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Efficiency analysis of the Portuguese wine industry using accounting and operational metrics

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ABSTRACT

Wine is an integral part of the economy and culture of many countries. Despite that, in Portugal – one of the main wine-producers – there is a lack of empirical evidence regarding the efficiency of these firms. Thus, the purpose of this article is to assess such efficiency using a four-step approach, which includes the selection of relevant financial and operational variables, a cluster analysis for the identification of homogenous decision making units, a data envelopment analysis for the efficiency quantification, and an econometric model to determine the variables with most influence on efficiency. The results indicate that 36% of the firms are efficient, in part due to the considerable number of inefficient firms in the regions of North, Centre, and Lisbon and Tejo. The performance of the Setubal, and Alentejo and Algarve regions is noteworthy, since these obtained the highest percentage of efficient companies. The findings also suggest that, in order to improve efficiency, wine companies should reduce inventory and fixed assets and increase sales revenue.

1. Introduction

Wine is a relevant element in the culture of many countries. From an economic perspective, this beverage is also a fundamental part of several market segments [1–3]. Due to this importance, throughout the years, the wine industry has been subject of study by different authors, e.g. Refs. [4,5]. Moreover, the wine industry is considerably segmented, which results in different wines being produced, from table wines to super premium. In this complex and competitive context, where firms need to produce and trade in different segments, wine companies must meet their customers' needs at an affordable cost. Hence, to maintain the wine industry competitive in an increasingly global market, efficiency is a critical factor.

In Portugal, as in most Mediterranean countries, the wine industry has a great economic and social impact, representing 10% of companies in manufacturing industry and 25% of turnover, according to the [6]. In addition, and according to the OIV - [7] - Portugal is the 11th largest wine producer in the world with a production of 6.2 million hectolitres, and the 9th country in terms of vineyards (224 thousand hectares). It is also one of the largest consumers with a total consumption of 4.3 million hectolitres and a per capita consumption of 51.4 L [3].

Efficiency measurement constitutes a relevant topic, as it provides key insights for firm managers, decision- and policy-makers alike, hence contributing for improvements in the competitiveness of businesses in several industry sectors [8–10]. Therefore, it is important to quantify the performance of businesses and their processes, which includes the wine industry [11]. Several studies have proposed different approaches for efficiency measurement. Such approaches include, for instance, reference models, such as the Supply Chain Operations Reference (SCOR) [12,13], methods, such as the Balanced Scorecard [14–16], Analytic Hierarchy Process (AHP) [17].

Despite the relevance and validity of these approaches, a major limitation is that they do not allow a unified efficiency value to be computed, while also allowing insights to be inferred regarding the impact that certain variables have on others, hence affecting the overall efficiency.

Data Envelopment Analysis (DEA) is a nonparametric method of mathematical programming, which is used to assess the relative performance of Decision-Making Units (DMUs) in the presence of multiple criteria, comprised of several variables. Such variables can be inputs or outputs. Thus, the nonparametric frontier is built using output or input orientations, different returns to scale, and multiple inputs and outputs [18]. Based on such inputs and outputs, the approach estimates an efficiency frontier, whereas the multiple inputs and the outputs are the

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criteria, with inputs being preferred to be as small as possible, whilst outputs should be as big as possible [19]. Hence, this approach has been extensively used to quantify the efficiency of several scenarios in different types of systems [11,20].

DEA has also been applied to the wine industry. For such cases, see the works of [21]; who considered Spanish wineries; and [2]; who analysed French wineries. Other studies have also considered countries outside Europe, such as [22]; who analysed Chilean wineries. Other studies have also considered multiple countries, e.g. Ref. [23] considered Ukrainian and German wineries, and [24] considered small and medium firms from several European countries. However, while different countries have been considered and analysed with DEA, such studies considered different variables for the efficiency quantification, depending on their main purpose. For instance Ref. [11], aimed to evaluate the eco-efficiency of different farms, including those that produce wine, hence including variables such as net protein in food produced, net energy in food produced and the aquatic eco-toxicity potential. Conversely [2], wanted to verify the carbon footprint in French vineyards, hence ended up using variables such as agricultural area, net fixed assets, carbon footprint, and value of total production. Despite that, to the best of the authors' knowledge, no study has tried to address this challenge for the Portuguese wine-producing firms. Thus, the purpose of this paper is to address this gap, through the quantification of the individual firms' efficiency, by considering all large, medium and small firms of the wine industry in Portugal, and applying a framework based on the DEA approach for the assessment of these firm's efficiency. Thus, our proposed approach quantifies the performance of the analysed firms, using DEA, and also determines the variables with most influence on wine firms, using an econometrics analysis. With this research, the authors aim to provide the following main contributions. The first consists of providing empirical evidence regarding the efficiency of Portuguese wine firms. Whilst our study considers small, medium and large ones, it is not certain that the latter are more efficient than the former; however, even if that is the case, other questions arise, such as: (i) how much efficient are such firms? (ii) how can inefficient firms become efficient? and (iii) what are the factors that determine efficiency in wine firms? These are the main research questions that steer this work. Therefore, we also want to identify which factors explain efficiency in Portuguese wine companies.

The rest of the paper is organised as follows. Second section presents an analysis of previous works on the topics relevant for this research, i. e., efficiency measurement and the status of the application of DEA in the wine industry. Third section presents the methodology adopted for this study, including the description of the data and approach that were used. Fourth section describes the application of the adopted method, in order to identify homogeneous DMUs. Fifth section presents the main results for the efficiency assessment of wine firms and for the identification of the variables that mostly influence efficiency. Finally, sixth section presents the main findings, implications, limitations and future work of this study.

