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Efficiency of Micro and Small Wood-Processing Enterprises in the EU—Evidence from DEA and Fractional Regression Analysis

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Abstract: Micro and small wood-processing enterprises represent the heart of European forest-based industries, being among the key drivers of economic growth in rural, mountainous, and poor regions. Their economic efficiency is of fundamental importance for their existence and the provision of income for the local population in rural areas. Data Envelopment Analysis (DEA) is used in the current research, which is a nonparametric, linear-programming-based approach that is commonly used to analyse the efficiency of organisational units. The main objective of this study was to investigate and evaluate the economic efficiency of micro and small wood-processing enterprises in EU countries and reveal the hidden inputs that facilitate efficiency generation. The economic efficiency evaluation was carried out on the basis of the official statistical data for the micro and small wood-processing companies in EU member states for the period 2015–2020 by performing a two-stage DEA analysis. The data used were standardised by value per employee. In addition to the first stage of DEA, a fractional regression probit and logit models with four contextual variables were used to reveal the influence of the hidden inputs in the model. The results showed that the micro and small wood-processing enterprises can be regarded as more scale-efficient than technically efficient entities. The only contextual variable affecting the economic efficiency was Investments per Person Employed, improving the efficiency by 2% per 1% increase in the investments.

Keywords: DEA; wood processing enterprises; small enterprises; fractional regression

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1. Introduction

The economic efficiency of wood processing enterprises is a key factor for their development in the current conditions of the increased global competition and developed supply chains. Micro and small enterprises (MSE) play an important role in local economies [1]. They are considered the main driver of economic growth, especially in rural areas [2]. These reasons make the research on growth, performance, and the factors behind them to be more topical in recent years. Many researchers have investigated the efficiency of wood-processing enterprises. Medvedev et al. [3] analysed wood-processing enterprises and revealed the role of the optimal use of wood resources for enhancing their efficiency. In similar research, Lähtinen [4] outlined that diversified tangible and intangible resources are the key tools for the improvement of the economic performance of wood-processing enterprises. Kocianová et al. [5] surveyed 3500 wood-processing family enterprises. The authors revealed that the implementation of complex strategies is vital for the performance and development of micro and small enterprises. The reuse, recycling, and upcycling of wood waste and by-products play an important part in these strategies. This is the reason many other authors [6–11] analysed the efficiency of the whole forest-wood value chain. Korkmaz [6] and Sporcic et al. [7] estimated the efficiency of forest enterprises. Korkmaz [6] assessed the selected efficiency determinants of 37 forest enterprises, such as the capital, production in value and quantity, number of employees, value-added, and others. Sporcic et al. [7] investigated determinants like revenues, labour, and expenditures. Kovalcik [8] compared the Slovak forestry efficiency to other European countries using determinants such as taxes, subsidiaries, and interests. Zhang et al. [10] and Han et al. [11] included as determinants (in the context of inputs in the methodology implemented) the trivial factors of production such as land, capital invested, etc. The approach regarding the determinants for wood-processing and furniture enterprises [12,13] is similar. In many studies [14–19], the so-called parametric approaches [18–25] have been used. This means that the exact functional form of the relation between determinants (factors) and efficiency is implemented. Sedivka [14] calculated the technical efficiency of 203 Czech sawmills using the Cobb–Douglass production function. Prasetiyo et al. [15] used the Pareto analysis, X-Y matrix, and process capability analysis. Sujova et al. [16] used ratios to estimate the efficiency of the investments in the entire Czech wood-processing industry. Sedliačiková et al. [18] provided a MANOVA analysis to outline the important managerial determinants of wood-processing enterprises' performance that influence the efficient financial model. The nonparametric methodologies in addition to relaxing the analysis of the exact functional form (technology) between inputs (determinants) and outputs of a certain production, define the stochastic frontier of efficiency. One of the most applied nonparametric linear approaches is Data Envelopment Analysis (DEA) [24] that "envelopes" the observed input and output data for each Decision-Making Unit (DMU) [26]. DEA is among the widely used methodologies when analysing the efficiency of wood-processing enterprises [27–34].

