MEASURING THE EFFICIENCY OF SPAIN'S WINERIES THROUGH DATA ENVELOPMENT ANALYSIS

Maja Borlinič Gačnik
University of Maribor, Faculty of Tourism
Cesta prvih borcev 36,8250 Brežice, Slovenia
E-mail: maja.borlinic@um.si

Boris Prevolšek
University of Maribor, Faculty of Tourism
Cesta prvih borcev 36,8250 Brežice, Slovenia
E-mail: boris.prevolsek@um.si

Antonio Peláez Verdet
University of Malaga, Faculty of Tourism
C/León Tolstoi, 4, Campus Teatinos, 29071 Malaga, Spain
E-mail: apv@uma.es

Alfonso Cerezo Medina
University of Malaga, Faculty of Tourism
C/León Tolstoi, 4, Campus Teatinos, 29071 Malaga, Spain
E-mail: alfcermed@uma.es

Črtomir Rozman
University of Maribor, Faculty of agriculture and life sciences
Pivola 10, 2311 Hoče, Slovenia
E-mail:crt.rozman@um.si

Abstract: The research evaluates the efficiency of wineries in Spain using the DEA (Data Envelopment Analysis) model. The study utilizes the CCR (Charnes-Cooper-Rhodes) model within DEA, which assumes constant returns to scale. Input and output data from 849 wineries were collected and normalized for analysis. The results indicate that only one winery operated at maximum efficiency, achieving the best possible results compared to others. The findings highlight the importance of efficient processes, resource allocation, and management practices in achieving optimal performance. Further research could explore efficiency comparisons among wineries with different activities, such as diversification into tourism.

Keywords: efficiency measurement, DEA model, Spain's wineries, agrarian economics

1 INTRODUCTION

Performance efficiency is essential for organizations because it allows them to maximize resource usage [7], cut expenses [11], boost production [4], acquire a competitive edge [3], boost customer happiness [2], encourage sustainability [6], and realize total organizational effectiveness. In today's dynamic and competitive business world, it is essential to success and long-term sustainability. Many methods exist (qualitative and quantitative) for efficiency evaluation across various fields. Among the typical forms of qualitative efficiency evaluation methods are classified metrics of KPIs (Key Performance Indicators), different Benchmarking analyses, the framework of a Balanced Scorecard, etc.

The Data Envelopment Analysis (DEA) and Stochastic Frontier Analysis (SFA) methods represent typical quantitative methods for measuring the effectiveness of organizations. SFA is a parametric performance evaluation method that considers technical inefficiency and random error. It determines the inefficiency of decision-making units concerning an estimated production frontier. The methodology was developed by economists Arie Kapteyn and Jan van den Berg in the late 1970s. A non-parametric technique for evaluating the relative effectiveness of decision-making units is called DEA. It considers the capacity of various departments to transform inputs into outputs to compare their efficiency. DEA was developed by Abraham Charnes, William W. Cooper, and Edwardo Rhodes in the late 1970s [1]. In a time when agricultural and other economic sectors are mainly focused on reducing negative environmental impacts and increasing positive effects on people and capital, there is an even greater need for studying efficiency [5], [8], [9].

Sistema de Análisis de Balances Ibéricos, commonly known as SABI, a financial database and analysis system that provides comprehensive financial information and analysis of companies in Spain and Portugal, was the source of data for our research on measuring the efficiency of wineries in Spain [10]. Through the database, we have accessed 2.880 wineries in Spain that have their wine cellars in all the country's wine regions on that part of the Iberian Peninsula.

After the introductory part, where we present the importance of efficiency research, there follows a chapter on methodology, where we present the development of the used DEA model. The results section follows. The article concludes with a summary of the main findings, advantages, limitations, possibilities of application and direction for further research.

2 DATA COLLECTION AND METHODOLOGY

After collecting and editing the data, the DEA model was created: first, we defined the objective function and the constraints that encompass the efficiency evaluation process. This was followed by preparing data for analysis by normalizing inputs and outputs. This step ensures that the variables are comparable and that the DEA model can accurately estimate efficiency.