2. Literature review

This section reviews the topics associated with this paper. First subsection focuses on existing frameworks and methods to analyse the efficiency of firms. Second subsection analyses the main performance measures that are usually associated to the measurement of efficiency and, last subsection summarizes the main works that have used DEA, while also highlighting the main gaps in literature.

2.1. Efficiency measurement

The task of measuring its efficiency is often difficult, e.g., due to difficulties in accessing data, dispersed information, the time and financial resources required, lack of coherence between performance metrics, the existence of conflicting metrics and deficient communication [13,25].

Many studies have measured performance following distinct approaches, e.g., see the work of [26] and the therein cited references. Certain frameworks only consider operational processes, such as the works of Ross and Yearworth and [27].

Alternatively, the Balanced Scorecard (BSC) is also an often-adopted approach to evaluate firms' performance [16]. used BSC combined with AHP to evaluate a firm's performance [28]. studied the role of BSC in evaluating uncertainty, and [29] used the BSC to assess lean and green performances.

Many authors also use the SCOR model proposed by the Supply Chain Council, e.g., see the works of [12,30]. AHP is another commonly used approach, wherein numerical weights are assigned to each element of the hierarchy, allowing pairwise comparisons. For examples of the application of this approach, see the works of [31,32].

However, a major limitation of these approaches is that they do not provide a unified performance value, allowing the assessment of the impact that certain measures – inputs – have on other measures – output- in what is the efficiency of a firm. It is in this regard that DEA can be emphasized as a helpful technique that measures performance in terms of inputs and outputs, as well as to understand the effect of inputs in efficiency through the associated outputs [33,34].

2.2. DEA in the wine industry

In what concerns the application of DEA in the wine industry, some examples can also be highlighted. For instance Ref. [21], employed a DEA analysis to the data of Spanish wineries, in order to measure and decompose revenue inefficiency of mainly designation of origin wine producers. The variables selected by the authors consisted of hectares of surface area, number of winegrowers, domestic and foreign sales. Another study that focused on Spanish firms was the work of [35]; who analysed data of 40 firms from a particular region. The authors adopted an approach consisting of using DEA and Life Cycle Assessment for the assessment of environmental impacts. As such, both environmental and operational variables were considered in this study. In its turn [36], considered 64 wineries, but also considered cheese factories. The authors considered variables such as profit, number of employees, debt, assets, among others. With the purpose of studying the environmental performance of the analysed firms, and the impact of their activities on the environment [2], applied a DEA to a sample of 38 firms located in France. The data contained the firms' agricultural area, net fixed assets, carbon footprint, and value of total production, throughout 3 years.

Italian wine producers were also considered in the study of [37]. The authors calculated the efficiency based on the firms' gross marketable output, value of the land, value of labour and value of the working capital. The authors also used data from 2005 to 2010, in order to assess the evolution throughout time.

Other studies have also analysed data of wine producers from a single country. For instance, in the work of [11]; the authors analysed the efficiency using data from 6 farms. They aimed to evaluate the eco-efficiency of these farms, thus they included variables, such as net protein in food produced, net energy in food produced and the aquatic eco-toxicity potential.

Authors have also analysed data from multiple countries. In this regard [24], used a data sample comprised of 572 small and medium firms of the European Union countries, from which 65.56% were firms of the wine sector. The authors used data from 5 consecutive years (2011–2015), in order to establish the evolution throughout time, by considering turnover, earnings before interest and tax, number of employees, total assets, profit, long-term debt, stakeholders' funds, liabilities and cash-to-cash equivalents.

Goncharuk [23,38] also used DEA to compare the efficiency of a total of 36 wines divided between Germany and Ukraine. For such comparison, the author used the number of employees, fixed assets, material costs and net sales.

Finally, similar studies have also been conducted outside Europe. For instance Ref. [22], analysed 100 Chilean wineries using inventories, assets, land area and total revenue as variables. Portugal has also been subject to the use of DEA to quantify the efficiency of wine firms, namely see the work of [39]. The collected data on the field, ending with a sample of 110 firms. The authors used production volume, income, land area, capital, goods' and services' value as main variables. However, the authors have only considered data from a single region from Portugal, which is the Douro region.

As such, grounded on the reviewed works and to the best of the authors' knowledge this is the first scientific work that aims to use data from all wine firms (micro, small and medium, and big) of every region in Portugal. Likewise, this is also the first study to analyse the efficiency of Portuguese wine firms, as well as to analyse what measures contribute the most for an efficient firm, hence providing useful information for firms aiming to improve their efficiency.

3. Methodology

This section describes the methodology of this research. First subsection describes the data gathering, and second subsection describes the adopted approach.

3.1. Data gathering

The sample used in this study includes data from Portuguese wine companies. Data collection related to financial and operational measures, is a time-consuming task and often consists a barrier for this type of analysis [13,40]. To overcome this, data from the Amadeus database was used for this research. Amadeus provides data for 847 companies in this context. However, after verifying the companies for which Amadeus provides full data, the sample was reduced to 382 companies.

3.2. Adopted approach

To achieve the designed objectives for this paper, the authors propose a framework, which comprises four steps, as illustrated by Fig. 1. Additional detailed information for each step is provided in the respective subsection.