Second stage DEA with the implementation of some type of regression as a second stage is quite involved in the literature. Some are quite theoretical. Johnson and Kuosmanen [35] described many of the possible regression models after DEA like OLS of the convex nonparametric least squares (CNLS) regression. Ramalho et al. [36] profoundly discussed the applicability of different regression models for the second stage DEA, outlining the benefits of fractional regression. All these authors used Monte Carlo experiments. Two-stage DEA with regression as a second stage has many practical applications in the financial sector [37–41] or energy efficiency [42,43]. When considering the fractional or Tobit regression in the second stage of DEA, regarding the forestry of forest-based industries, there are few research studies. Diaz-Balteiro et al. [44] proposed logistic regression to determine the factors of influence on Spain's wood-based industry. Their model investigated 141 enterprises of various sizes and assumed the probability of an enterprise to be efficient as Binomial. This simplification of the assumptions needs to be developed by more concrete estimations through fractional or Tobit regression. Gutiérrez and Lozano [45] implemented fractional regression as a second stage for the European forest sector. They provide beneficial and profound research, but unfortunately only for forestry in Europe, and not for forest-based industries. He and Weng [46] use the fractional regression model for saw-milling enterprises in China. They used dummy variables for their regression and focused mostly on the managerial peculiarities of the efficiency, i.e., internal environment. Tan et al. [47] is close to the current research providing Tobit regression for a eco-efficiency analysis of regional forestry considering the external environment. As mentioned before, there is no exact research dedicated to the factors of economic efficiency in wood-processing enterprises, and there is also no research on micro and small wood-processing enterprises. This is the reason for current research to provide a good base for revealing the main factors of efficiency in EU's wood-processing enterprises, which will be valuable for different stakeholders in the wood supply chain.

2. Materials and Methods

2.1. Data Envelopment Analysis (DEA)

Data Envelopment Analysis (DEA) was developed by Charnes, Cooper, and Rhodes [48] with the so-called (CCR) model (CCR). Charnes et al. [49] stated that the efficiency of DMUs can be obtained from the maximum of ratio of weighted outputs to weighted inputs. Banker, Charnes, and Cooper [50] further developed DEA with a model (BCC) that is applicable in so-called variable returns to scale and estimates the pure technical efficiency of the enterprises. Coelli et al. [26] described DEA as a linear programming technique, which gives a linear frontier that "envelopes" the observed input and output data for different units being researched, which are called Decision Making Units (DMUs). The DEA approach includes various models, from the classic ones to more complicated ones like Slack Based Measurement [51,52]. The key principle of applying DEA is to maximise the efficiency rate. DEA estimates the efficiency scores of all DMUs by comparing the efficiency rate of each unit with that of the best performer. Cook et al. [53,54] and Zhu [55] pointed out that the main issue when using DEA is to preliminarily define the purpose of the estimation. In the current research, for the purpose of the first stage of DEA analysis, the input-oriented CCR (also called CRS—constant returns to scale) model was used, following the requirements set by Fernandes et al. [37] that this model does not overestimate the efficiencies of the larger DMUs. The model for CCR is the following:

$$\begin{array}{l} \min\theta_{CRS} \\ \sum_{j=1}^{n} \lambda_j x_{ij} \leq \theta x_{i0} \\ \sum_{j=1}^{n} \lambda_j y_{rj} \geq y_{r0} \end{array} \quad c \tag{1}$$

where λ_j are the individual scalars of each DMUj $j\epsilon[1, n]$, x_{ij} are the amounts of inputs of type i in DMU j, x_{i0} is the amount of i-th input of DMU0 under the efficiency estimation. The y_{rj} are the outputs of type r in DMU j, and the consequent y_{r0} for the DMU, which is being assessed. If the sum of lambdas (λ) equals unity ($\Sigma\lambda = 1$), then the model becomes BCC with variable returns to scale. The BCC efficiency is the so-called pure technical efficiency (PTE) and is usually denoted by BCC or VRS (θ_{VRS}). This model calculates the pure ability of the DEA inputs to transform into DEA outputs, taking into account the different scales of each DMU.

The scale efficiency (SE) is a very important indicator that combines CCR and BCC efficiencies. It is a proportion of CCR efficiency in the BCC efficiency. The model is as follows [24]:

$$SE = \frac{\theta_{CCR}}{\theta_{BCC}} \tag{2}$$

Ana Isabel Martins [56] stated that the independent variables in the regression model for the second stage might correspond to input variables used in the DEA model or including other variables. This can be quite questionable in the context of other research works. Simar and Wilson [57–59] write about the incontrollable variables, or environmental, until in their DEA model the variables are actually controllable. The meaning of the term "controllable" should also be considered. In the context of the DEA analysis, DMUs can control their inputs and outputs.

The selection of the inputs and outputs for the first stage (DEA analysis) is vital for further analysis with the regression model. Some of the most commonly used variables for inputs/outputs in research related to forestry and forest-based industries are given in Table 1.

As can be observed, the authors used very typical economic unit variables like revenues and expenditures. Some of the authors [13,33] used relative variables per the unit of measure as a capital or output value. This is a good approach for reducing the differences between each DMU, in this way making the comparison better and easier to interpret. The usage of the total amount of input/outputs is a trivial alternative that does not reduce the applicability of DEA, but the later analysis with the recommendations of DEA-proposed slacks is sometimes not quite applicable in the way the model proposes the reduction in inputs or increase in outputs.

