table 8 shows that cluster 1 presented the highest productivity averages in the Malmquist indices of the financial division, and in the sporting cumulative division, but numbers very close to cluster 2. Although Ceará is the most efficient club in the sample, Ceará's productivity is below 1 in most indicators, and overall, meaning that efficiency shows a static position compared to the other clubs in the sample, but when we add individual performance, through the Malmquist index, over time, the evolution of these clubs showed a loss of productivity. The clubs that present the highest productivity values overall are Vasco, São Paulo, Atlético-MG, Flamengo, and Corinthians.

[INSERT TABLE 8 HERE]

4.5 Regression model results

Tables 9 and 10 present the results of Generalised Estimating Equation (GEE) models. The three models found a statistically significant positive relationship between the Debt Ratio and the Sporting, Financial, and Overall DEA, with a significance level of 1%. The result contrasts with the expected sign, which was a significant negative relationship. This means that the most indebted clubs are more efficient on average than the others. This suggests that an increase in liabilities may lead to a reduction in the financial power of the club, which in turn may lead to a reduction in the team's value and sporting performance. In this case, this contradicts the result presented in Acero, Serrano and Dimitropoulos (2017), who found no evidence of the relationship between debt and financial performance.

Clubs that built new stadiums throughout the period were more efficient than other clubs in the sporting division. This result contradicts previous findings from Nowland and Sankara (2024), who did not show a significant relationship between investments in stadiums with sports performance. The COVID dummy, as expected, showed a significant negative relationship in all models. Our regression models suggest that the COVID-19 pandemic has reduced the efficiency of the clubs. This corroborates with Hammerschmidt, Durst, Kraus & Puumalaine (2021), who exhibited that the effects of COVID-19 led to a collapse in football club revenues in the top five European football leagues. Furthermore, that same study suggested liquidity problems and the potential discontinuity or bankruptcy of clubs if the pandemic continued longer. Additionally, Alabi and Urquart (2023) show evidence that profitability deteriorated during the pandemic in the two main English football leagues.

The Financial Division model presented the variable Relegated t-1 with a significant positive relationship with the dependent variable. This relationship demonstrates that clubs that are relegated to the previous one start to spend less in Série B, or even return to the “normal” level, and thus tend to increase financial efficiency. In comparison, Speer (2023) analysed the consequences of relegation in European soccer leagues: England (Premier League), Spain (La Liga), France (Ligue 1), and Germany (the Bundesliga). According to the author, relegation can be associated with devastating financial consequences within 7 years, costing between US$ 225–262 million. Gasparetto and Barajas (2022) also showed evidence of a similar negative economic impact from relegation in Brazilian football leagues.

[INSERT TABLES 9 AND 10 HERE]

Table 10 presents the models with the dependent variables being the Malmquist indices. In the first model, Sporting Division Malmquist, the Debt Ratio contradicts the result of the sports DEA model, presenting a negative relationship with the productivity index. As previously discussed, efficiency is a static model, productivity from one period to another indicates that clubs must reduce their debts to be productive about their sporting performance. However, in the Financial Division model, this relationship does not exist.

Clubs that built a new stadium have shown a significant relationship with the coefficient in all sports models and the financial division. The results regarding the financial division are in line with the study by Nowland and Sankara (2024), who found evidence that investments in stadiums have a significant positive relationship with financial performance in the Premier League. The pandemic year also only showed statistical significance in the sporting division models, similar to what Hammerschmidt, Durst, Kraus and Puumalaine (2021) and Alabi and Urquart (2023) previously suggested.

Clubs that were promoted from division in the year before the year evaluated have, on average, reduced productivity in the sports division models. The teams promoted generally do not keep up with the teams already stabilised in the first division, increasing their expenses, but not obtaining corresponding sporting results with the investment. In the case of the study by Speer (2023), evidence was found that on-field, promotion has lasting impacts, with significant effects that last 3 or more years positively.

Clubs that participated in the Libertadores in the year analysed were more financially productive on average than the others. Participation in the Copa Libertadores creates conditions for increased revenue, which justifies the result.

Finally, Cluster 3 in all models presented a negative and significant coefficient. The smallest clubs are less productive than the other clusters. Ceará, the most efficient club, is one of the least productive in the sample. Thus, it can be seen that the complementary analysis with the Malmquist index reveals this type of situation. As the DEA-BCC result gives greater importance to the difference between DMU's, this specific club is compared with clubs of its size, which contributes to a high-efficiency index. However, the calculation of productivity is individual, and in this case, it reveals that even efficient clubs in a specific year may not be productive.

4.6 Discussion

The overall efficiency average for the entire period is 0.8144, as shown in Table 7. Barros, Assaf & Sá-Earp (2010), analysing just one season, found an average of 0.8708. Barros, Assaf & Araújo Júnior (2011) found an average of 0.7643, between 2003 and 2007. Barros, Wanke & Figueiredo (2015) presented 0.899 and 0.820 in the two proposed models, in 8 seasons. Despite the differences in models, seasons, and variables, both models focused on maximising the utility of clubs, as they added variables of sporting, financial, and attendance performance in the Brazilian football environment. Roboredo, Aizemberg & Meza (2015) only used one output, the total points of the 2014 season of Brazilian football, reaching an average in the BCC and Cross-efficiency models of 0.900 and 0.8582, respectively. In our sports dimension, the average efficiency of clubs for the entire period was 0.8193. We highlight that, when compared to the previous literature that used Brazilian football clubs, our results indicate lower averages in all aspects (overall, financial, and sporting).