As the figure shows, firstly, the performance metrics were selected. This stage consisted of analysing literature in order to find the most relevant variables that were used to assess the efficiency of firms of the wine industry sector. Furthermore, the variables available in the database were also considered and compared to those that were considered in similar studies, in order to establish the final set of variables. In the second step, a cluster analysis was performed to obtain homogeneous DMUs. Additional details regarding the methods used in this step are provided in subsection 3.2.2. In the third step, an efficiency analysis was carried out using a DEA model. This allowed us to calculate the average efficiency scores for each set of homogeneous DMUs, as determined in the second step. The model that was used is described in detail in subsection 3.2.3. Finally, in the fourth step, a regression analysis was implemented to determine what factors influence the efficiency scores. In this last step, we mainly applied Ordinary Least Squares to estimate the parameters of the regression analysis that allow this analysis to be performed.

3.2.1. Selection of metrics

Regarding the variables or performance metrics selected for this study, the authors conducted a review of similar studies to identify the most relevant ones used on the quantification of efficiency, in particular for wine firms. In light of this [41], analysed 83 studies on performance assessment and provided an overview on the metrics used. These authors concluded that the most popular metrics are cost, finance and metrics related to customer satisfaction, internal processes, learning and innovation, flexibility and reliability and responsiveness [42]. argued that to

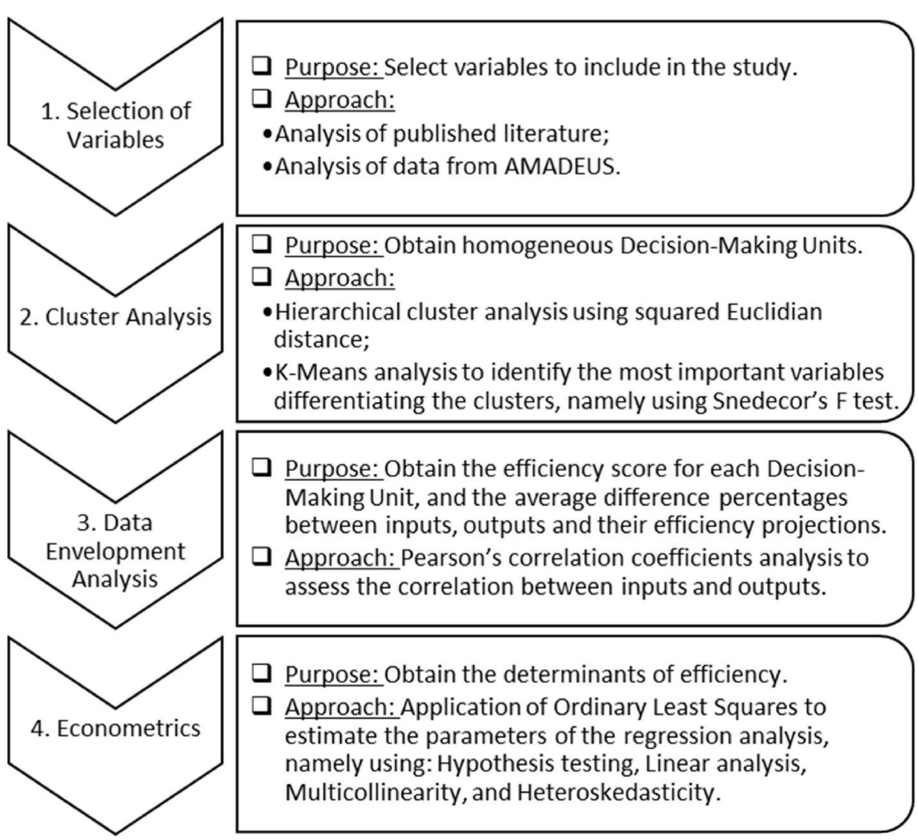

Fig. 1. Structure and overview of the proposed 4-step approach.

measure performance, a set of financial metrics are required, such as Return On Equity (ROI), Return On Assets (ROA), Accounts Payable Turnover (APT), Accounts Receivable Turnover (ART), Inventory Turnover (INVT), Property, Plant and Equipment Turnover (PPET) and Cash-to-Cash cycle (C2C). This last indicator roughly measures the average time spent from when cash enters a process until it is collected as revenue, and it is calculated as:

$$C2C = -\frac{1}{APT} + \frac{1}{ART} + \frac{1}{INVT}$$

As can be seen, different studies on efficiency measurement have focused on distinct metrics; however, some of these metrics are common among studies. Furthermore, we also analysed literature that specifically used DEA to quantify the efficiency of wineries, e.g. the works of [23,24, 38]. Therefore, having analysed such studies and considering the ones for which the used database offers full data availability, the selected metrics were the following:

- Operational profit;
- Sales revenue;
- Operational costs;
- Fixed assets;
- Inventory management;
- C2C;
- Cash-flow;
- Number of employees.

Nowadays, the turbulent environment in which companies operate has made the financial dimension increasingly important. Thus, the selected metrics for this study considers a financial perspective, namely the influence of cash-flow, albeit it also considers other dimensions, such as resource utilization (number of employees, fixed assets) and operational metrics, portraying a thorough analysis on efficiency.