Table 1. Selected research on DEA with some of their inputs/outputs.

Inputs	Outputs	Publication
Capital, production costs, employee costs, and total amount of employees	Amount of production, amount of sales, value added	Korkmaz [6]
Expenditures	Revenues	Sporcic et al. [7]
Compensation of Employees' fixed capital consumption, other taxes on production, interests, and rents paid	Total output of the forestry, other subsidies on production, and interest receivable	Kovalčík [8]
Labour, material, and overhead costs	Amount of wood-furniture produced in units	Sari et al. [12]
Fixed assets, factory area, staff numbers, and employee salary	Per capital output value, annual gross output value, and annual operating income	Ma [13]
Labour, material costs, and other costs	Revenues	Krišťáková et al. [27]
Employees, energy use per unit of output value, and fixed asset inputs per unit of output value	Wood-processing output value and man-made board output value	Zhang et al. [33]

Fernandes et al. [40] stated that consistent results can be reached by reducing the number of inputs and outputs compared to that of DMUs. They followed the 'rule of thumb' [60], which means that the number of DMUs under evaluation by DEA must be three times higher than the number of inputs and outputs. The same approach was selected in the current study, as it is widely used by many authors. The following variables (xi) were incorporated as inputs for DEA analysis:

Total purchases per employee (TPRCH). Costs of goods and services form a significant share of the costs of woodworking companies. Companies in each of the countries can be compared in terms of the amount of these costs per employee. In this way, the differences arising from the different numbers of personnel within the intervals defined by Eurostat for the size of small and medium-sized enterprises are removed. This indicator reveals the ability of companies to optimally plan their procurement.

Personnel cost per employee (PCOST). This input reveals the ability of companies in the countries being compared to provide the necessary remuneration for pooled labour resources. At the same time, it also shows the securities burden, which can affect economic efficiency.

Outputs for DEA were also estimated per employee. They were as follows:

1. Revenues per employee (REV). Revenue is a key indicator that characterises the ability of companies to carry out market transactions.
2. Value added per employee (VADDED). The main source of efficiency for wood-processing companies is their ability to add value. The higher added value per employee indicates the quality of the human resources used and the entrepreneurial skills of the managers. By means of added value, the prerequisites for some companies to be less efficient than others are revealed.

2.2. Fractional Regression Model (FRM)

Two stage DEA has been implemented by many authors [38,39,61–65], considering regression as a second stage. The fractional regression model was developed by Papke and Wooldridge [66]. According to Ramalho et al. [36], the FRM only requires a specification of the regression equation and type of the probability distribution, i.e., functional form. As Ana Isabel Martins [56] states in her research on FRM, it does not require transformations to the original data, as it is in the traditionalists' models like OLS or Tobit regression models, and allows for the direct estimation of the dependent variable. For these preliminary actions, Papke and Wooldridge also made a special note that their model did not need any ad hoc transformations. All described features of FRM make it very easily applicable and interpretable. The FRM is widely implemented with logit, probit, and the heteroskedastic probit function. The estimation procedure is based on the Bernoulli log-likelihood function [66]:

$$lnL = y_i ln\{G(x_i b)\} + (1 - y_i)\{ln[1 - G(x_i b)]\}, \quad (3)$$

where y_i is the dependent variable.The $G(x_i b)$ is a known nonlinear function [67], $0 < G(x_i b) < 1$. The b is the vector of coefficients of the covariates; x_i are explanatory variables.

The functional forms for the G(xib) used in the current research are:

$$\text{Logit: } G(x_i b) = \exp(x_i b)/\{1 + \exp(x_i b)\}, \quad (4)$$

$$\text{Probit: } G(x_i b) = \Phi(x_i b), \quad (5)$$

where $\Phi(x_i b)$ is a cumulative distribution function of a standard normal distribution

2.3. Variables for the Second-Stage Fractional Regression Analysis

As previously mentioned, many authors stated in their research that the second stage's variables in the regression model are contextual variables.

The variables used in the time series analysis, like covariates, are the following:

1. Gross domestic product (GDP) [37,47,64]. The GDP reveals the overall conditions of the economy in each studied country.
2. Harmonised index of consumer prices (HICP) (defined as inflation [40,64]). Inflation influences the share of expenditures for furniture, homes, etc., in the household's budget. Inflation, if higher, can be very dangerous from one side because consumers spend more on other goods and services with higher priority. On the other side, inflation can be a trigger for people to invest their money. In this study, we examine the influence of this variable.
3. Investment per person employed (approximate approach is used in [31,64] for all sectors of interest (IVP)—wood processing. This indicator reveals the overall investment dynamics in the sector regardless of the size of the enterprises. It reveals the innovativeness of the enterprises.
4. Index of Number of enterprises for all C16 sectors (ENTNUM). This variable provides information about expectations and the competition. The number of enterprises indirectly reveals the expansion. It is not in the meaning of the business cycle but of the understanding of economic conditions by the entrepreneurs after the annual improvement of the economy.

