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# A Longitudinal Analysis of Economic Activities' Relative Efficiency Using the DEA Approach

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**Abstract:** Economic activities' efficiency represents the level of performance that uses the lowest quantity of inputs to achieve the highest possible amount of output. This paper presents the process of calculating the relative efficiency of separate non-financial activities in an economy using the DEA methodology. The purpose of this paper was to create the DEA model for monitoring the relative efficiency of individual non-financial activities of the economy. The purpose was achieved through the realization of two objectives. The first one included the determination of the relative efficiency of the above-mentioned activities in the period from 2002 to 2020 using the data from non-financial entities in the Republic of Croatia. The second objective consisted of ranking the economic activities according to their relative efficiency. An output variable that measures the efficiency was presented using the return on assets, while the total debt to EBITDA, EBITDA per employee, assets turnover and human capital efficiency were used as input variables. Research results indicate that the DEA methodology could be used as an economic activity's relative efficiency measurement tool, giving the possibility to rank it according to its relative efficiency using the accounting ratios. Research results show that service sectors' economic activities were the most efficient ones according to the lower assets engagement and the respective sources of financing that dominate. The highest average relative efficiency in 19 years was scored using wholesale, retail and repair activities as well as information, communication and education. The lowest average relative efficiency was achieved in construction, water supply, sewerage, waste management and remediation activities as well as accommodation and food service activities, which is the consequence of their low level of activity and profitability and high indebtedness in the analyzed period. The relative efficiency scores calculated using the DEA methodology could be used as a benchmark for companies on a micro level, while on the macro level decision-makers can obtain a deeper insight into the relative efficiency of the nonfinancial activities.

**Keywords:** economic activity efficiency; accounting ratios; data envelopment analysis; return on assets; total debt to EBITDA; assets turnover; EBITDA per employee; human capital efficiency

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## 1. Introduction

Efficiency is a well-known measurable concept representing the level of performance that uses the lowest quantity or amount of inputs to achieve the highest possible quantity or amount of output. The economic activities' efficiency measurement model includes a set of four relevant inputs and one output accounting ratio calculated and analyzed for the 19 years of the 17 nonfinancial activities of the Croatian economy. The return on assets (ROA) represents the output or dependent variable that measures efficiency, while the input or independent variables are the total debt to EBITDA, solvency ratio, EBITDA per employee, productivity ratio, assets turnover, activity ratio and human capital efficiency. The last one represents the most significant segment of intellectual capital efficiency.

This research aims to monitor the relative efficiency of particular nonfinancial activities of the economy using the DEA approach, which represents an innovation. According to the authors' knowledge, the DEA application in measuring all nonfinancial economic activities' efficiency on the state level has not been performed yet. To achieve the above-mentioned objective, the relative efficiency of particular nonfinancial activities of the economy is to be scored and compared. In this way, the companies operating in a particular nonfinancial activity could use the scores as a benchmark and the macroeconomic decision makers can obtain a deeper insight into the relative efficiency of the nonfinancial activities.

To reach the central research objective, the relative performance (i.e., efficiency) of individual nonfinancial activities of the Croatian economy was measured in the time interval from 2002 to 2020. Consequently, the economic activities were ranked according to their long-term relative efficiency, thus fulfilling the second research objective.

The purpose of this paper is to provide a decision-making tool by creating the DEA model for monitoring the relative efficiency of individual nonfinancial activities of the economy. In this context, the next hypothesis will be tested:

**Hypothesis 1.** *The DEA method is applicable to economic activities' relative efficiency measurement using the accounting ratios.*

The next sections explain the variables, the employed methodology, and obtained results, while the conclusions and open questions are presented at the end.

## 2. Literature Review

The efficiency of nonfinancial economic activities was measured using the return on assets (ROA). This well-known profitability ratio measures how efficiently the company manages its assets and is calculated as shown in Equation (1):

$$\text{ROA} = (\text{Net income} + \text{Interest expense}) \div \text{Total assets} \tag{1}$$

It shows how successfully the management uses all sources of the company's financing and how successfully it manages the assets. Various research has identified several ROA determinants among which the authors selected three of them, namely solvency, activity and productivity ratios. The authors included a significant segment of intellectual capital efficiency—human capital efficiency (HCE)—because intellectual capital became a critical success factor in the last decades. HCE can be characterized as an accounting ratio because it includes accounting variables in its equation. Equation (2) shows how the HCE is calculated (Pulić 2008).

$$\text{HCE} = \text{Value added} \div \text{Human capital} \tag{2}$$

where Value added = Net income + Human capital + Depreciation, and Human capital = Total cost of employees' salaries with taxes and contributions + other benefits for employees + cost of employing part-time employees via agencies + costs related to students' work + scholarships.

HCE was proven to be a significant determinant of ROA. Salim and Winanto (2020) showed that ROA was partially influenced by a significant positive HCE. Rahim et al. (2017), Tran et al. (2020), and Adegbayibi (2021) all confirmed that HCE made a positive and significant contribution to firms' performance. At the same time, there was some criticism of HCE. Ståhle et al. (2011) criticized the measure of added value, stating that it was generally influenced by business decisions made by the management. Another criticism arises from the fact that human capital efficiency could increase if companies invested more in their employees, expecting a consequent increase in value added. However, the reverse is also possible and not rare, namely that companies increase the human capital efficiency by reducing the investment in employees, which results in a short-term increase in the coefficient (Zenzerović et al. 2023).

Solvency ratios are presented using the total debt to EBITDA ratio, which shows how many years it takes for a company to pay out the total debt from EBITDA. This isnconsidered to be a good approximation of the company's cash flow. The authors have chosen this dynamic solvency ratio because it considers the paying ability of a company from its earnings in the long run. Škuflić et al. (2016) proved that the debt to EBITDA ratio had a strong and negative relation to profitability.

Asset turnover was selected from a group of activity ratios. Many studies have proven that it has a significant influence on ROA. Mubin et al. (2013) proved that asset turnover was the most influential factor among the variables used in the Dupont model that influenced ROA. Xu and Banchuenvijit (2014) found that asset turnover had a positive and significant relationship with ROA, while the leverage relation with the profitability measure was negative.