3.2.2. Cluster analysis

To obtain homogenous sets of DMUs, Portuguese wine-producing regions were aggregated into five main regions and, for each one, a cluster analysis was performed. There are several clustering techniques, which generally are classified as partition based clustering, hierarchical clustering and density based clustering. These techniques have different clusters analysis approaches and the most suitable for a given data set is difficult to predict [43]. Nevertheless, Euclidian distance and K-Means are the most frequent clustering techniques used in social science studies [44]. [45] highlight the K-Means as a simple and efficient technique that can split the data set into k distinct non-overlapping clusters.

The adopted procedure followed two steps. First, we conducted a hierarchical cluster analysis using squared Euclidian distance as a measure of dissimilarity. We decided the number of clusters to retain based on the criterion of R^2. Afterwards, to classify each DMU in a cluster, we conducted a K-Means analysis, followed by a Snedecor's F test of the cluster ANOVA to identify the most important variables differentiating the clusters. This cluster analysis considered the previously presented and discussed variables. To implement this analysis, SPSS software was used.

3.2.3. DEA model

The DEA model was solved using the General Algebraic Modelling System (GAMS), a modelling software for mathematical optimization. The problem was formulated as an input-oriented model, wherein inputs are minimized for a given level of outputs. In this case, the BCC (Banker, Charnes, Cooper) model, proposed by Ref. [46]; which assumes variable returns to scale, was used. It was considered an input-oriented model, where the level of inputs is minimized for a given level of outputs. The general formulation of the model is as follows:

$$min\theta_0 = -\varepsilon\left(\sum_{i=1}^{I} s_{io}^- + \sum_{r=1}^{R} s_{ro}^+\right) \tag{1}$$

s.t.

$$\theta_0 x_{i0} = \sum_{j=1}^{J} x_{ij}\lambda_j + s_{i0}^-, \quad \forall\, i \in I \tag{2}$$

$$y_{r0} = \sum_{j=1}^{J} y_{rj}\lambda_j + s_{r0}^+, \quad \forall\, r \in R \tag{3}$$

$$\sum_{j=1}^{J} \lambda_j = 1 \tag{4}$$

$$\lambda_j, s_i,\ s_r \geq 0 \tag{5}$$

Where, $J = \{1, \ldots, j, \ldots [J]\}$ is a set of homogeneous DMUs, $I = \{1, \ldots, i, \ldots, [I]\}$ is a set of inputs, $R = \{1, \ldots, r, \ldots, [R]\}$ is a set of outputs, x_{ij} is a vector of inputs, y_{ij} is a vector of outputs, ε is a small "non-Archimedeon" quantity, s_r^+ and s_i^- are positive slack variables, θ is the efficiency score, and λ_j are the weights of inputs and outputs in each DMUs. Thus, each DMU is characterized by a vector x_{ij} of inputs and by a vector y_{rj} of outputs.

Regarding considerations of efficiency, DMU_0 is efficient if the score $\theta = 1$ and the slacks $s_i^{-*} = s_r^{+*} = 0$. In its turn, DMU_0 is weakly efficient if $\theta = 1$, but $s_i^{-*} \neq 0$ and/or $\theta = 1$ and $s_r^{+*} \neq 0$. Otherwise, DMU_0 is inefficient.

Using the following formulae, each inefficient DMU can be projected to the efficiency frontier as a combination of DMUs:

$$\widehat{x}_0 = X\lambda^* = \theta_0^* x_0 - s^{-*} \tag{6}$$

$$\widehat{y}_0 = Y\lambda^* = y_0 + s^{+*} \tag{7}$$

The projections on the efficiency frontier reveal how an inefficient DMU can change its inputs and outputs to become relatively efficient. In this regard, the following metrics were considered as inputs: operational costs, inventory and fixed assets; and the following were considered as outputs: sales revenue, cash-flow and operational profit.

3.2.4. Econometric model

After obtaining the efficiency scores, a multiple regression analysis was developed to identify the determinants of efficiency. The aim is to determine the variables with most influence on wine firms' efficiency [47,48]. For this analysis, an Ordinary Least Squares model was specified by considering the efficiency scores obtained with the DEA models as dependent variable. This econometric model was solved using the Statistical Package for Social Sciences (SPSS), which is the most used statistical software in social sciences [49].

The Ordinary Least Squares method estimates the regression parameters that minimise the sum of squared residuals. This is one of the most commonly used estimation techniques in econometrics, because it is an efficient method and simple to apply [50].

One drawback of multiple regression models is the correlation between explanatory variables. To verify that, the Pearson correlation was calculated for each pair of variables and, according to the criterion of the p-value, a value below 0.05 indicates non-zero correlations statistically significant at the 95% confidence level. After carrying out this procedure, the econometric model was specified considering natural logs for the independent variables. The regression model with natural logs allows us to ignore the measurement of variables and satisfy the Multiple Linear Regression (MLR) assumptions, such as linearity, random sampling, no perfect collinearity, zero conditional mean and heteroscedasticity, and reduce problems of heteroskedastic of skewed distributions [50]. The linearity implies that in the population model the parameters are linear. We have a random sample of n observations following the population model considered in the linearity assumption. A non-perfect collinearity means that none of the independent variables is constant and there are non-exact linear relationships among the independent variables. Zero conditional mean indicates that the error term must have an expected mean value of zero given any values of the independent variables. The heteroscedasticity assumption is related to the acceptance of the null hypothesis, which states that the error has the same variance, given any value of the explanatory variables.