Another distinctive aspect of our study is that we propose a clustering approach to analyse the efficiency and Malmquist indicators, comparing clubs of similar size, as was also conducted by Guzmán-Raja & Guzmán-Raja (2021). We observe that the country's major clubs are grouped into three clusters, and their outcomes are compared, thereby enhancing the comprehension of efficiency indicators. These indicators yield comparable results across clubs of varying sizes and objectives.

The results of the regression models presented in Tables 9 and 10 indicate a significant relationship between the variation in the Debt Ratio. Football clubs, in their pursuit of improved on-field performance, often increase their spending, sometimes without the availability of sufficient resources, leading to an accumulation of debts and consequently reducing financial productivity over time. Halkoz & Tzeremes (2013), for instance, did not find evidence of a relationship between debts and efficiency, with sports-related variables, among European clubs. Moreover, Acero, Serrano & Dimitropoulos (2017) do not find significant evidence of a relationship between debts and financial performance variables in the top 5 European leagues.

The main practical implication of our findings is the genuine perception of agency conflict within the club. The rise in expenditures may lead to an increase in the clubs' liabilities, progressively diminishing their ability to afford high-quality players for the team, thus reducing its overall value. Moreover, certain teams with larger budgets might achieve results that fall below expectations, or their sporting outcomes could be similar to those of teams with lower budgets. As a result, in comparative terms, the performance result in terms of sports productivity, according to the methodology employed in this research, may also decline with an increase in liabilities.

In light of the DEA-Malmquist analysis, it is evident that the financial division outperforms the sports division in terms of efficiency. This finding can be contextualised through the lens of Game Theory. The optimisation of sports performance operates as a Zero-Sum Game, where the success of one club invariably results in a corresponding loss for another, both at the micro-level of individual matches and across the league as a whole. Solberg and Haugen (2010) suggest that while clubs generally aim to improve upon their previous season's performance, the zero-sum nature of sports tournaments makes this an exceedingly challenging, if not impossible, goal for all clubs simultaneously.

In sports competitions, the aggregate utility of all participants remains constant, encapsulating the essence of the Zero-Sum Game. Our model further illustrates this by defining the input for the sports division as the value of the player's squad. When a club acquires a player, it effectively transfers "value" from another club or even from the league itself, potentially diminishing the efficiency of the selling club. The carry-over in this context is represented by Total Assets. These variables, which denote investments in fixed assets, are juxtaposed with the output, as indicated by the CBF Ranking. A comparison of the standard deviations of the efficiency indicators between the two divisions reveals greater variance in the sports division, supporting the concept of dependency on the zero-sum dynamic. The sports division's efficiency is more contingent upon the performance of other Decision-Making Units (DMUs), further underscoring the interconnectedness inherent in the zero-sum game, particularly within established clusters.

Moreover, the zero-sum nature of the sports division, as discussed in this paper, aligns with the "Tragedy of the Commons" (Hardin, 1968). Translating it into professional sports, when a prominent team increases its budget, competing teams often follow suit, striving to remain competitive. This reactionary investment, however, can diminish overall efficiency, as greater expenditure on assets without a corresponding improvement in sporting performance exacerbates inefficiencies across clubs. This dynamic also drives inflation in player prices, posing additional short-term financial challenges for clubs.

Conversely, the financial division indicates a positive-sum game, where the net gains and losses exceed zero. As Solberg and Haugen (2010) argue, higher revenue is typically generated through successful sporting performance. The authors assert that investment in quality players is the most effective means of enhancing sporting outcomes, thereby linking financial performance directly to sporting success. However, this relationship also raises concerns regarding club efficiency, as escalating player salaries can precipitate significant financial strain (Haugen & Solberg, 2010). Solberg and Haugen (2010) further explain the necessity for regulatory frameworks, such as the UEFA Financial Fair Play regulations, to ensure financial sustainability within European leagues. Instruments like salary caps serve to prevent wealthier teams from monopolising top talent, thus fostering competitive balance (Kesenne, 2000). In Brazil, legislative efforts, including the Programme for the Modernisation of Management and Fiscal Responsibility of Brazilian Football (Profut), instituted by Law No. 13,155/15, aim to instil greater financial responsibility within the country's clubs, potentially mitigating the Tragedy of the Commons in Brazilian football.

Efficiency in professional open leagues, such as the Brazilian League, is crucial for the long-term sustainability and competitive balance of the league. In an open system, where relegation and promotion are constant threats, clubs must optimise resource allocation to maintain their position (Noll, 2002). Financial efficiency enables clubs to compete effectively, even in the face of revenue disparities, which is essential for preserving the league's overall unpredictability and appeal (Kesenne, 2006).