The group of productivity ratios is presented using EBITDA per employee. It is a measure of overall productivity as well as labor and capital productivity, and their management positively affects the company's profitability. Muminović and Aljinović Barać (2015) indicated that this comprehensive measure of productivity had a statistically significant positive impact on a company's profitability measured using ROA.

Although there are many types of research carried out using the DEA approach, there are no articles that cover the analysis of relative efficiency among the economic activities using the variables engaged in this research. The preparation for this research revealed some recent scientific papers dealing with DEA methodology applied to industry and/or country-level research.

A paper authored by Novickytė and Droždz (2018) elaborated on DEA models in the Lithuanian banking sector using different data sets. It showed the usage of DEA methodology on the country level, as well as efficiency scores comparison with ROA. A state-level environmental performance analysis using DEA models was carried out by Avilés-Sacoto et al. (2021). It showed a performance measurement using data without explicit relation between the DEA model inputs and outputs applied to environmental performance measurement. Shah et al. (2022) employed DEA to explore the impact of nonperforming loans on the operational efficiency of commercial banks in Pakistan. A DEA methodology application to global carbon dioxide emission and industry with emission reduction potentials was carried out by Iqbal et al. (2019) while time-period-dependent performance measurement on the industry level using a nonparametric approach was carried out by Krišťáková et al. (2021).

## 3. Methodology

Research was performed using the data from the financial statements of all nonfinancial entities based in the Republic of Croatia. According to the sectorial classification of institutional units, the nonfinancial sector includes institutional units whose distribution and financial transactions differ from those of their owners, which are market producers, and whose main activity is the production of goods and nonfinancial services (Central Bureau of Statistics). The group of nonfinancial entities includes all bodies recognized as independent legal entities, which, in addition to companies, also include cooperatives, nonprofit institutions, and associations. The collected data were structured in 17 nonfinancial sections according to national classifications of economic activities: A—Agriculture, forestry and fishing, B—Mining and quarrying, C—Manufacturing, D—Electricity, gas, steam, and air conditioning supply, E—Water supply; sewerage, waste management, and remediation activities, F—Construction, G—Wholesale and retail trade; repair of motor vehicles and motorcycles, H—Transportation and storage, I—Accommodation and food service activities, J—Information and communication, L—Real estate activities, M—Professional, scientific, and technical activities, N—Administrative and support service activities, P—Education, Q—Human health and social work activities, R—Arts, entertainment, and recreation, and S—Other service activities. For each of the 17 activities, the output and input variables were calculated and used in the DEA analysis.

The data from the financial statements were collected from the database of the Financial Agency (Fina), the body that is in charge of collecting them. The period for which the data were collected covered the time interval from the beginning of their systematic collection to the last available period, i.e., from 2002 to 2020. The population of nonfinancial entities whose data from the financial statements were included in the analysis ranged from 61,674 in 2002 to 132,461 entities in 2020. In the nineteen years of the analysis, they employed an average of 820 thousand employees, generating EUR 79 billion in revenue and EUR 18 billion in value added.

The economic activities' efficiency was carried out using the data envelopment analysis (DEA) method. It represents the methodology used to calculate the relative efficiency of entities, identifying the most efficient ones. This paper deals with the economic activities attributed to a particular year between 2002 and 2020. Each economic activity is presented as a process with its inputs and outputs, and it is considered a separate entity called the Decision-Making Unit (DMU). The DMUs are, therefore, marked with letters from A to S accompanied with the years from 2002 to 2020, respectively. Due to the DEA advantages, the nonparametric approach was used, all the data were nondimensional, and there was no established explicit relationship between inputs and outputs. During the research, the capability of transforming the inputs into outputs was measured as an efficiency score. An economic activity gaining more output for fewer inputs in a particular year or period is considered more efficient. In DEA models, the efficiency scores range from 0 to 1. The efficient DMUs have an efficiency score of 1 and those DMUs create the efficient frontier. Efficient DMUs are the benchmark for all other researched DMUs. The DMUs with an efficiency score of less than 1 are considered nonefficient.

The data envelopment analysis (DEA) methodology was introduced by Charnes et al. (1978). DEA is based on linear programming and evaluates the relative efficiency of the researched operating entities, named Decision-Making Units (DMUs). Each DMU possesses a set of empirical data divided into inputs and outputs which are homogenous. According to the DEA calculations related to the existing DMUs' data, an efficient frontier is created. The efficient frontier contains the efficient DMUs with efficiency scores equal to 1 and these DMUs are considered as benchmarks for the remaining DMUs with lower efficiency scores. The remaining DMUs, with an efficiency score of less than 1, are considered inefficient, as they are situated outside the efficient frontier. DEA adds value to the researched DMUs and their data set with a simplified display of the inefficient DMUs, the ability to point out peers as possible efficiency improvement targets, and makes calculations about the underperforming DMUs' projections to the efficient frontier to determine the improvements which they need to reach the efficient frontier. This paper uses the two basic models used for efficiency calculation purposes—the CCR model dealing with the constant returns to the scale proposed by Charnes et al. (1978), and the BCC model dealing with the variable returns to the scale proposed by Banker et al. (1984).

The measure of inefficiency is calculated as the distance between the inefficient DMU and the efficient frontier, which corresponds to input excesses or output shortfalls. The DEA model can be input-reduction- or output-augmentation-oriented. This paper deals with the input-oriented models, which express the management intention to reduce input data and maintain the outputs. The DMU efficiency can be described as the ratio between outputs and inputs as presented in Equation (3):

$$\text{Efficiency DMU} = \frac{\sum_{r=1}^{s} u_r y_r}{\sum_{i=1}^{m} v_i x_i} \tag{3}$$

where:

$y_r$ = output r;
$u_r$ = output r weight;
$x_i$ = input i;
$v_i$ = input i weight.