2.4. Data for the Analysis

In the current study, we used data from the Eurostat Structural Business Statistics Historical Data by Enterprise Size Class [68] for DEA inputs and outputs in the sector C16 "Manufacture of wood and of products of wood and cork, except furniture; manufacture of articles of straw and plaiting materials", Eurostat Structural Business Statistics Historical Data [69] for the "Investment per person employed" in the C16 variable. For the "Harmonised index or consumer prices" [70] and GDP, we used the National Accounts folder of the Eurostat database [71]. The period of research was 2015–2020, which is appropriate to reveal the recent and at the same time structural features of the efficiency of micro and small wood-processing enterprises. At the same time, the defined time period is relevant in terms of the availability of comparable data within the Eurostat database.

To achieve the objective of the current study, the following hypotheses were tested:

H1. *The efficiency of micro and small wood-processing enterprises is influenced by the interaction between GDP and the sector-specifics, technological advancements, and market dynamics, with the expectation that the effect is not always linear. Currently, research on the topic does not provide clear information on whether the increase in GDP leads to a positive effect on the efficiency of woodworking enterprises. There are many assumptions about this. It is hypothesised that GDP influences positively the micro and small wood-processing enterprises through the generation of more income. This is in line with the findings reported by Da Silva et al.* [64]*.*

H2. *The inflation rate (HIPC) influences the ability of the economic agents to purchase commodities like wooden materials, furniture, or housing. The relationship between HICP and efficiency is contingent on the extent to which HIPC impacts input costs, consumer demand for wood products, and the ability of enterprises to adjust pricing strategies in response to changing inflationary conditions. Some authors* [65] *used the purchasing power standards to reveal the ability of households and enterprises to purchase. It has not been tested in previous research on whether the inflation reduces the efficiency or whether it can have a positive impact in the short run. The current research has a task to assess that.*

H3. *The efficiency generated by increased investments per person employed are subject to the level of technological sophistication, skill enhancement, and innovation facilitated by these investments, and the relationship may cause increasing returns to scale or pure technical efficiency improvements. According to Diaz-Balteiro et al.* [45]*, Da Silva et al.* [64]*, and other, investments in R&D or any innovative activities have a positive influence on efficiency.*

H4. *The relationship between the number of enterprises and efficiency is contingent on market competition, regulatory environment, and the presence of complementary industries, suggesting that an optimal level of competition may exist that fosters efficiency improvements, beyond which diminishing returns are observed. The number of enterprises has an impact on efficiency levels. Da Silva et al.* [64] *estimated the negative influence of the trade freedom, and despite being insignificant in their model, it provides a clue that the competition can have an effect on the efficiency. Whether the competition has a negative impact in the short run or has a motivating effect on entrepreneurs to improve the efficiency is tested in this research.*

3. Results

3.1. Descriptive Statistics

The analysis of the DEA efficiency requires a profound study of inputs' and outputs' statistical features. They reveal the comparative position of each country before the efficiency scores estimation. The results for the descriptive statistics of inputs and outputs for EU member states in the period 2015–2020 are presented in Table 2.

Table 2. Average amount in euro per employee and variation of DEA inputs and outputs for the period 2015–2020.