The importance of efficiency in such a context is twofold. Firstly, financial efficiency is critical in ensuring that clubs can sustain operations and invest strategically in player talent, facilities, and youth development (Gerrard, 2005). Research has shown that clubs that manage their financial resources effectively tend to have better long-term performance, as they can reinvest profits into improving both their sporting and commercial operations (Ribeiro & Lima, 2012; Di Simone & Zanardi, 2020). Efficient clubs are also better positioned to navigate the economic fluctuations that are common in professional sports, where revenue streams can be volatile due to changes in sponsorship, broadcasting deals, and fan engagement (Bouchet et al., 2020).

Secondly, efficiency contributes to the overall competitive balance within the league, which is a key factor in maintaining the league's attractiveness and commercial value (Neale, 1964; Szymanski, 2003). A league where only a few clubs dominate due to inefficient resource distribution tends to lose its competitive appeal, leading to reduced fan interest and lower revenues for all clubs involved (Rottenberg, 1956). Therefore, fostering efficiency at both the club and league levels is essential for maintaining a dynamic competition where clubs are incentivised to innovate and improve continuously, thus enhancing the overall quality and financial health of the league.

The results of this study corroborate the notion that financial efficiency surpasses sports efficiency, as evidenced by the higher DEA-Malmquist productivity indicators in the financial division. Notably, the sports division's Malmquist indices often indicate declines in productivity across several years. It is crucial to acknowledge that increases in financial efficiency and productivity on a broader scale suggest that the league itself is also becoming more efficient and productive. Financial growth within the league enhances the distribution of revenues, such as those from broadcasting rights, among clubs. Despite the constraints imposed by the zero-sum nature of sports efficiency, both the league and the clubs must prioritise financial efficiency to preserve the league's competitive stature and ensure a positive-sum outcome in this financial domain.

5 Conclusions

This paper demonstrated the usefulness of using SBM Network Dynamic DEA to calculate efficiency. Additionally, given the small sample size and differences between clubs, cluster analysis can be an effective way to separate and compare DMUs (decision-making units) in the context of Brazilian football. The Malmquist index can be used as a dependent variable in regression models as an alternative to efficiency indicators. In this research, DEA was calculated for 23 DMUs (decision-making units) using seven variables, which may have contributed to the high number of units with a value of "1," resulting in a lack of variability when using this result as a dependent variable. The Malmquist index, which measures changes in productivity over the analysed periods, would be a more suitable dependent variable for regression models, as it does not lose important observations.

We recommend applying the DEA model proposed in this research to other leagues. We believe that this methodology is well-suited to the issue of utility maximisation, as proposed by Sloane (1971) and Dietl, Grossmann, and Lang (2011), as it allows for the efficiency of teams to be examined by division and the relationship between them to be observed. Another suggestion is to try to measure the performance of a club in leagues where the championship is determined through play-offs and incorporate this into the DEA calculation, as a club may win all its matches but lose the title due to a single defeat, which could negatively impact its position but not its overall performance. One final suggestion would be to investigate whether there was a decline in efficiency or productivity during the pandemic period and when it began to recover in the post-pandemic period.

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Table 1. Research about the efficiency of football clubs

Authors (Year)	DMUs League/ (Period) / Method	Inputs (SFA independent variables)	Outputs (SFA dependent variables)
Haas (2003)	Premier League (2000/01) DEA	Total Wage, Coach Wage, Team home city population	Season total points, Season total revenue
Haas (2003)	Major League Soccer (2000) DEA	Total Wage, Coach Wage	Season total points, Season total revenue, attendance
Haas, Kocher & Sutter (2004)	Bundesliga (1999/2000) DEA	Total Wage, Coach Wage	Season total points, Season total revenue, attendance average
Barros & Leach (2006)	Premier League (1998/99 to 2002/03) DEA	Number of players, player salary, net assets, stadium structure expenses	Points, number of tickets sold, sales
García-Sánchez (2007)	La Liga (2002/03 a 2004/05) DEA	Attacks, passes to the area, shots on goal, ball recovery, goalkeeper saves, stadium capacity, province population	Goals scored, the inverse of goals conceded, final position in the league final table, home attendance
Barros, Assaf & Sá-Earp (2010)	20 Brazilian clubs 2006 to 2007 DEA (Super efficiency)	Operating Costs, Total Assets, and staff wage	Attendance, Total revenue, and championship points
González-Gómez & Pícazo-Tadeo (2010)	La Liga (2001/02 a 2006/07) DEA	Number of players, attendance average per match, number of seasons played in the First Division, trophies won in competitions	Season total points, number of rounds played in Copa del Rey, number of matches played in European competitions
Pícazo-Tadeo & González-Gómez (2010)	La Liga (2001/02 a 2007/08) DEA	Number of players, attendance average per match, number of seasons played in the First Division, number of matches played in European competitions and the Copa del Rey	Season total points
Barros & García-del-Barrio (2011)	La Liga (1996/97 a 2003/04) DEA	Operating costs, total assets, staff payroll	Attendance revenue, other revenue
Barros, Assaf & Araújo Júnior (2011)	20 Brazilian clubs 2003 to 2007 SFA	(Attendance, Total Revenues, Championship Total Points, Total Labor Expenses divided per Number of Employees, Amortization divided per Total Assets)	(Operational cost)