The resulting econometric model tries to reveal the relationships between some performance metrics and efficiency scores, being formulated as follows:

$$y = \beta_0 - \beta_1 logx_1 - \beta_2 logx_2 - \beta_3 logx_3 - \beta_4 logx_4 - \beta_5 logx_5 + \beta_6 logx_6 + \varepsilon \quad (8)$$

wherein, y are the efficiency scores obtained with DEA models, x_1 is the number of employees, x_2 are operational costs, x_3 is the inventory value, x_4 are fixed assets, x_5 is the C2C cycle, x_6 are sales revenue, β_0 is the intercept coefficient, β_1 to β_6 are the respective coefficients of explanatory variables and ε is the error term.

Thus, this econometric model tests if the number of employees, operation costs, inventory value, fixed assets and C2C cycle have a negative influence on efficiency, and if sales revenue has a positive influence. In addition, the determination of the variable parameters values in this model allow us to know the magnitude of these influences.

Afterwards, the parameter and residuals of the econometric model were analysed in order to find errors of specification. The normal distribution of residuals was assessed using the normal probability plot of standardised residuals. The linearity of the model and heteroskedasticity were also graphically verified. For the independence of residuals, the Durbin Watson statistic was used as the decision criterion, accepting the null hypothesis for values around 2. The level of significance of each explanatory variable was measured using the Student's t-test and the aggregate level of significance of these variables was assessed using Snedecor's F test.

4. Cluster analysis: homogenous DMUs

This section describes the steps conducted and addresses the results obtained for the task of obtaining homogeneous DMUs through a cluster analysis. Table 1 presents the results of ANOVA regarding the number of clusters retained and the respective R^2, and the classification of cases in the clusters obtained with the k-means method is presented in Table 2. The criteria established for the number of clusters to retain was the minimum number of clusters that explain between 70% and 80% of total variance. Thus, we considered 3 k-mean clusters for the regions of North, Lisbon & Tejo and Alentejo & Algarve and 2 k-mean clusters for the regions of Centre and Setubal.

The results of F statistics in Table 3 show that all dimensions analysed, except C2C, contributed to differentiating the clusters in all regions at the 0.01 level of significance, allowing us to conclude that the dissimilarity between clusters C1 and C2 is considerable.

Table 1
Number clusters retained and R^2 per region.

Number of clusters retained	North	Centre	Lisbon & Tejo	Setubal	Alentejo & Algarve
9	0.972	0.971	0.954	0.999	0.949
8	0.970	0.963	0.929	0.999	0.874
7	0.968	0.954	0.925	0.999	0.841
6	0.917	0.945	0.914	0.999	0.816
5	0.913	0.933	0.905	0.998	0.802
4	0.831	0.913	0.901	0.996	0.787
3	0.678	0.901	0.723	0.976	0.637
2	0.230	0.846	0.559	0.856	0.523

Source: Cluster analysis – Anova.

Table 2
Number of cases in each cluster per region.

	North	Centre	Lisbon & Tejo	Setúbal	Alentejo & Algarve
Cluster 1	162	63	51	23	55
Cluster 2	8	3	2	2	2
Cluster 3	2	–	2		8
Total	172	66	55	25	65

Source: Non-hierarchical cluster analysis.

Table 3
F statistics for each dimension of Wescheler's scale per region.

	North	Centre	Lisbon & Tejo	Setubal	Alentejo & Algarve
No.of employees	475.2***	59.1***	86.4***	130.2***	88.8***
Inventory	207.8***	193.6***	75.0***	30.4***	118.7***
Operational costs	870.5***	693.9***	64.3***	64.0***	135.1***
Sales revenue	1141.8***	590.3***	54.1***	58.6***	106.9***
Cash-flow	483.1***	256.9***	11.9***	127.6***	16.3***
Operational profit	431.8***	282.9***	32.5***	159.0***	7.0***
Cash-to-Cash	0.1	.272	.122	.342	.532
Fixed assets	101.3***	26.9***	12.1***	265.8***	30.2***

Note: *** - at the 0.01 level of significance.
Source: Non-hierarchical cluster analysis.

The C2 and C3 clusters of North, Lisbon & Tejo and Alentejo & Algarve were aggregated into cluster C2. Therefore, as shown in Table 4, all regions concentrate most cases in one homogeneous cluster (Cluster C1) mainly comprised of medium-sized and small wine companies and presenting one cluster with a few large or very large companies (Cluster C2), which was aggregated in a national cluster composed of large wine companies from all regions. For instance, the North region has 164 (95.5%) small and medium sized companies in cluster C1 and 7 (4.5%) large companies in cluster C2.

Table 5 shows the average values of the variables used in our analysis and the respective coefficient of variation for small and medium-sized companies of each region and for the large companies. These figures show two different situations between small and medium-sized companies and large companies. Regarding the former, the average operational profit is highest in the regions of Setubal (211 thousand euros) and North (140 thousand euros), while the Centre and Alentejo & Algarve present on average negative operational profits and the highest coefficient of variation, as well as for the cash-flow variable. The remaining financial variables and the number of employees show a similar situation, wherein Setubal and North present the highest values, while the Centre and Alentejo & Algarve have the lowest. Regarding the C2C indicator, its average value varies between 158 weeks in Setubal and 395 weeks in the North, where the coefficient of variation is also the highest (4.64).