According to Cooper et al. (2007), if a set of n DMUs is considered ($DMU_j$, j = 1, 2,. . ., n), each of them gives s outputs using m inputs. Let the $x_j = \{x_{ij}$, i = 1, 2,. . ., m$\}$ be the input vector, and $y_j = \{y_{rj}$, r = 1, 2,. . ., s$\}$ the output vector of $DMU_j$. The data set is described using input matrix X = ($x_{ij}$, i = 1, 2,. . ., m, j = 1, 2,. . ., n), and output matrix Y = ($y_{rj}$, r = 1, 2,. . ., s, j = 1, 2,. . ., n).

The DEA model is based on the efficiency assessment of $DMU_o$, o ∈ {1, 2,. . ., n}, and seeks for a virtual DMU in which inputs and outputs are defined in the form of the linear combination of inputs and outputs of the rest of the DMUs in a calculated DMU set, namely the Xλ and Yλ. λ = ($\lambda_1$, $\lambda_2$,. . ., $\lambda_n$), λ > 0 corresponds to the proportions contributed with efficient DMUs to the projections of $DMU_o$ onto the efficient frontier, while e is a row vector with all elements equal to 1. The virtual DMU has to be better (at least not worse) than $DMU_o$. Searching for the virtual DMU could be in general, expressed as a standard linear programming problem:

Input-oriented model:

$$\min_{\theta,\,\lambda} \theta \tag{4}$$

subject to

$$\theta x_0 - X\lambda \geq 0 \tag{5}$$

$$Y\lambda \geq y_o \tag{6}$$

$$\lambda \geq 0 \tag{7}$$

$$e\lambda = 1 \tag{8}$$

Constraints (4) to (7) create the DEA CCR model, and the DEA BCC model is generated using limitations (4) to (8). Formulas (5) and (6) represent the input excesses and the output shortfalls, i.e., "slack" vectors:

$$s^- = \theta x_0 - X\lambda \tag{9}$$

$$s^+ = Y\lambda - y_o \tag{10}$$

where the efficiency is expressed as θ.

A $DMU_o$ is considered efficient if the optimal solution ($\theta^*$, $\lambda^*$, $s^{-*}$, $s^{+*}$), as a result of minimizing θ and minimizing the sum of $s^{-*}$ and $s^{+*}$, reaches $\theta^* = 1$ and $s^{-*} = 0$, $s^{+*} = 0$; otherwise, it is not efficient.

The CCR efficiency $\theta^*_{CCR}$ is named technical efficiency, and the BCC efficiency $\theta^*_{BCC}$ is named pure technical efficiency.

The DEA limitations are (i) missing data fragility, (ii) sensitivity to extreme data readings, and (iii) collecting data mistakes. This was previously researched by Coelli et al. (2005), Kahraman (2008), Velasquez and Hester (2013) and Korhonen and Wallenius (2020).

The strengths of using the DEA methodology are (i) the explicit relation between inputs and outputs does not need to be established; (ii) the researchers have the freedom to choose the inputs and outputs depending on research demand; (iii) it is adaptable to the management strategy through the orientation of the model to inputs or outputs; (iv) the model is adaptable to different types of returns to scale (constant or variable); (v) there is no need to rely on expert opinion on input and output weights as the model itself calculates the best set of weights for each observed DMU, which is why subjective assessment could be excluded, thus contributing to the objectivity of the analysis.

The DEA methodology was chosen in this research due to its strengths and flexibility in selecting inputs and outputs, as well as the model orientation, i.e., whether the management priority is to reduce the selected inputs or to increase the selected outputs.

According to Banker et al. (1989), the number of researched DMUs has to be at least three times higher than the sum of inputs and outputs to obtain DMU discrimination properly. This was the case in our research.

To calculate the DMUs' efficiency change over time, the DEA methodology extension called the DEA Window Analysis was used. The researched entities, or DMUs, which were nonfinancial activities marked from A to Q, were researched from the year 2002 to the year 2020. There were 17 nonfinancial activities in 19 years. Basic DEA models considered them as 17 DMUs, and the DEA Window Analysis considered them as 323 DMUs in extreme cases with a 1-year window width ($323 = 17 \times 19$).

To meet the DEA methodology requirements, the longitudinal analysis of economic activities was described as a process with its inputs and outputs. Following the DEA methodology, it was confirmed that the data set for each studied nonfinancial entity was homogenous. Consequently, the same categories of data were collected for all entities: (i) the ratio between total liabilities and EBITDA, (I)LIAB_EBITDA; (ii) entities' asset turn, (I)ASSET_TURNs; (iii) EBITDA using the number of employees, (I)EBITDA_EMPs; (iv) the HCE value marked as (I)HCEs for each entity as process inputs; and vi) ROA value, marked as (O)ROA, as process output.

Figure 1 shows the DEA efficiency measurement process, as well as the inputs/output division.