Country	TPRCH		PCOST		REV		VADDED	
	Average Amount	Variation, %	Average Amount	Variation, %	Average Amount	Variation, %	Average Amount	Variation, %
Belgium	231,645.5	7.60%	42,550.58	2.74%	308,226.28	7.55%	77,109.16	13.15%
Bulgaria	22,024.36	5.12%	3808.019	14.78%	27,361.51	7.94%	7188.434	15.89%
Czechia	75,141.35	11.14%	11,924.06	15.40%	104,138.15	12.01%	31,287.16	12.59%
Denmark	120,904.3	10.79%	46,195.97	9.43%	180,376.28	11.10%	62,947.75	11.01%
Germany	84,170.28	6.84%	30,077.29	6.27%	132,561.80	3.64%	47,262.78	3.63%
Estonia	90,413.42	11.10%	15,053.14	12.30%	112,673.98	9.52%	24,223.99	11.97%
Ireland	100,088.9	12.82%	40,530.96	4.65%	158,446.84	9.69%	60,592.93	7.31%
Greece	77,306.84	13.95%	11,715.92	12.10%	90,243.05	14.81%	14,446.85	14.80%
Spain	92,430.95	5.11%	26,159.6	5.30%	126,925.96	5.00%	36,278.86	6.06%
France	117,996.4	18.85%	39,385.57	14.30%	167,944.21	16.80%	49,206.02	13.51%
Croatia	47,993.15	8.91%	9436.786	11.84%	59,581.79	7.54%	15,608.56	8.85%
Italy	128,534.4	3.95%	29,788.09	3.82%	180,587.31	3.77%	52,348.79	4.96%
Cyprus	45,620.9	6.90%	16,803.78	4.90%	75,087.36	6.85%	29,226.04	9.42%
Latvia	44,996.85	12.98%	7386.606	17.15%	57,383.50	14.30%	13,232.22	18.89%
Lithuania	29,951.19	16.17%	7723.088	18.14%	41,341.14	16.48%	12,194.75	19.50%
Hungary	37,445.33	9.83%	7155.067	11.60%	49,455.53	11.72%	12,525.39	18.99%
Netherlands	244,957.5	5.13%	57,875.63	10.74%	350,841.10	5.47%	108,709.6	8.04%
Austria	141,691.8	2.37%	37,213.83	4.91%	201,411.15	3.12%	61,228.8	5.94%
Poland	50,712.18	12.46%	7618.106	11.06%	68,673.89	8.76%	14,315.15	18.69%
Portugal	64,570.62	4.15%	14,582.28	5.41%	85,303.53	4.21%	22,119.7	7.24%
Romania	29,597.36	6.38%	5120.616	16.67%	36,326.12	8.55%	8425.515	31.17%
Slovenia	102,777.2	12.77%	19,909.61	16.70%	139,455.35	12.74%	37,941.55	12.27%
Slovakia	75,815.82	4.08%	8884.362	11.51%	93,868.74	4.21%	18,505.81	6.22%
Finland	197,969.5	7.08%	37,486.78	3.16%	247,110.58	6.97%	54,868.86	5.38%
Sweden	176,350.3	4.95%	45,461.04	2.83%	239,331.85	4.26%	66,221.07	4.93%
Average	97,244.26	8.86%	23,193.87	9.91%	133,386.28	8.68%	37,520.63	11.62%

The data included in Table 2 shows that revenues (REV) and expenditure on goods and services (TPRCH) were closely related to each other. The average variation of purchased goods and services for the studied population was 8.86%, and the variation of income was 8.68%. The correlation coefficient between the two variables is 0.99. This reveals that efficiency is hardly supported by the adaptability of inventory management to market fluctuations. This is something usual for micro and small enterprises which do not manufacture production series in large quantities. The variation of personnel costs (PCOST) was higher than that of revenues and purchases (9.91%). If such an input is not so strongly related to the output, it can endanger the efficiency. The correlation coefficient is 0.92, which means that the micro and small enterprises adapt their personnel annually. The output with the higher variation was value added (VADDED). The reason for that is not quite clear, but this result reveals the danger that can affect micro and small enterprises. For them, it is vital to have stability when adding value that facilitates their efforts for improvement. The correlation coefficient between REV and VADDED is 0.95.

For the research period, the trade with wood products in the meaning of revenues faced slight growth. Every year, the sales have increased by about 2.5% in comparison to the previous year. Only in 2020 was there a slight downturn. The output part of DEA provided good possibilities to the enterprises in order to gain efficiency. The production also faced a slight growth during the period of research. It raised every year by about 2.5%–5.9%. In terms of the difference of the trade, the production did not have a downturn in 2020. This revealed the expectations of small and micro wood-processing enterprises in the EU.

3.2. DEA Analysis

The results obtained for the DEA efficiency are presented in Table 3. The efficiency scores are given for each country and estimated with the respective descriptive statistics.

Table 3. DEA-CCR scores for combined efficiency (CCR) estimated by the model (1).

DMU	2015	2016	2017	2018	2019	2020	Average	Variation
Belgium	0.92	0.92	0.87	0.93	0.94	1.00	0.93	3.56%
Bulgaria	0.85	0.87	0.90	0.88	0.88	0.90	0.88	1.76%
Czechia	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.00%
Denmark	0.89	0.91	0.96	0.90	0.88	0.91	0.91	2.50%
Germany	0.96	0.97	0.98	0.97	0.95	1.00	0.97	1.59%
Estonia	0.92	0.90	0.89	0.86	0.86	0.91	0.89	2.33%
Ireland	0.96	1.00	0.94	0.98	0.96	1.00	0.97	2.10%
Greece	0.89	0.82	0.86	0.87	0.85	0.87	0.86	2.43%
Spain	0.88	0.89	0.90	0.89	0.88	0.89	0.89	0.73%
France	0.87	0.90	0.94	0.89	0.86	0.90	0.89	2.71%
Croatia	0.89	0.88	0.84	0.85	0.85	0.86	0.86	2.07%
Italy	0.95	0.96	0.94	0.93	0.94	0.96	0.95	0.83%
Cyprus	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.00%
Latvia	0.90	0.90	0.88	0.91	0.90	0.94	0.91	1.87%
Lithuania	0.91	0.91	0.91	0.91	0.89	0.92	0.91	0.78%
Hungary	0.90	0.89	0.86	0.95	0.96	0.94	0.92	3.61%
Netherlands	0.92	0.97	0.97	0.96	0.98	0.96	0.96	1.80%
Austria	0.93	0.94	0.92	0.93	0.94	0.95	0.93	1.06%
Poland	1.00	1.00	1.00	0.97	0.98	0.99	0.99	1.03%
Portugal	0.87	0.89	0.88	0.89	0.92	0.90	0.89	1.58%
Romania	0.88	0.85	0.78	0.88	0.90	0.92	0.87	4.93%
Slovenia	0.96	0.95	0.93	0.96	0.92	0.94	0.94	1.22%
Slovakia	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.00%
Finland	0.86	0.87	0.84	0.87	0.87	0.89	0.87	1.61%
Sweden	0.89	0.89	0.88	0.90	0.89	0.92	0.89	1.22%
Average	0.92	0.92	0.91	0.92	0.92	0.94	0.92	1.73%