In our sample, large companies represent 5.8% of the total, but they account for almost 60% of sales revenue. As expected, all the variables show greater values than in small and medium-sized companies. The average operational profit and cash-flow are 3841 thousand euros and 3792 thousand euros. The inventory ascends to 20,131 thousand euros, while C2C is only 91 weeks, and the coefficient of variation of all variables is smaller for small and medium-sized companies, varying between 0.83 and 1.59. In its turn, it is noted that inventory and C2C present relatively high values. However, this can be considered normal in the wine industry, since wine is produced only in a specific period of the year and many types of wines require storage, which significantly increases the weeks of inventory.

Table 4
Number of cases per region and final cluster.

	North		Centre		Lisbon & Tejo		Setubal		Alentejo & Algarve		Total	
	No.	%	No.	%	No.	%	No.	%	No.	%	No.	%
Cluster C1	164	95.9	64	97.0	52	94.5	24	96.0	56	86.2	360	94.2
Cluster C2	7	4.1	2	3.0	3	5.5	1	4.0	9	13.8	22	5.8
Total	171	100.0	66	100.0	55	100.0	25	100.0	65	100.0	382	100.0

Source: Cluster analysis.

Table 5
Average and coefficient of variation for the variables analysed.

	Small and medium sized companies – cluster C1					Large
	North	Centre	Lisbon & Tejo	Setubal	Alentejo & Algarve	companies cluster C2
No.of employees	9	6	8	11	3	92
	1.23	1.04	0.95	1.88	0.73	1.32
Inventory	1125	408	492	1265	221	20,131
(th euros)	3.18	1.23	1.33	2.82	1.34	1.59
Operational costs	1292	534	971	2112	229	23,171
(th. euros)	1.70	1.21	1.57	2.50	0.64	1.06
Sales revenue	1310	481	933	2115	206	25,470
(th euros)	1.81	1.22	1.68	2.50	0.77	1.20
Cash	176	13	106	259	15	3841
(th euros)	2.14	11.39	1.80	2.39	4.55	1.36
Operational profit	140	−15	62	211	−16	3792
(th euros)	2.66	8.62	2.59	2.52	4.61	1.52
Cash-to-Cash	395	256	229	158	210	91
(th euros)	4.64	2.26	1.83	1.08	1.36	0.83
Fixed assets	1404	694	1174	2073	344	25,806
(th euros)	1.67	1.58	1.52	2.99	1.01	1.53

Source: Cluster analysis.

5. Results

This section presents the results obtained for this research. First subsection analyses the results of the DEA model and second subsection addresses the econometric analysis.

5.1. Analysis of the DEA model results

Before solving the DEA model, we performed a correlation analysis between the variables used as input and output, which is presented in Table 6. This leads to concluding that all inputs are significantly correlated with all outputs, except C2C, whose Pearson correlation coefficients present values close to zero.

Table 7 presents the average efficiency scores and the number of efficient and inefficient wine companies (DMU) for the regional clusters C1 and for cluster C2 of large companies. The average scores range between 0.733 (North in C1) and 0.932 (C2). Among the C1 cluster, Setubal obtained the highest efficiency score (0.914) followed by Alentejo & Algarve (0.842), while Centre and Lisbon & Tejo respectively obtained 0.797 and 0.764, which is close to the values obtained by North. The average scores of inefficient DMUs are also highest in C2, closely followed by Setubal and Alentejo & Algarve of C1. Cluster C2 also presents major differences between the average scores of total DMU and average scores of inefficient DMU.

The results of Table 7 also allow us to assess how efficiently distributed in each cluster DMUs are. In this regard, cluster C2 has the highest percentage of efficient companies (68.2%). In its turn, in C1 cluster, Setubal and Alentejo & Algarve have the highest percentages of efficient DMUs (62.5% and 44.6%, respectively), while the North has the highest number of inefficient DMUs (74.4%). The results indicate that only roughly 36% of the firms are efficient, a percentage that is influenced by the performance of firms of North, Centre and Lisbon & Tejo, as these 3 regions accrue for 81% of the total inefficient firms of the sample.

Table 8 presents average input and output values of efficient companies, per cluster, and indicates (between brackets) statistically different values from inefficient companies at the 0.01, 0.05 and 0.1 levels of significance (respectively represented as "***", "**" and "*"). The results show that the differences between efficient and inefficient DMUs are statistically significant mainly in output variables. Sales revenue, cash-flow and operational profit are different from inefficient DMUs at high levels of significance (0.01 and 0.05) in the North, Centre and Lisbon & Tejo of C1. In Alentejo & Algarve, cash-flow is also different from inefficient DMUs at the 0.05 level of significance.

Table 6
Pearson's correlation coefficients between variables of efficiency analysis.

	Num. of employees	Inventory	Operational costs	Sales revenue	Fixed assets	Cash-to-cash cycle	Cash flow	Operational Profit
Num. of employees	1	0.750***	0.890***	0.893***	0.676***	−0.038	0.848***	0.826**
Inventory	0.750***	1	0.876***	0.895***	0.632***	−0.016	0.846***	0.874**
Operational costs	0.890***	0.876***	1	0.991***	0.693***	−0.045	0.882***	0.869***
Sales revenue	0.893***	0.895***	0.991***	1	0.686***	−0.040	0.909***	0.900***
Fixed assets	0.676***	0.632***	0.693***	0.686***	1	−0.020	0.838***	0.822*`**
Cash-to-cash	−0.038	−0.016	−0.045	−0.040	−0.020	1	−0.034	−0.030
Cash flow	0.848***	0.846***	0.882***	0.909***	0.838***	−0.034	1	0.977***
Operational Profit	0.826***	0.874***	0.869***	0.900***	0.822*`**	−0.030	0.977***	1

Note: *** - the correlation is significant at the 0.01 level.