Kern, Schwarzmann & Wiedenegger (2012)	Premier League (2006/07 to 2008/09) DEA	Salary expenses, net transfers, market value	Market Value, Average Points, Total Revenue, Attendance
Barros, Wanke & Figueiredo (2015)	Campeonato Brasileiro – Série A (2003 to 2011) SFA	(Trend and squared variables, salary divided per number of workers, amortization divided per total assets, financial costs divided per liabilities, attendance, total revenue, number of championship points, remote clubs, number of club fans)	(Operational cost)
Roboredo, Aizemberg & Meza (2015)	20 Brazilian clubs (2014) DEA *Game cross efficiency*	Home matches, attendance average, and points average from 2010 to 2013	Total points in 2014
Barros, Mandlaze & Tainsky (2016)	Liga Moçambicana de Futebol - Moçambola (2008 to 2014) SFA	(Trend and squared variables, salary divided per number of workers, amortization divided per total assets, financial costs divided per liabilities, attendance, total revenue, number of championship points, clubs located in Maputo, Muslim football club, relegated clubs)	(Operational cost)
Miragaia, Ferreira, Carvalho & Ratten (2019)	15 professional European clubs that won the five main European league (2009 to 2014) DEA	General expenditure	General revenues, Television broadcast revenues, Commercial income, Match day income, Coefficient of points
Terrien & Andreff (2020)	36 European leagues DEA	GDP, population, number of players	UEFA Index, Payroll by Turnover, Herfindahl Index, Added Value of Players, Average Attendance
Özaydin & Donduran (2020)	Süper Lig (2012/13 to 2017/18) SFA	Players' Market Value, Stadium Capacity, GDP Per Capita, Population	Attendance
Guzmán-Raja & Guzmán-Raja (2021)	La Liga – 13 clubs (2012/13 to 2015/16) DEA	Staff cost, Other expenses	Turnover, Points won
Cifuentes-Faura (2022)	La Liga and Spanish second division (2015 to 2019) DEA	Personnel Costs, Club Debt	Total Income, Inverse of the Final Classification of the League
Pérez-González, Carlos & Alén (2022)	La Liga (2016/17) Network DEA	Total Assets, Operating Expenses (Social and Sports Division)	Percentage of Spectator Attendance, Social Media Presence (Social Division); Points Obtained in all National and International Competitions (Sports Division); Revenue (Economic Division)

Fan, Liu, Yi & Gong (2023)	Chinese Super League – 24 clubs (2014 to 2019) Bootstrapped DEA	Player salaries; squad market value	League Points, Net Income, Expenditure on Transfer Fees, Stadium Capacity Utilization, Social Media Interaction Index

Note. Source: Authors own work. Adapted from Villa & Lozano (2016)

Table 2. Network Dynamic DEA Variables

Dimension	Variables	Source	Classification
Sporting	Team Value (in €)	Transfermarkt website	Input
	Total Assets (in BRL / R$)	Clubs Balance Sheet	Free Carry-Over
	Ranking CBF	Confederação Brasileira de Futebol (CBF) website	Output
-	Tickets Solds (attendance)	CBF matches financial bulletins website	Link Good
Financial	Operational Expenses (in BRL / R$)	Clubs Balance Sheet	Input
	Total Liabilities (in BRL / R$)	Clubs Balance Sheet	Bad Carry-Over
	Net Revenue (in BRL / R$)	Clubs Balance Sheet	Output

Note. Source: Authors own work.

Table 3. Independent variables coefficients expected signs in regression models

Variable	Acronym in regression models	Variable construction	Expected Outcome
Debt Ratio	$DebtRatio_{jt}$	Division between Liabilities and assets multiplied by 100	-
New Stadium	$NewStadium_{jt}$	1 for clubs that built stadiums between 2012 and 2015	+
Covid	$Covid_{jt}$	1 for observations of the year 2020	-
Série A	$SérieA_{jt}$	1 for Série A clubs in period t	+
Promotion	$Prom_{jt}$	1 for promoted Serie B clubs to Serie A in period t	+
Promotion t-1	$Prom_{jt-1}$	1 for promoted Serie B clubs to Serie A in period t-1	+
Libertadores Zone	$LibertZone_{jt}$	1 for Serie A clubs in Copa Libertadores Zone in period t	+
Libertadores Participation	$LibertPart_{jt}$	1 for clubs that played in the Copa Libertadores in period t	+/-
Relegated	$Relegated_{jt}$	1 for relegated Serie A clubs to Serie B in period t	-
Relegated t-1	$Relegated_{jt-1}$	1 for relegated Serie A clubs to Serie B in period t-1	+/-

Note. Source: Authors own work.