The table shows that in general, the wood-processing enterprises in the studied countries were quite efficient. The efficiency scores of some countries were much higher than that in the previous research by Krišťáková et al. [27]. In the table, there are countries with very stable efficiency like the Czech Republic, Slovakia, Cyprus, Lithuania, and Spain, which are below the level of the average EU variation. Enterprises in the Czech Republic, Slovakia, and Cyprus are leaders in CCR efficiency. These are results based on the historical improvement of efficiency during the period of research. On the other side of efficiency are the wood-processing enterprises in Bulgaria, Romania, Greece, and Spain. They have a lower average efficiency and above-average variation. Here, the appearance of Finland is interesting. Enterprises in industrial giants like Germany and Italy are characterised by a lower efficiency than the leaders with above-average variation. Due to the narrower focus of the current research, particularly on micro and small enterprises, some of the results can differ from the other research. The results in Table 2 differ from those reported by Schmidt-Ehmcke [72] which placed Germany and Denmark on the top of the efficiency ranking. At the same time, the results obtained are in line with previous studies like Krišťáková et al. [27] that the Slovak wood-processing enterprises performed better than the Bulgarian ones in terms of CCR efficiency. The relations of the CCR efficiency can be revealed in Figure 1, with a comparison between efficiency scores and revenues. Costs are in high correlation with revenues, and determine revenues like sufficient variables for the comparison. They are inputs in the DEA model from one side and elements of the cost efficiency from another.

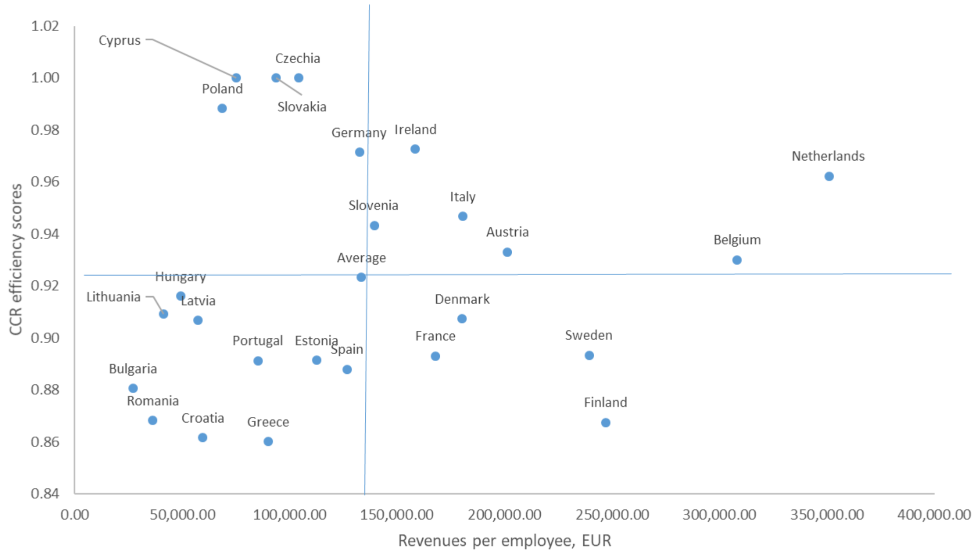

Figure 1. Scatterplot between CCR and the revenues per employee of the wood-processing micro and small companies in the EU member states for the period 2015–2020. The vertical line depicts the border of the revenues, and the horizontal one depicts average efficiency.