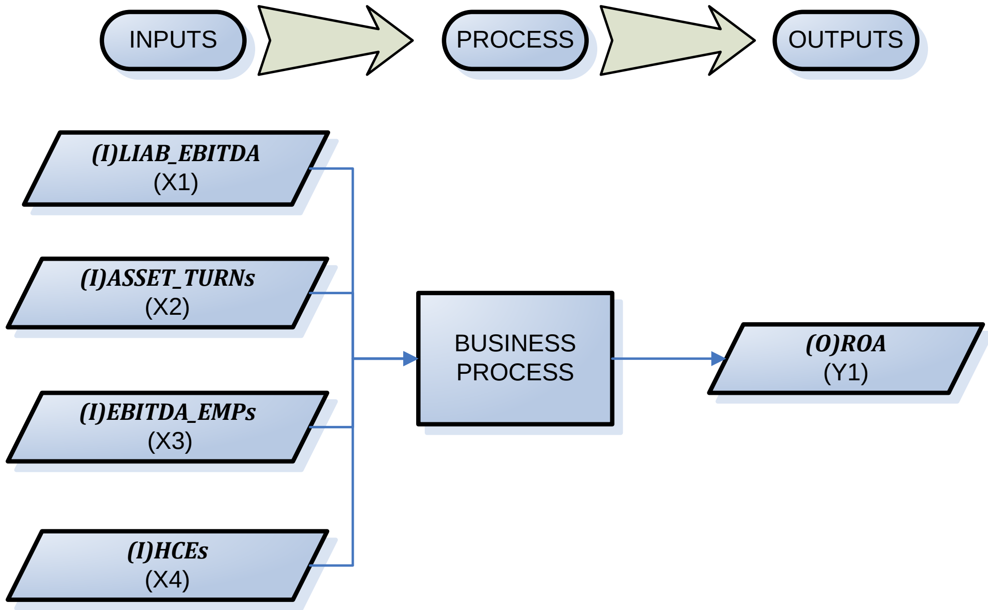


**Figure 1.** DEA efficiency measurement process.

In DEA data modeling, outputs tend to be increased and inputs tend to be decreased. In that situation, some inputs were undesirable. The data scaling solved the undesirable input issue. The data scaling was performed by taking reciprocals considering Golany and Roll (1989), Lovell et al. (1995) and Liu et al. (2010) recommendations.

Before running the model, it is necessary to prove its reliability, for which the requirement of isotonicity between input and output variables remains to be verified. Accordingly, if the inputs used expand, the corresponding outputs should not be reduced and vice versa. For this purpose, Pearson's correlation was used, which did not result in a recommendation to omit any of the selected variables from the model (for detailed information on Pearson correlation criteria for variable reduction, see Byers and Waylett (1984, p. 72)).

The calculations were carried out with DEA Solver Pro 7.0 software. After the DEA calculations were carried out, the output values were recalculated from the scaled to the original ones to compute their proposed absolute and relative improvements. The scaled inputs were marked with the suffix "s" added to their names. Analysts should take care of data scaling to "unscale" them or return to original values when they use data for decision making.

The model orientation depends on the management decision. In this particular case, it was concluded that the DEA model needs to be input-oriented. This decision is based on the fact that the output represents the process result in the form of return on assets as a measure of efficiency, which needs to be maintained, while the inputs need to be minimized to obtain a level of return on assets.

The input-oriented constant return to the scale model and input-oriented variable return to the scale model were marked as CCR-I and BCC-I models, respectively.

Calculations and results interpretation will be followed by recommendations given by Dyson et al. (2001) and Cook et al. (2014).

## 4. Research Results

The available data were used to carry out the numerical research. The data set descriptive statistics are shown in Table 1.

**Table 1.** Data set descriptive statistics.

| **Heading** | **Inputs** | | | | **Output** |
|---|---|---|---|---|---|
| Data | (I)LIAB_EBITDA | (I)ASSET_TURN | (I)EBITDA_EMP | (I)HCE | (O)ROA |
| Maximum value | 192.3816 | 1.5437 | 412,964.7174 | 3.4499 | 7.9402 |
| Minimum value | 1.1076 | 0.1275 | 2,645.5781 | 1.0371 | 0.7478 |
| Average value | 13.1147 | 0.6653 | 80,207.1953 | 1.6717 | 2.3373 |
| Standard deviation | 15.3650 | 0.3713 | 77,153.2836 | 0.4481 | 1.6203 |
| Max/Min ratio | 173.6853 | 12.1025 | 156.0962 | 3.3266 | 10.6179 |
| Data count | 323 | 323 | 323 | 323 | 323 |

It can be noticed that the data set shows a wide span of data dispersion, which is particularly shown in the ratio of the minimum/maximum values with values between 3.32 and 176.32. These variations are expected according to differences in assets used, structure of financing and number of employees, as well as according to profitability between economic activities.

The relative efficiency calculation results using CCR and BCC input-oriented (CCR-I and BCC-I) DEA models using a 19-year data window width are shown in Tables 2 and 3 for the CCR-I model and Tables 4 and 5 for the BCC-I model, respectively. Using the 19-year time window, the 17 DMUs are calculated as 323 DMUs in total, enabling the research of every DMU combination in the entire period.

According to the results shown in Tables 2–5, it is noted that DEA models are discriminatory to the data set, resulting in a limited number of efficient DMUs and allowing filtering out of the proper DMUs for benchmarking the inefficient DMUs. Research results indicate that the hypothesis could be accepted, proving that the DEA is a representative method for economic activities' relative efficiency measurement.

The CCR-I and BCC-I models' calculation results are presented in Tables 2 and 3, respectively. The calculation results show that there are six efficient DMUs in the CCR-I model, DMU-B-2006, DMU-B-2008, DMU-J-2002, DMU-J-2007, DMU-P-2006, and DMU-Q-2019. The BCC-I model calculation results show the following efficient DMUs: DMU-B-2006, DMU-B-2008, DMU-J-2002, DMU-J-2007, DMU-P-2006, and DMU-Q-2019, which are also CCR-I efficient DMUs, and DMU-D-2014, DMU-D-2020, DMU-G-2002, DMU-G-2003, DMU-G-2007, DMU-G-2018, DMU-G-2019, DMU-J-2005, and DMU-J-2006. These 15 DMUs create the efficient frontier and represent the benchmarks for the remaining DMUs in this research. Given that more DMUs are create a BCC-I efficient frontier, it can be concluded that the data set behaves with variable returns to scale, i.e., BCC-I is a representative model for measuring the economic activities' relative efficiency using the accounting ratios.