Table 4. Pearson correlation of Network Dynamic DEA variables

	Team Value	Ranking CBF	Tickets Sold	Total Assets	Oper. Expense	Net Revenue	Liabilities
Team Value	1						
Ranking CBF	0.7450***	1					
Tickets Sold	0.5341***	0.4590***	1				
Total Assets	0.6989***	0.6169***	0.4348***	1			
Oper.Expense	0.8591***	0.7763***	0.5057***	0.7106***	1		
Net Revenue	0.8505***	0.7370***	0.5343***	0.6970***	0.9366***	1	
Liabilities	0.6459***	0.6102***	0.3896***	0.7766***	0.7346***	0.6818***	1

Note. Source: Authors own work.
p<0,01 = ***; p<0,05 = **; p<0,10 = *

Table 5. Descriptive statistic of Network Dynamic DEA model variables

Variables	Desc. Statistic	2014	2015	2016	2017	2018	2019	2020	2021	2022
Team Values (in € millions)	Average	30.320	52.204	50.640	45.625	49.430	54.509	44.293	51.081	56.170
	Maximum	89.100	112.050	92.680	92.330	122.130	139.850	113.450	185.600	181.950
	Minimum	3.050	8.550	10.550	15.330	7.500	6.600	11.050	9.630	13.880
	St. Dev.	24.049	30.290	23.913	22.009	318.857	37.257	28.318	46.888	45.249
Ranking CBF	Average	10,773	10,575	10,447	10,559	10,528	10,478	10,366	10,232	10,197
	Maximum	15,328	14,664	15,038	15,288	16,914	16,640	16,768	17,054	17,210
	Minimum	5,150	5,202	5,443	5,553	6,136	5,834	5,819	5,200	4,687
	St. Dev.	3,257	3,140	3,300	3,398	3,362	3,498	3,228	3,271	3,249
Tickets Sold	Average	288,572	312,421	279,657	314,294	341,421	374,326	1	110,080	428,124
	Maximum	579,227	661,723	617,874	760,142	973,265	1,126,406	1	422,997	1,035,098
	Minimum	40,574	44,495	81,715	99,331	64,237	74,242	1	14,740	72,749
	St. Dev.	164,339	170,587	162,015	173,856	229,248	232,386	0	97,589	251,688
Total Assets (in R$ millions)	Average	349.014	386.759	399.240	394.586	389.029	418.290	452.989	508,020	581.363
	Maximum	1,125.541	1,351.700	1,331.079	1,214.864	1,142.007	1,293.045	1,380.168	1,628.173	1,936.672
	Minimum	3.50	4.372	7.081	7.966	13.827	23,388	23,009	25.684	22.310
	St. Dev.	343.915	405.385	380,279	358.854	341.478	381.561	423.535	502.593	531,864
Oper.Expense (in R$ millions)	Average	142.292	149.828	171.226	198.533	206.844	264.899	246.948	274.391	306.337
	Maximum	319.178	359.227	373.465	431.300	600.805	818.636	709.707	837.283	955.753
	Minimum	13.092	11.636	21.533	24.675	33.406	26.734	42.710	43.430	35.224
	St. Dev.	102.250	108.361	113.718	140.913	158.792	217.861	199.034	222.913	246.543
Net Revenue (in R$ millions)	Average	131.599	159.265	205.692	221.258	223.935	256.627	215.711	300.427	354.457
	Maximum	334.308	351.480	483.493	623.682	653.850	914.041	644.093	1,025.428	1,112.429
	Minimum	8.397	12.101	20.242	31.901	26.952	23.599	28.177	24.200	36.714
	St. Dev.	92.258	114.405	150.603	169.575	174.490	220.795	179.037	283.195	300.662
Liabilities (in R$ millions)	Average	393.369	426.598	403.278	399.427	421.209	487.588	569.651	606.306	652.183
	Maximum	1,146.668	1,469.912	924.211	932.226	846.411	1,000.469	1,326.987	1,473.127	1,711.037
	Minimum	4.975	5.413	12.689	10.146	13.012	16.804	35.264	37.229	25.564
	St. Dev.	328.460	366.783	294.075	286.349	297.608	354.067	428.982	470.946	513.651

Note. Source: Authors own work.

Table 6. Continuous variables average and dummies frequency

Dummies Variables (frequency = "1")	2014	2015	2016	2017	2018	2019	2020	2021	2022
New Stadiums	6	6	6	6	6	6	6	6	6
Série A	16	18	17	19	18	18	18	16	16
Promotion	3	2	4	3	2	3	2	4	4
Promotion t-1	3	3	2	4	3	2	3	2	4
Libertadores Zone	4	4	6	7	7	7	8	6	7
Libertadores Participation	6	5	5	8	8	8	8	8	7
Relegated	2	3	2	4	2	3	4	4	3
Relegated t-1	2	2	3	2	4	2	3	4	4
Covid	0	0	0	0	0	0	23	0	0
Continuous Variables (average)	**2014**	**2015**	**2016**	**2017**	**2018**	**2019**	**2020**	**2021**	**2022**
Debt Ratio	171.16	157.10	144.23	140.05	145.92	152.58	182.33	187.95	158.79

Note. Source: Authors own work.