Table 7
Average efficiency scores and efficient and inefficient DMU.

	Average score	Average scores of inefficient DMU	Efficient DMU		Inefficient DMU		Total DMU
			No.	%	No.	%	
Clusters C1:							
North	0.733	0.641	42	25.6	122	74.4	164
Centre	0.797	0.683	23	35.9	41	64.1	64
Lisbon & Tejo	0.764	0.650	17	32.7	35	67.3	52
Setubal	0.914	0.772	15	62.5	9	37.5	24
Alentejo &Algarve	0.842	0.714	25	44.6	31	55.4	56
Cluster C2:							
Large companies	0.932	0.788	15	68.2	7	31.8	22

Source: DEA model results.

Table 8
Average input and output values of efficient DMUs.

	Small and medium-sized companies – cluster C1					Large
	North	Centre	Lisbon & Tejo	Setubal	Alentejo & Algarve	Companies cluster C2
Inputs:						
Operational costs (th. euros)	2,101	725	1,725	1,906	726	25,090
	(2.82)***	(1.80)*	(2.59)***	(-0.236)	(-1.01)	(0.52)
Inventory (th euros)	1,872	467	817	719	457	25,660
	(1.57)*	(0.69)	(2.59)***	(-0.94)	(-1.63)*	(-1.69)*
Fixed assets (th euros)	1,336	945	1,491	1,174	554	27,537
	(0.95)	(1.36)	(0.88)	(-0.89)	(-3.12)***	(0.29)
Outputs:						
Sales revenue (th euros)	2,278	719	1,754	1,979	719	29,316
	(3.13)***	(2.52)***	(2.77)**	(-0.16)	(0.14)	(0.84)
Cash-flow (th euros)	399	94	246	288	118	4,926
	(4.71)***	(3.65)***	(4.27)***	(0.28)	(2.38)**	(1.82)*
Operational profit (th euros)	387	58	190	232	43	4,988
	(5.38)***	(3.70)***	(4.79)***	(0.23)	(1.38)	(1.87)*

Note: * - indicates a significantly different average from one of the inefficient companies at the 0.1 level of significance.
** - indicates a significantly different average from one of the inefficient companies at the 0.05 level of significance.
*** - indicates a significantly different average from one of the inefficient companies at the 0.01 level of significance.
Source: DEA model results.

On the input side, only operational costs in the North and Lisbon & Tejo, inventory in Lisbon & Tejo and fixed assets in Alentejo & Algarve are different from inefficient DMUs at the 0.01 level of significance. The differences in the remaining variables between efficient and inefficient DMUs are not statistically significant, or are only at the 0.1 level of significance. Furthermore, it is also interesting to note that the only region in C1 without any statistically significant difference in inputs and outputs is Setubal, while in C2 inventory is the only different input at the 0.1 level of significance.

In our analysis, we also compared the inputs and outputs of inefficient companies with their projections on the efficient frontier, by using formulae (6) and (7), in order to identify how firms can improve their efficiency. Table 9 shows, for the inefficient companies, the percentage of average difference of inputs and outputs from their efficient projections per cluster. The major differences occur mainly in the output variables of cash-flow and operational profit in the Centre region of C1 (162.8% and 239.2%) and Alentejo & Algarve (113% and 784.2%). The smallest differences in outputs for these variables (cash-flow and operational profit) occur in the North and Setubal of C1 (respectively 4.6% and 36.9%). Sales revenue is the variable with the smallest average differences, with Lisbon & Tejo and Setubal of C1 and C2 having values lower than 1.

Regarding inputs, the differences from efficient projections are considerable for fixed assets and inventory in all clusters. In fact, for fixed assets, the differences range from 42% in Centre to 77.2% in Alentejo & Algarve, while in the latter, the differences are between 34.7% in Lisbon & Tejo and 60.7 in Setubal. Finally, cluster C2 presents the smallest differences from efficient projections, since they only vary between 0.3% in sales revenue and 51.2% in fixed assets.

Table 9
Percentage of average input and output differences from efficient projections.

	Small and medium-sized companies – clusters C1					Large
	North	Centre	Lisbon & Tejo	Setubal	Alentejo & Algarve	companies cluster C2
Inputs:						
Operational costs	22.7	25.9	21.0	8.4	27.5	24.2
Inventory	45.5	46.4	34.7	60.7	45.8	25.9
Fixed assets	64.5	42.0	69.8	74.9	77.2	51.2
Outputs:						
Sales revenue	7.9	1.5	0.8	0.6	4.6	0.3
Cash-flow	4.6	162.8	62.2	39.9	113.0	47.3
Operational profit	71.5	239.2	100.7	36.9	784.2	43.3

Source: DEA model results.

5.2. Analysis of the econometric model results

This subsection presents the results obtained by the linear regression model to determine which factors have most influence on the firms' performance. Table 10 presents the model coefficients (regression parameters and their standard deviation) and some quality indicators, such as R-squared, Adjusted R-squared, Sum of squares of regression, Sum of squares of residuals and F-Statistics.

As the F-Statistics show, the regression model is highly significant and explains 36.7% of the efficiency scores variance. The analysis of residuals and tests to check the existence of multicollinearity and heteroskedasticity did not reveal major problems with the model specification.

Source: Econometric model results.