**Table 2.** Efficiency results in the CCR-I model, 19-year window width, for the period 2002–2011.

| | Years | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| **DMU** | **2002** | **2003** | **2004** | **2005** | **2006** | **2007** | **2008** | **2009** | **2010** | **2011** |
| A | 0.2504 | 0.2308 | 0.2981 | 0.3387 | 0.2864 | 0.3321 | 0.3302 | 0.2372 | 0.314 | 0.3383 |
| B | 0.4329 | 0.6811 | 0.5438 | 0.7168 | 1 | 0.5988 | 1 | 0.5213 | 0.2612 | 0.2611 |
| C | 0.6039 | 0.3676 | 0.365 | 0.4242 | 0.4374 | 0.4703 | 0.4894 | 0.3671 | 0.4169 | 0.5578 |
| D | 0.2895 | 0.2994 | 0.3485 | 0.3237 | 0.2945 | 0.2491 | 0.2766 | 0.3055 | 0.4501 | 0.2945 |
| E | 0.1874 | 0.2136 | 0.2289 | 0.223 | 0.2345 | 0.2361 | 0.2606 | 0.2333 | 0.2121 | 0.2456 |
| F | 0.2056 | 0.2268 | 0.2368 | 0.2233 | 0.2453 | 0.2329 | 0.2515 | 0.2263 | 0.2008 | 0.1836 |
| G | 0.8449 | 0.7911 | 0.7578 | 0.8133 | 0.8542 | 0.936 | 0.8915 | 0.6219 | 0.6085 | 0.6901 |
| H | 0.2593 | 0.3022 | 0.3119 | 0.3664 | 0.3448 | 0.3294 | 0.358 | 0.2457 | 0.254 | 0.2459 |
| I | 0.2038 | 0.2575 | 0.2005 | 0.2248 | 0.2105 | 0.2353 | 0.2158 | 0.1921 | 0.1852 | 0.1976 |
| J | 1 | 0.827 | 0.8422 | 0.9722 | 0.9611 | 1 | 0.8887 | 0.6853 | 0.7403 | 0.7917 |
| L | 0.2207 | 0.2577 | 0.2889 | 0.2374 | 0.2818 | 0.2367 | 0.271 | 0.2598 | 0.2119 | 0.2629 |
| M | 0.3126 | 0.3104 | 0.3783 | 0.3073 | 0.3342 | 0.3319 | 0.3359 | 0.2912 | 0.2792 | 0.2588 |
| N | 0.452 | 0.3872 | 0.3947 | 0.4216 | 0.3266 | 0.3854 | 0.5918 | 0.3661 | 0.3676 | 0.4038 |
| P | 0.7838 | 0.704 | 0.7834 | 0.7739 | 1 | 0.9231 | 0.7901 | 0.7753 | 0.7807 | 0.8387 |
| Q | 0.6432 | 0.5344 | 0.6303 | 0.6662 | 0.7943 | 0.7844 | 0.7953 | 0.7363 | 0.6753 | 0.5856 |
| R | 0.2098 | 0.2954 | 0.273 | 0.364 | 0.3014 | 0.3352 | 0.3347 | 0.2213 | 0.1967 | 0.2506 |
| S | 0.5044 | 0.3379 | 0.4419 | 0.4426 | 0.6914 | 0.6034 | 0.4924 | 0.6186 | 0.4651 | 0.5143 |
| Average by year | 0.4355 | 0.4132 | 0.4308 | 0.4611 | 0.5058 | 0.4835 | 0.5043 | 0.4061 | 0.3894 | 0.4071 |

**Table 3.** Efficiency results in CCR-I model, 19-year window width, for the period 2012–2020.

| | Years | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| **DMU** | **2012** | **2013** | **2014** | **2015** | **2016** | **2017** | **2018** | **2019** | **2020** | **Average by DMU** |
| A | 0.3266 | 0.2995 | 0.2979 | 0.3224 | 0.3528 | 0.3464 | 0.3107 | 0.374 | 0.3658 | 0.31329 |
| B | 0.459 | 0.6527 | 0.722 | 0.2835 | 0.1104 | 0.3267 | 0.4266 | 0.2856 | 0.183 | 0.49824 |
| C | 0.5983 | 0.4435 | 0.4884 | 0.4883 | 0.4937 | 0.5157 | 0.528 | 0.5446 | 0.5004 | 0.47897 |
| D | 0.3024 | 0.5653 | 0.7704 | 0.766 | 0.7209 | 0.609 | 0.559 | 0.6022 | 0.7001 | 0.45931 |
| E | 0.235 | 0.2115 | 0.2212 | 0.2359 | 0.2319 | 0.2359 | 0.2432 | 0.2428 | 0.222 | 0.22918 |
| F | 0.1422 | 0.1929 | 0.2136 | 0.2196 | 0.2392 | 0.2227 | 0.2326 | 0.2164 | 0.2181 | 0.21738 |
| G | 0.598 | 0.6158 | 0.7053 | 0.8165 | 0.8349 | 0.8873 | 0.9408 | 0.937 | 0.8704 | 0.79028 |
| H | 0.1794 | 0.221 | 0.233 | 0.2764 | 0.2821 | 0.2941 | 0.2722 | 0.2433 | 0.1915 | 0.27425 |
| I | 0.2307 | 0.2668 | 0.2244 | 0.2881 | 0.3049 | 0.3019 | 0.3025 | 0.2773 | 0.0894 | 0.23206 |
| J | 0.6806 | 0.6016 | 0.6053 | 0.5776 | 0.5966 | 0.5924 | 0.7094 | 0.6569 | 0.6949 | 0.75915 |
| L | 0.2678 | 0.2823 | 0.2374 | 0.2984 | 0.3136 | 0.2184 | 0.3752 | 0.4643 | 0.3699 | 0.28190 |
| M | 0.2335 | 0.2291 | 0.1671 | 0.2685 | 0.2763 | 0.241 | 0.3116 | 0.3145 | 0.2879 | 0.28786 |
| N | 0.4464 | 0.4791 | 0.4906 | 0.5207 | 0.5907 | 0.6516 | 0.6347 | 0.6787 | 0.255 | 0.46549 |
| P | 0.7625 | 0.7419 | 0.8154 | 0.8091 | 0.8234 | 0.8365 | 0.7936 | 0.8416 | 0.7996 | 0.80929 |
| Q | 0.5446 | 0.5638 | 0.5965 | 0.7555 | 0.7558 | 0.7424 | 0.8275 | 1 | 0.9105 | 0.71273 |
| R | 0.2581 | 0.3618 | 0.4249 | 0.3621 | 0.3755 | 0.3572 | 0.466 | 0.5291 | 0.3819 | 0.33150 |
| S | 0.4872 | 0.5761 | 0.5772 | 0.4972 | 0.5561 | 0.5731 | 0.7066 | 0.5821 | 0.5009 | 0.53518 |
| Average by year | 0.3972 | 0.4297 | 0.4583 | 0.458 | 0.4623 | 0.4678 | 0.5082 | 0.5171 | 0.4436 | |