Table 7. Average of efficiency indicators per cluster

Cluster	DMU	Sporting	Financial	Overall
1	Athletico-PR	1.0000	0.9596	0.9595
	Atlético-MG	0.8041	0.9548	0.8272
	Corinthians	0.8435	0.8552	0.8197
	Flamengo	0.9690	0.9934	0.9844
	Internacional	0.6819	0.6665	0.6257
	Palmeiras	0.9924	0.9703	0.9787
	São Paulo	0.6349	0.8698	0.7422
	Average	**0.8465**	**0.8957**	**0.8482**
2	Botafogo	0.8158	0.9753	0.8351
	Cruzeiro	0.9588	0.9507	0.7628
	Fluminense	0.6445	0.9810	0.7259
	Grêmio	0.9516	0.9801	0.9005
	Santos	0.8618	0.8760	0.7818
	Vasco	0.6598	0.9426	0.7914
	Average	**0.8154**	**0.9510**	**0.7996**
3	América-MG	0.8714	0.9466	0.7614
	Atlético-GO	0.9668	0.9653	0.9826
	Avaí	0.7117	0.7451	0.6146
	Bahia	0.8519	0.8907	0.8431
	Ceará	1.0000	1.0000	1.0000
	Chapecoense	0.9590	1.0000	0.9204
	Coritiba	0.6891	0.7750	0.7071
	Goiás	0.6890	0.9209	0.7601
	Ponte Preta	0.6375	0.7304	0.6776
	Sport Recife	0.6489	0.7457	0.7292
	Average	**0.8025**	**0.8720**	**0.7996**
	Total Average	**0.8193**	**0.8998**	**0.8144**

Note. Source: Authors own work.

Table 8. Malmquist indices average per cluster

Cluster	DMU	Sporting Division Malmquist (Average)	Sporting Division Cumulative Malmquist (2014-2022)	Financial Division Malmquist (Average)	Financial Division Cumulative Malmquist (2014-2022)	Overall	Overall Cumulative
1	Athletico-PR	0.9395	0.6068	1.0230	1.1996	0.9804	0.8532
	Atlético-MG	1.0818	1.8757	1.1826	3.8255	1.1311	2.6787
	Corinthians	1.0785	1.8302	1.1485	3.0280	1.1129	2.3541
	Flamengo	1.1467	2.9902	1.0899	1.9913	1.1179	2.4402
	Internacional	0.9773	0.8322	1.0089	1.0730	0.9930	0.9450
	Palmeiras	0.9458	0.6403	1.1304	2.6665	1.0340	1.3067
	São Paulo	1.1550	3.1664	1.1161	2.4073	1.1354	2.7609
	Average	**1.0464**	**1.7060**	**1.0999**	**2.3130**	**1.0721**	**1.9055**
2	Botafogo	0.9275	0.5477	1.1012	2.1624	1.0106	1.0883
	Cruzeiro	1.0666	1.6756	1.0747	1.7801	1.0706	1.7271
	Fluminense	1.1178	2.4383	1.0774	1.8155	1.0974	2.104
	Grêmio	1.0521	1.5014	1.0286	1.2356	1.0394	1.3620
	Santos	1.0477	1.4511	1.0761	1.7983	1.0618	1.6154
	Vasco	1.0698	1.7160	1.2085	4.5501	1.1370	2.7943
	Average	**1.0469**	**1.5550**	**1.0944**	**2.2237**	**1.0695**	**1.7819**
3	América-MG	0.7565	0.1073	0.8992	0.4276	0.8248	0.2142
	Atlético-GO	0.9684	0.7734	0.8705	0.3298	0.9181	0.5050
	Avaí	0.8713	0.3323	0.8343	0.2347	0.8526	0.2793
	Bahia	1.0702	1.7213	0.9993	0.9943	1.0341	1.3082
	Ceará	0.9381	0.5999	0.9577	0.7076	0.9478	0.6515
	Chapecoense	0.8036	0.1740	1.0044	1.0354	0.8984	0.4245
	Coritiba	1.0687	1.7007	1.0043	1.0346	1.0360	1.3265
	Goiás	0.8947	0.4107	0.9354	0.5862	0.9148	0.4907
	Ponte Preta	0.9105	0.4724	0.9604	0.7234	0.9351	0.5846
	Sport Recife	1.0590	1.5821	0.9938	0.9518	1.0259	1.2271
	Average	**0.9341**	**0.7874**	**0.9459**	**0.7025**	**0.9388**	**0.7012**
	Total Average	**0.9977**	**1.2672**	**1.0315**	**1.5895**	**1.0134**	**1.3496**

Note. Source: Authors own work.

Table 9. Results of GEE Regression DEA models

Independents / Dependents variables	Sporting Division DEA	Financial Division DEA	TOTAL DEA
Debt Ratio	0.0003*** (0.0001)	0.0001*** (0.0060)	0.0003*** (0.0000)
New Stadium	0.1154** (0.0584)	0.0079 (0.0490)	0.0519 (0.0512)
Covid	-0.1254*** (0.0418)	-0.0953** (0.0416)	-0.0773*** (0.030)
Série A	-0.0880 (0.0778)	0.0643 (0.0499)	-0.0614 (0.0560)
Promotion	-0.0099 (0.0525)	-0.0302 (0.0381)	-0.0203 (0.0575)
Promotion t-1	-0.0535 (0.0444)	-0.0684 (0.0445)	-0.0358 (0.0356)
Libertadores Zone	0.0799* (0.0437)	0.0110 (0.0203)	0.0471 (0.0319)
Libertadores Participation	0.0488 (0.0379)	-0.0256 (0.0185)	0.0213 (0.0272)
Relegated	0.0179 (0.0433)	0.0030 (0.0246)	-0.0093 (0.0386)
Relegated t-1	-0.0839* (0.0471)	0.0493 (0.0340)	-0.1022*** (0.0455)
Cluster 1	0.0062 (0.0706)	-0,0406 (0.0429)	0.0305 (0.0572)
Cluster 3	0.0614 (0.0713)	-0.0401 (0.0268)	0.0661* (0.0393)
Constant	0.7683*** (0.1099)	0.8621*** (0.0459)	0.7972*** (0.0596)
Corr	Independent	Exchangeable	Independent
Family	Gaussian	Gaussian	Gaussian
Link	Identity	Identity	Identity
Qic	45.148	39.364	43.560
Observations	207	207	207