The figure shows that there were low-efficient wood-processing enterprises with low levels of revenue in Bulgaria, Romania, Greece, Croatia, Greece, Portugal, Spain, Estonia, Lithuania, Latvia, and Hungary. The average efficiency in these countries was 0.89 and the variation was 2.31%, which is higher than the average EU level. Enterprises with higher revenues than the average and lower efficiency are located in France, Denmark, Finland, and Sweden. Their efficiency was lower than the average for small and micro wood-processing enterprises in the EU. The usual relationship with higher revenues and high efficiency scores was determined for the wood-processing enterprises in Ireland, Italy, Austria Belgium, Slovenia, and the Netherlands. The excellent enterprises are in the quadrant with lower revenues and higher efficiency. Germany has the worst position there, and Czech Republic, Slovakia, and Cyprus are the best performers. The results can be additionally supported by the calculation of scale efficiency (SE). Table 4 presents the results for the scale efficiency scores obtained from model (2).

Table 4. Scale Efficiency scores from model (2).

DMU	2015	2016	2017	2018	2019	2020	Average	Variation	RTS
Belgium	0.92	0.96	0.87	0.94	0.94	1.00	0.94	3.70%	DRS
Bulgaria	0.85	0.87	0.90	0.88	0.97	0.90	0.89	3.73%	IRS
Czechia	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.00%	IRS
Denmark	0.93	0.95	0.96	0.94	0.91	0.94	0.94	1.46%	CRS
Germany	0.96	0.97	0.98	0.97	0.95	1.00	0.97	1.54%	IRS
Estonia	0.95	1.00	0.98	1.00	1.00	1.00	0.99	1.66%	DRS
Ireland	0.96	1.00	0.94	0.98	0.96	1.00	0.97	2.10%	IRS
Greece	0.95	1.00	0.97	0.98	0.98	0.99	0.98	1.56%	CRS
Spain	0.96	0.99	0.98	0.98	0.99	0.99	0.98	0.98%	IRS
France	0.95	0.97	0.99	0.95	0.94	0.97	0.96	1.61%	CRS
Croatia	0.97	0.99	0.98	0.97	0.97	0.97	0.97	0.66%	IRS
Italy	0.95	0.98	0.97	0.97	0.99	1.00	0.98	1.36%	DRS
Cyprus	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.00%	IRS
Latvia	0.96	0.97	0.97	0.96	0.96	0.97	0.97	0.49%	IRS
Lithuania	0.91	0.91	0.91	0.94	0.95	0.96	0.93	2.13%	IRS
Hungary	0.94	0.96	0.97	0.95	0.96	0.96	0.96	0.76%	IRS
Netherlands	0.92	0.97	0.97	0.96	0.98	0.96	0.96	1.80%	DRS
Austria	0.94	0.97	0.96	0.97	0.97	0.98	0.97	1.13%	DRS

Table 4. Cont.

DMU	2015	2016	2017	2018	2019	2020	Average	Variation	RTS
Poland	1.00	1.00	1.00	0.97	0.98	0.99	0.99	1.03%	IRS
Portugal	0.98	1.00	0.99	0.99	0.99	0.99	0.99	0.50%	IRS
Romania	0.90	0.92	0.88	0.92	0.92	0.93	0.91	1.78%	IRS
Slovenia	0.96	0.96	0.97	0.99	0.99	1.00	0.98	1.57%	DRS
Slovakia	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.00%	IRS
Finland	0.93	0.98	0.91	0.92	0.96	1.00	0.95	3.12%	DRS
Sweden	0.93	0.97	0.95	0.96	0.97	0.98	0.96	1.62%	DRS
Average	0.95	0.97	0.96	0.97	0.97	0.98	0.97	1.45%	IRS

The results present the higher-scale efficiency of the micro and small wood-processing enterprises in the EU member states in comparison with the determined CCR efficiency. This means that the scale is the main strength of these enterprises. When using DEA, it is common to obtain higher results for the scale efficiency, but in this case, the scale of the enterprises in the studied countries is a factor for their overall efficiency. In general, the returns for the scale of the EU micro and small wood-processing enterprises are increasing. This means that an increase in productivity surpasses the increase in costs. The role of the scale for wood-processing enterprises is better revealed in Figure 2.