**Table 4.** Efficiency results in BCC-I model, 19-year window width, for the period 2002–2011.

| | Years | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| **DMU** | **2002** | **2003** | **2004** | **2005** | **2006** | **2007** | **2008** | **2009** | **2010** | **2011** |
| A | 0.5394 | 0.5078 | 0.5517 | 0.5312 | 0.5166 | 0.5187 | 0.5114 | 0.4536 | 0.5594 | 0.6101 |
| B | 0.7635 | 0.8064 | 0.7947 | 0.8687 | 1 | 0.8678 | 1 | 0.8633 | 0.6058 | 0.5679 |
| C | 0.7063 | 0.6604 | 0.6835 | 0.7001 | 0.6964 | 0.7037 | 0.7176 | 0.6358 | 0.6776 | 0.7653 |
| D | 0.6069 | 0.6184 | 0.6967 | 0.6673 | 0.6364 | 0.5681 | 0.6081 | 0.6506 | 0.8022 | 0.6181 |
| E | 0.4137 | 0.4587 | 0.4748 | 0.4649 | 0.4907 | 0.4901 | 0.5117 | 0.4827 | 0.4287 | 0.477 |

**Table 4.** *Cont.*

| | Years | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| **DMU** | **2002** | **2003** | **2004** | **2005** | **2006** | **2007** | **2008** | **2009** | **2010** | **2011** |
| F | 0.4604 | 0.5039 | 0.5173 | 0.474 | 0.5065 | 0.4923 | 0.5181 | 0.4785 | 0.4319 | 0.4112 |
| G | 1 | 1 | 0.9577 | 0.9508 | 0.9775 | 1 | 0.9809 | 0.828 | 0.8088 | 0.8598 |
| H | 0.524 | 0.5426 | 0.5733 | 0.5716 | 0.5798 | 0.573 | 0.5872 | 0.5055 | 0.5058 | 0.4974 |
| I | 0.4396 | 0.4821 | 0.4517 | 0.4626 | 0.4533 | 0.4854 | 0.454 | 0.4306 | 0.4261 | 0.4444 |
| J | 1 | 0.9805 | 0.922 | 1 | 1 | 1 | 0.9384 | 0.8716 | 0.8968 | 0.9292 |
| L | 0.4863 | 0.5638 | 0.6117 | 0.5544 | 0.5621 | 0.475 | 0.4976 | 0.5087 | 0.4861 | 0.5587 |
| M | 0.5677 | 0.5967 | 0.5716 | 0.5322 | 0.543 | 0.5317 | 0.542 | 0.4966 | 0.4617 | 0.4632 |
| N | 0.7013 | 0.6712 | 0.6635 | 0.6493 | 0.5949 | 0.6486 | 0.7065 | 0.621 | 0.6362 | 0.6358 |
| P | 0.9364 | 0.9525 | 0.9567 | 0.8991 | 1 | 0.9378 | 0.9075 | 0.8674 | 0.8446 | 0.872 |
| Q | 0.6839 | 0.7371 | 0.7761 | 0.8202 | 0.8554 | 0.865 | 0.8705 | 0.8499 | 0.8226 | 0.7594 |
| R | 0.5914 | 0.5592 | 0.5624 | 0.6172 | 0.5223 | 0.57 | 0.5722 | 0.5148 | 0.4549 | 0.5046 |
| S | 0.7178 | 0.683 | 0.6798 | 0.6669 | 0.817 | 0.749 | 0.6798 | 0.737 | 0.6661 | 0.6845 |
| Average by year | 0.6552 | 0.6661 | 0.6733 | 0.6724 | 0.6913 | 0.6751 | 0.6826 | 0.6350 | 0.6185 | 0.6270 |

**Table 5.** Efficiency results in BCC-I model, 19-year window width, for the period 2012–2020.

| | Years | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| **DMU** | **2012** | **2013** | **2014** | **2015** | **2016** | **2017** | **2018** | **2019** | **2020** | **Average by DMU** |
| A | 0.6004 | 0.5888 | 0.6076 | 0.6072 | 0.631 | 0.6334 | 0.6043 | 0.6689 | 0.6747 | 0.5745 |
| B | 0.6942 | 0.8591 | 0.8232 | 0.615 | 0.5195 | 0.601 | 0.6842 | 0.6519 | 0.5416 | 0.7436 |
| C | 0.789 | 0.7017 | 0.7169 | 0.7246 | 0.7424 | 0.7572 | 0.7635 | 0.7711 | 0.7357 | 0.7184 |
| D | 0.6353 | 0.8493 | 1 | 0.9935 | 0.98 | 0.9198 | 0.8825 | 0.9149 | 1 | 0.7710 |
| E | 0.462 | 0.4352 | 0.4555 | 0.4774 | 0.4822 | 0.4871 | 0.5012 | 0.5015 | 0.4689 | 0.4718 |
| F | 0.3487 | 0.4247 | 0.4338 | 0.4729 | 0.502 | 0.4752 | 0.4839 | 0.4727 | 0.4665 | 0.4671 |
| G | 0.8201 | 0.8411 | 0.8699 | 0.9178 | 0.9448 | 0.9681 | 1 | 1 | 0.9765 | 0.9317 |
| H | 0.4617 | 0.4892 | 0.5161 | 0.5276 | 0.5343 | 0.5508 | 0.5387 | 0.5037 | 0.4569 | 0.5284 |
| I | 0.4875 | 0.5116 | 0.4893 | 0.5554 | 0.5587 | 0.5574 | 0.5473 | 0.5326 | 0.3181 | 0.4783 |
| J | 0.8615 | 0.8133 | 0.8113 | 0.8251 | 0.8414 | 0.8525 | 0.9074 | 0.8885 | 0.9207 | 0.9084 |
| L | 0.5637 | 0.565 | 0.5542 | 0.592 | 0.6238 | 0.4985 | 0.7536 | 0.8734 | 0.8765 | 0.5897 |
| M | 0.4442 | 0.4362 | 0.4505 | 0.4232 | 0.4938 | 0.4827 | 0.5043 | 0.5025 | 0.4951 | 0.5020 |
| N | 0.6463 | 0.6717 | 0.6792 | 0.6919 | 0.7508 | 0.788 | 0.7897 | 0.8372 | 0.5686 | 0.6817 |
| P | 0.8536 | 0.7878 | 0.86 | 0.8816 | 0.9313 | 0.8889 | 0.8689 | 0.8758 | 0.8399 | 0.8927 |
| Q | 0.7389 | 0.7281 | 0.7423 | 0.8221 | 0.8289 | 0.8463 | 0.8938 | 1 | 0.9355 | 0.8198 |
| R | 0.4888 | 0.5776 | 0.6132 | 0.5909 | 0.6221 | 0.6413 | 0.7037 | 0.7161 | 0.6419 | 0.5823 |
| S | 0.6742 | 0.7106 | 0.6968 | 0.6944 | 0.7037 | 0.7345 | 0.7981 | 0.7494 | 0.6882 | 0.7122 |
| Average by year | 0.6218 | 0.6465 | 0.6659 | 0.6713 | 0.6877 | 0.6872 | 0.7191 | 0.7330 | 0.6827 | |