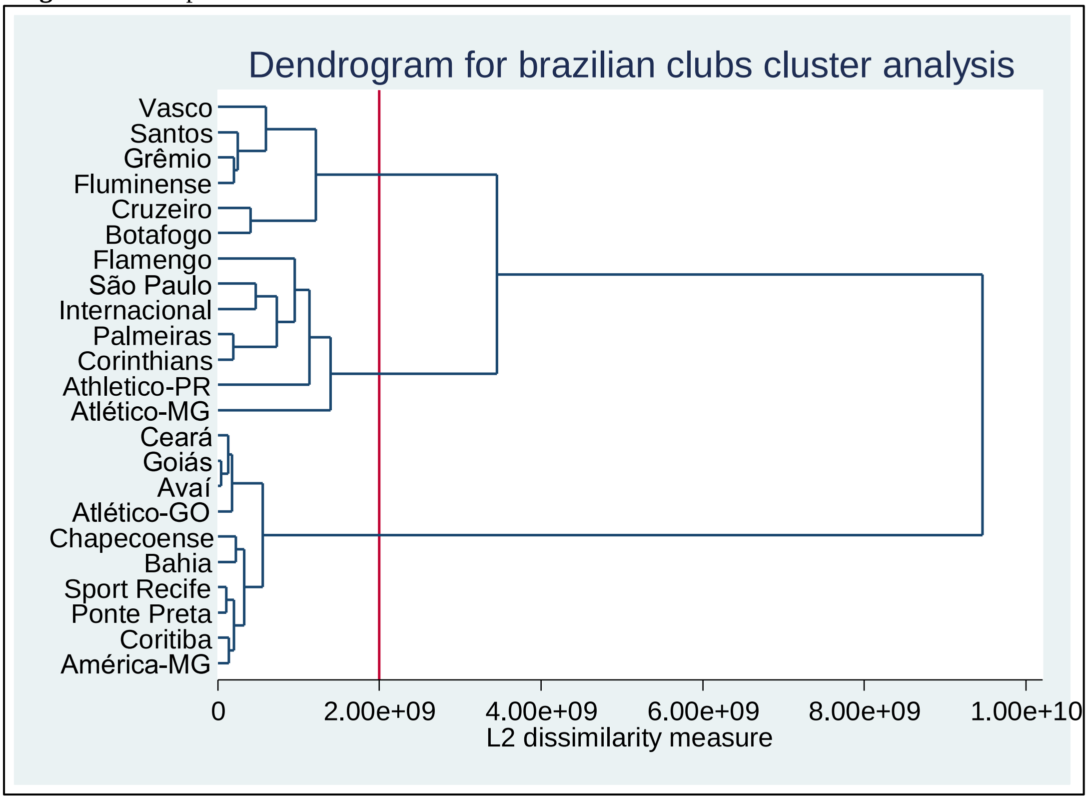
Note. Source: Authors own work.
p<0,01 = ***; p<0,05 = **; p<0,10 = *

Table 10. Results of GEE Regression models

Independents / Dependents variables	Sporting Division Malmquist	Sporting Division Cumulative Malmquist	Financial Division Malmquist	Financial Division Cumulative Malmquist
Debt Ratio	-0.0009*** (0.0002)	-0.0006*** (0.0002)	0.0002 (0.0001)	-0.0008** (0.0003)
New Stadium	-0.2144*** (0.0818)	-0.4521*** (0.0833)	-0.0703** (0.0317)	-0.3032* (0.1793)
Covid	-0.3217*** (0.0924)	-0.1420*** (0.0412)	-0.3400*** (0.0445)	-0.2655*** (0.0602)
Série A	-0.0089 (0.1900)	-0.1219 (0.1923)	-0.0407 (0.0842)	-0.1941 (0.1659)
Promotion	0.3037 (0.3600)	0.0486 (0.1709)	-0.1423 (0.0941)	-0.0702 (0.0996)
Promotion t-1	-0.2750** (0.1232)	-0.0503 (0.0780)	0.0752 (0.0903)	0.2701 (0.0554)
Libertadores Zone	0.1737 (0.1172)	0.1618* (0.0859)	-0.0222 (0.0440)	0.0277 (0.0718)
Libertadores Participation	-0.1516 (0.1189)	0.0381 (0.0961)	0.0806** (0.0386)	0.1025 (0.0777)
Relegated	0.0781 (0.1356)	-0.0141 (0.0674)	0.0460 (0.0749)	0.0424 (0.0429)
Relegated t-1	0.4225 (0.4519)	0.0343 (0.1478)	0.0059 (0.0862)	-0.1531 (0.1508)
Cluster 1	-0.0976 (0.0734)	0.2012* (0.1197)	0.0302 (0.0318)	0.0788 (0.1908)
Cluster 3	-0.1990* (0.1063)	-0.3850*** (0.1202)	-0.1166** (0.0546)	-0.7459*** (0.1999)
Constant	1.4729*** (0.2247)	1.0422*** (0.2114)	1.1688*** (0.0882)	2.0126*** (0.2739)
Corr	Exchangeable	Independent	Exchangeable	Autoregressive
Family	Gaussian	Gaussian	Gaussian	Gaussian
Link	Identity	Identity	Identity	Identity
Qic	136.248	60.978	34.913	99.061
Observations	184	184	184	184