Sales revenue shows a positive, significant influence on efficiency scores, indicating that, on average, an increase of 10% in this variable leads to an efficiency score increase of 0.0153. There is a negative influence of inventory on efficiency, since an increase of 10% leads to decreasing the efficiency scores by 0.0058. Fixed assets also have a negative significant effect on efficiency scores, with an increase of 10% resulting in an efficiency decrease of 0.0035. Operational cost is another variable with negative influence on efficiency, but it is only significant at the 0.1 level. The number of employees has a negative influence on efficiency, but it is not statistically significant.

6. Conclusion

The wine industry is predominant in Portugal for its culture and economy, and the country plays an important role in the international marketplace as one of the important wine producers. Motivated by the lack of empirical studies assessing the performance of firms of the wine industry sector, this article conducted an efficiency analysis, employing a Data Envelopment Analysis (DEA) and using real data from the Portuguese industry. This section presents the main conclusions of this research, namely first subsection presents and discusses the main findings, while second subsection establishes the main implications of this work, with the last subsection discussing the main limitations and future research.

6.1. Findings and discussion

This research considered accounting and operational variables and was applied to homogeneous sets of companies. Moreover, an econometric model was implemented, considering the efficiency scores obtained as the dependent variable, in order to determine the factors with most influence on efficiency.

Table 10
Results obtained with the estimated econometric model.

	Model coefficients		Indicators	
	β	STD		
Constant	.670***	.082	N	382
Num. of employees	-.005	.016	R-Squared	0.377
Operational costs	-.043*	.025	Adjusted R- Squared	0.367
Inventory	-.058***	.012	Sum of squares of regression	7.759
Fixed assets	-.035***	.008	Sum of squares residuals	12.827
Cash-to-Cash	.003	.010	F-Statistics	37.805***
Sales revenue	.153***	.018		

Note: * - indicates if the regression parameter is significantly different from zero at the 0.1 level of significance.
** - indicates if the regression parameter is significantly different from zero at the 0.05 level of significance.
*** - indicates if the regression parameter is significantly different from zero at the 0.01 level of significance.

While it is not obvious that large companies are always the most efficient, this study contributed with empirical evidence supporting that this is true for the wine Portuguese companies. Notwithstanding, companies of regions such as Setubal and Alentejo & Algarve also obtained considerable efficiencies, being the most efficient non-large companies. From the set of small and medium firms, Setubal and Alentejo & Algarve are also the regions with the highest percentage of efficient companies, while the North region is on average the least efficient and has less efficient companies. In fact, while only 36% of the firms are efficient, this is in part due to the considerable number of inefficiency firms in the North, Centre and Lisbon & Tejo regions, which accrued 81% of the total number of inefficient firms.

This study also found that efficient and inefficient companies differ mainly in output variables, namely sales revenue, cash-flow and operational profit. Comparing the inputs and outputs of inefficient companies with their efficient projections, the major differences are also in cash-flow and operational profit and mainly in small and medium-sized companies of the Centre and Alentejo & Algarve. On the input side, the largest differences were found in inventory and fixed assets.

This research also determined, using an econometric model, the variables that influence efficiency the most. According to these results, we concluded that, to improve efficiency, wine companies should mainly increase sales revenue and decrease inventory and fixed assets. As examples, this can be achieved raising customers' perception of quality, monitoring the inventory, adopting operation strategies that reduce inventory levels or outsourcing several services to move assets off the balance sheet. However, due to the particular characteristics of the wine industry, high levels of inventory are standard in companies. Thus, efforts should be made to keep inventories at acceptable levels, e.g., by improving their monitoring, and adopting strategies that minimise inventory needs, in order to increase its turnover.

The wine industry also makes considerable use of fixed assets, such as property, plant and equipment turnover. Such assets are mainly associated with vineyards, wineries, bottling plants, warehouses and diverse equipment such as agricultural machinery, winery and bottling equipment, handling equipment and vehicles. Thus, strategies to reduce such costs should also be implemented, e.g., by outsourcing certain activities, in order to move assets off their balance sheet.

6.2. Implications

This research contributed with a framework that can be applied to similar studies in other geographic locations and possibly even in other industry sectors. Furthermore, due to the lack of empirical data in the Portuguese wine industry, this research also contributed in this regard, and may even serve as benchmarking for other countries.

From a managerial perspective, this research also contributes with findings that allow, e.g., managers and decision-makers from similar firms to identify strategies to improve their firm's efficiency, by focusing on improving specific variables with influence on said efficiency. This can also be relevant from an investment perspective, as decision-makers from these regions know which processes should be improved, while the ones of other regions may apply the provided methodology, to achieve and interpret their own findings, hence improving business performance and overall competitiveness.

6.3. Limitations and future work

Nevertheless, this research also has some limitations. First, the obtained results are related to the data that was used, which was limited in terms of the available variables, complete data for each firm, and the available time frame. Therefore, this study did not consider, e.g., all Portuguese wine producing firms, neither the evolution in time of the firms' efficiency.

Regarding further research, the abovementioned limitations should be addressed. Apart from that, other interesting research works could consist of applying the provided framework to other wine-producing countries without considerable empirical evidence to evaluate the firms' efficiency.

Author statement

Rui Fragoso: Conceptualization, Methodology, Validation, Formal analysis, Data curation, Writing – original draft, Writing – review & editing, Funding acquisition, **António A. C.** Vieira: Conceptualization, Methodology, Validation, Formal analysis, Data curation, Writing – original draft, Writing – review & editing

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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