Table 6 represents the descriptive statistics for CCR-I and BCC-I models calculated for the 19-year window.

**Table 6.** CCR-I and BCC-I models' descriptive statistics, 19-year window.

| **DEA Model Used** | **CCR-I** | **BCC-I** |
|---|---|---|
| Number of DMUs | 323 | 323 |
| No. of efficient DMUs | 6 | 15 |
| No. of inefficient DMUs | 317 | 308 |
| Average efficiency score | 0.451532677 | 0.669030984 |
| Data standard deviation | 0.228316501 | 0.172904637 |
| Maximum efficiency score | 1 | 1 |
| Minimum efficiency score | 0.089442985 | 0.318144208 |
| Minimum efficiency score | 189 (58%) | 175 (54%) |

As the research results confirmed the research hypothesis, and the relative efficiency of nonfinancial economic activities was calculated, the authors ranked them according to the average efficiency for the 19-year period (Table 7). Entities operating in service sectors were ranked as the most efficient ones because they were generating higher revenues and profit with lower asset engagement and had a more favorable structure of financing sources, which directly affected ROA, activity, and solvency ratio. In the observed 19 years, the highest average relative efficiency was scored using G—wholesale, retail, and repair activities, as well as J—information and communication, and education. Activity G showed a steady efficiency level in the period 2002–2008, while for the period from 2009 to 2016 it showed a certain decline. The period from 2017 onwards showed efficiency rise and activity recovery. Activity J showed a similar trend as activity G, but there was no significant recovery trend after the efficiency drop in 2009. On the other side, the lowest average relative efficiency was achieved in F—construction; E—water supply and sewerage, waste management, and remediation activities; as well as I—accommodation and food service activities, which is the consequence of their low level of activity and profitability, and high indebtedness, in the analyzed period. The E and F activities were showing steady efficiency scores throughout the researched period, which implies that these activities are low-efficient and resilient. Activity I maintained the efficiency level throughout the entire observed period except in the year 2020 when a significant efficiency drop was noticed. This efficiency drop could be linked to global health and consequent traveling issues.

**Table 7.** The rank of economic activities' BCC-I model average efficiency for a 19-year period.

| Rank | Activities | Average Efficiency |
|---|---|---|
| 1 | G—Wholesale and retail trade; repair of motor vehicles and motorcycles | 0.93166 |
| 2 | J—Information and communication | 0.90844 |
| 3 | P—Education | 0.89273 |
| 4 | Q—Human health and social work activities | 0.81979 |
| 5 | D—Electricity, gas, steam, and air conditioning supply | 0.77095 |
| 6 | B—Mining and quarrying | 0.74356 |
| 7 | C—Manufacturing | 0.71836 |
| 8 | S—Other service activities | 0.71215 |
| 9 | N—Administrative and support service activities | 0.68167 |
| 10 | L—Real estate activities | 0.58974 |
| 11 | R—Arts, entertainment, and recreation | 0.58235 |
| 12 | A—Agriculture, forestry, and fishing | 0.57453 |
| 13 | H—Transportation and storage | 0.52838 |
| 14 | M—Professional, scientific, and technical activities | 0.50205 |
| 15 | I—Accommodation and food service activities | 0.47830 |
| 16 | E—Water supply; sewerage, waste management, and remediation activities | 0.47178 |
| 17 | F—Construction | 0.46707 |
| | Total Average | 0.66903 |

Finally, the authors tried to perform a simplified trend analysis by comparing the average CCR and BCC model's efficiency with gross value added (GVA) as a measure of economic activity. Figure 2 shows the average data set efficiency using the time compared to the Croatian GVA indexed to the year 2019. The GVA figures range from 0 to 1 to enable the comparison to the efficiency values. The GVA in the year 2019 is indexed as 1 (100%), and all other GVA values in different years were recalculated according to the year 2019. It is noted that GVA was gradually increasing from the beginning of the researched period up to the year 2008, then decreasing up to the year 2010, and keeping a steady level until the year 2014. From the year 2014 to the year 2019, the GVA was increasing. The next turnover point was the year 2019 because 2020 recorded the GVA decrease according to the pandemic.