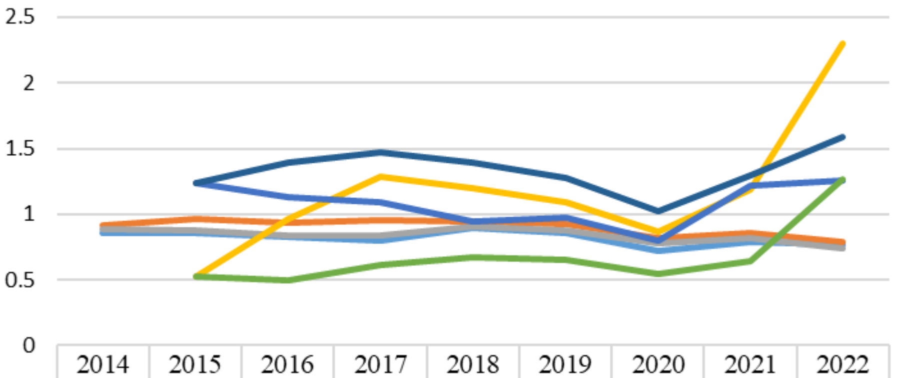
Note. Source: Authors own work.
p<0,01 = ***; p<0,05 = **; p<0,10 = *

Figure 1. The optimal number of clusters for the DMUs



Note. Source: Authors own work.

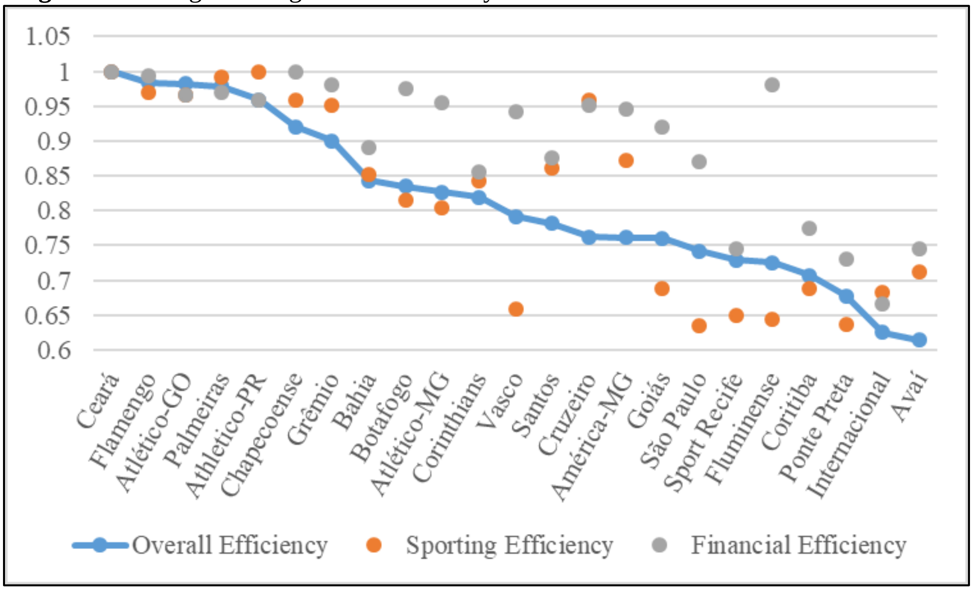
Figure 2. Efficiencies and Malmquist's Averages by division and overall



	2014	2015	2016	2017	2018	2019	2020	2021	2022
Sporting Efficiency	0.8531	0.8554	0.8318	0.8013	0.8977	0.8536	0.7214	0.7885	0.7707
Financial Efficiency	0.9112	0.9605	0.9319	0.9516	0.9483	0.9279	0.8212	0.8591	0.7863
Overall Efficiency	0.8859	0.8728	0.8361	0.8408	0.9082	0.8749	0.7799	0.8154	0.741
Sporting Malmquist		0.5245	0.9622	1.2848	1.1971	1.0953	0.8678	1.192	2.2996
Financial Malmquist		1.2354	1.1274	1.0861	0.9418	0.9765	0.7949	1.2186	1.2536
Sporting Cumulative Malmquist		0.5245	0.4992	0.6138	0.6686	0.6523	0.5446	0.6386	1.2672
Financial Cumulative Malmquist		1.2354	1.3918	1.4752	1.3898	1.2796	1.0222	1.2997	1.5895

Note. Source: Authors own work.

Figure 3. Average ranking of club efficiency



Note. Source: Authors own work.