In the case of evaluating the efficiency of Spanish wineries, we focused on data from 2019. We could not access the latest data after the coronavirus period; for this, we used a database from the period before the outbreak of the epidemic, as the situation during the epidemic was quite different from the more normal one. We defined input and output data for the model. For the input data, we considered the number of employees in the winery in 2019, while the output data were 1) business revenue in 2019 and 2) profit per employee in 2019.

Among all 2.880 wineries, we eliminated all those for which we could not obtain all the data representing our inputs and outputs. Furthermore, we also cancelled those with a negative profit in 2019 (negative profit is understood as management inefficiency). This left us with 849 companies (wineries) in the set for further analysis, based on which we checked the mentioned efficiency.

The DEA model was developed using the MaxDEA 7 tool, Beijing Realworld Software Company Ltd. Within the DEA model methodology, the CCR model was used. The CCR model assumes constant returns to scale (CRS), assuming the DMUs operate at an optimal scale and any input/output quantities changes do not affect their efficiency. The model seeks to maximize the efficiency scores of the DMUs while ensuring that the weighted sum of their outputs does not exceed the sum of their inputs [1]. Mathematically, the CCR model can be formulated as a linear programming problem.

The formula for evaluating efficiency in the CCR model is expressed:

$$Max \frac{\sum_{r=1}^{n}(u_{rb})(y_{rb})}{\sum_{k=1}^{m}(v_{kb})(x_{kb})} \tag{1}$$

whereby the following conditions must be observed:

$$\frac{\sum_{r=1}^{n}(u_{rb})\,(y_{rj})}{\sum_{k=1}^{m}(v_{kb})\,(x_{kj})} \leq 1 \text{ for each unit } j$$
$$u_{rb}, v_{kb} \geq \varepsilon \text{ for each unit } r, k \tag{2}$$

y_{rj} = output vector *r* built with unit *j*
x_{kj} = input vector *k* built with unit *j*
u_r = output weight *r* on basic unit *b*
v_i = input weight I on basic unit b
j = number of DMU
r = number of outputs
k = number of inputs
ε = small positive number

3 RESULTS

3.1 CCR-I model

The efficiency score generated by the CCR model for each DMU represents the ratio of its weighted sum of outputs to the weighted sum of inputs (Charnes et al., 1978). An efficiency score of 1 indicates that the DMU is operating efficiently, utilizing its inputs effectively to generate results. Scores below 1 indicate relative inefficiency, with room for improvement. According to Charnes et al., (1978) when input and output-oriented technological efficiencies are equivalent, the technology demonstrates consistent returns to scale (CRS). The technology is inefficient if variable returns to scale (VRS) characterizes the technology, and this equality does not hold for each group of inputs and outputs.

Table 1: Results of input and output-oriented CCR model.

alternative (Winery)	***CCR - I***
DMU 1	0,137348
DMU 2	0,770799
DMU 3	1
DMU 4	0,337550
DMU 5	0,146867
DMU 6	0,108621

The results of the CCR-I model indicate that a winery is efficient when it is impossible to increase outputs without reducing residual outcomes or increasing any input. From the set of all companies analyzed, the DEA analysis of the CCR model showed total operational efficiency in only one winery. Table 1 shows a collection of the six most efficient (out of 849) wineries we got during the analysis. The average score of 0,770799 shows that the analyzed winery could operate at 77 % of the current output level with unchanged input quantities. Winery could increase its output by 23 % with unchanged inputs.

4 CONCLUSION

The DEA (Data Envelopment Analysis) performance measurement model is designed to assess the relative performance of decision units (DMUs) in a data set. The results of our analysis show that a particular DMU operates with maximum efficiency within a given input-output framework. In other words, it achieves the best possible results relative to the other units in the analysis. It is possible for a winery to implement effective processes, resource allocation strategies, and management practices. However, the effects of their technologies, resources, market position, and other expertise they manage also probably play an essential role. When interpreting the results, we should also consider that we used one input and two output data, which is a weakness for this type of analysis. For more accurate calculations, it would be necessary to check other DEA analysis models and supplement them with the AHP method. In the future, we could compare the effectiveness of DEA between wineries that only grow and sell grapes or wines compared to those that diversify their activity with other complementary activities (for example, tourism).

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