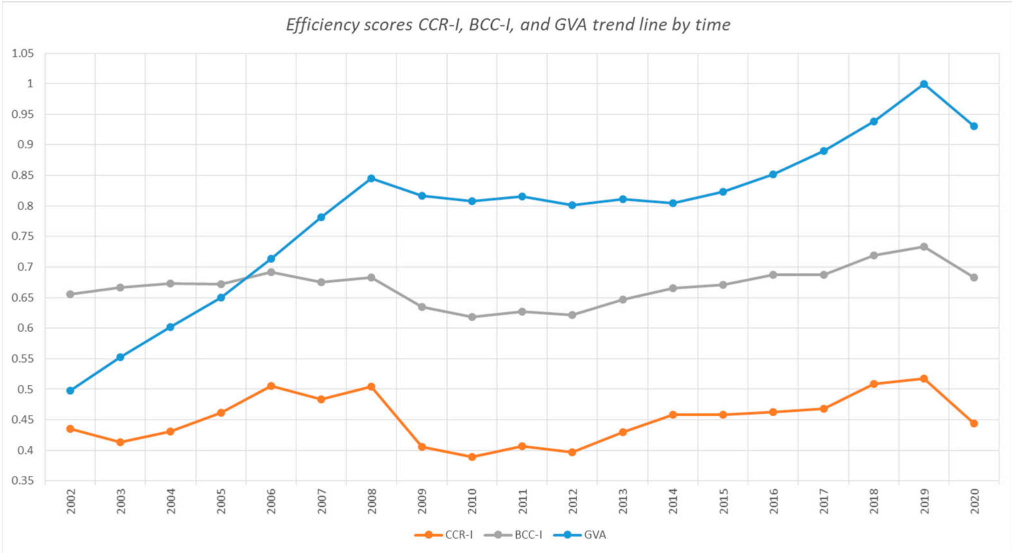


**Figure 2.** Efficiency scores CCR-I and BCC-I and GVA trend line using the time.

It is noted in Figure 2 that the trend lines of both used DEA models have a similar behavior. Namely, the local maximum values were recorded in the years 2006 and 2008. The efficiency score decline happened in the years 2009–2012, with a gradual efficiency increase up to the year 2019 when the maximum of the 19-year window width was achieved. The new efficiency decline happened in the year 2020 as a consequence of the pandemic.

Regarding Figure 2, it is interesting to notice that the average efficiency did not follow the GVA trend two years before the global 2008 crisis that influenced the Croatian economy, which started to suffer a year later. Namely, the economic activities rose strongly from the beginning of the period analyzed, while the efficiency had a slower increase up to 2006; afterward, they decreased as a consequence of lower asset turnover and higher debt through which the new assets were acquired in 2007. The relative efficiency slowly increased in 2008 as a consequence of rising asset turnover and stable ROA with rising debt. The strong impact of the global economic crisis was felt by the Croatian economy in 2009 and there should be 8 years to surpass the level of efficiency as well as the GVA level of the 2008 pre-crisis.

## 5. Discussion and Conclusions

The economic activities' relative efficiency was analyzed using five accounting ratios. ROA was considered a measure of efficiency and output variable in DEA methodology, while one representative of each group of solvency, productivity, and activity ratios, as well as human capital efficiency, were set as input variables.

Research results indicate that the DEA methodology can be used as an economic activity relative efficiency measurement tool. The suitability of the model was proven by identifying limited numbers of efficient DMUs. There were only six efficient ones out of 323 analyzed DMUs. They represented the benchmark for other DMUs that were considered inefficient. The data set behaved with constant returns to scale, making the BCC model representative and determining the efficient frontier of 15 DMUs as a benchmark to which all other 318 inefficient DMUs were striving. The model is input-oriented, which means that the decision makers should focus on a decrease in the input variables to achieve a level of output, i.e., ROA. Decision makers should take care that the activity and productivity ratio, as well as human capital efficiency, be "unscaled" or returned to their original values because they were scaled by using their reciprocals. The models allow decision makers to determine the level of change in input variables that are requested to achieve efficiency presented with the output variable. Afterward, decision makers should undertake activities that result in the improvement in solvency, productivity, activity, and/or human capital efficiency ratios.

This paper presents the possibilities of monitoring the relative efficiency of individual nonfinancial activities of the economy using the DEA methodology. It gives an insight into the most efficient activities in the Croatian economy during the 19-year period, which includes the period of economic expansion as well as contraction. The comparison of average relative efficiency for both CCR and BCC models with the trend of gross value added shows a mostly equal direction in trend, but with significant differences in the intensity of changes. This relation shows that economic expansion from 2002 to 2008 was followed by a smaller improvement in relative efficiency. The situation has changed since 2009 when the economy suffered a contraction followed by an expansion and then contraction again in the pandemic year. This period has been characterized by a closer relationship between relative efficiency and economic activity.

The average relative efficiency was calculated for 19 years and consequently, the nonfinancial activities were ranked, resulting in service sectors as the most efficient ones. The reason could lie in the fact that these activities generate revenues and profit with lower asset engagement and they finance the assets mostly from their own sources of financing.

Finally, the research results and the relative efficiency scores can be used as a benchmark for the companies operating in a particular nonfinancial activity. They could use the DEA methodology and approach applied in this paper with one output and four input variables to determine their level of relative efficiency. This is particularly the case for the benchmark in the long period analyzed in this paper. In future research, such a long 19-year period could be shortened so the DEA methodology could be employed on a shorter multi-year or even a yearly basis. This could make benchmarking and the whole analysis more detailed. The approach presented in this paper could use additional efficiency variables as well. In doing so, it could be reasonably expected that the introduction of other input and/or output variables would generate different results.

Further research could include the DEA models dealing with efficiency measurement over time such as the Malmquist Index model. There could be additional data included in the DEA calculation, depending on the data set behavior. The DEA Super-Efficiency and/or DEA Slack-Based Models could be used for the calculation results' fine-tuning. It could also be a challenging task to implement the Two-Stage DEA Model to compare to a particular company/institution within the nonfinancial activity.

The DEA methodology used in this paper can answer the level of improvements in input variables to improve the output variable, but does not give a solution on how to do that, which has been emphasized by Homburg. He showed that the information that DEA provides for inefficient DMUs is in general not sufficient to improve their activities. To improve inefficient activities, it is still necessary to analyze them in detail. Therefore, the main advantage of the proposed procedure is that it identifies critical activities without requiring too much information (Homburg 2001).

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