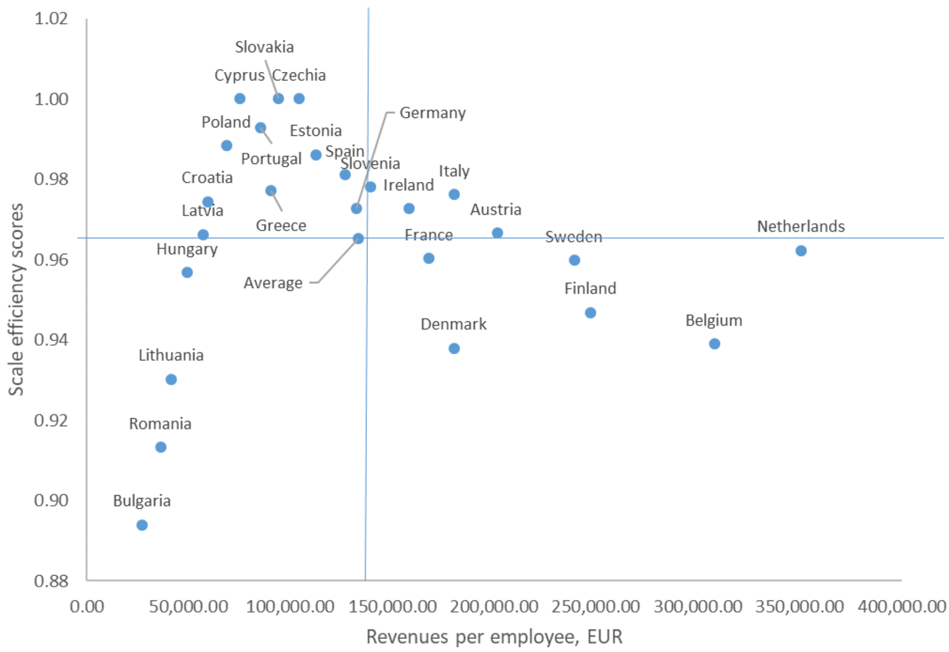

Figure 2. Scatterplot between scale efficiency and the revenues per employee of wood-processing micro and small companies in EU member states for the period 2015–2020.

The figure reveals that many enterprises in the low revenues quadrant with lower efficiency moved to the higher efficiency quadrant. This is a usual result according to other research studies [73]. The Bulgarian, Romanian, and Hungarian enterprises remained in the lower efficiency zone. The reason for that is the high pure technical efficiency. Otherwise, the scale efficiency leads, as in [7,8]. When the denominator of the model (2) was higher, i.e., BCC efficiency was better, the scale efficiency was not high. In the interval of the revenues per employee, up to 70,000–80,000 EUR per employee revenues, the tendency was for a constant increase in the scale efficiency. These enterprises rely on the scale to improve economic efficiency. All of these enterprises work in increasing returns to scale (IRS). This is probably the reason they focus mainly on scale efficiency but not to the same degree on pure technical efficiency (BCC). After the peak, composed of enterprises from Slovakia, the Czech Republic, and Cyprus, the trend is downward. This reveals that afterwards, the peak companies rely more on pure technical efficiency. This means that they have better capabilities to invest in newer and more productive technologies. Companies after the peak better allocate the inputs to outputs.

3.3. Fractional Regression

All the results are derived by separate calculations for CCR scores and BCC scores as dependent variables. Values of the CCR and BCC efficiency are calculated on an average basis for the entire period. The fractional regression analysis was made for probit (model (5)) and for logit (model (4)) models. Firstly, the analysis was made for the micro and small wood-processing enterprises and aft for the whole sector. The results of the fractional regression for the micro and small wood-processing enterprises are presented in Table 5.

Table 5. Results of cross-sectional analysis with two types of fractional regression by models (4) and (5).

Covariate	CCR-Dependent Coefficients in Each Model		BCC-Dependent Coefficients in Each Model	
	Probit	Logit	Probit	Logit
GDP	−0.00000010	−0.000000206	0.0000000	7.93×10^{-8}
HICP	0.0112011	0.0136995	0.1199848	0.260742
IVP	0.0022762	0.0035975	−0.0070483	−0.01579
ENTNUM	0.0000371 *	0.0000768 *	0.0000905	0.000192

* Statistically significant at $\alpha = 0.05$.

The results in the table reveal that the only significant factor for the micro and small wood-processing enterprises in the EU is the number of these enterprises. The first three hypotheses failed in this regression analysis. Neither the GDP, HICP, nor IVP influences the efficiency. Only the competition has an influence, but in the opposite way of the H4. The number of enterprises affected the efficiency. It drives enterprises toward efficiency and economies. The intense competition determines the wood-processing enterprises' production to be eco-friendlier and more sustainable, supporting the ongoing twin, e.g., digital and green transition of the industry in line with the circular economy principles [74]. The investments are not significant and this reveals that the enterprises tried to adapt their organisational and managerial capabilities to the external environment changes. This can be achieved by optimisation inside the micro and small enterprises. This optimisation did not include investments in technologies. This is why the IVP variable is not significant. The owners or entrepreneurs in wood-processing enterprises in the EU made decisions that mainly influenced the capacity. This is the reason models with CCR as dependent variables are significant and those with BCC are not. The results show that usual factors like R&D and FDI [31,45] do not influence small and micro enterprises in C16. This result is undesirable because it clarifies the strategy of entrepreneurs in this sector. It also reveals a problem with funding for these investments and the way the entrepreneurs obtain information about the available funding sources. The model in Table 4 was tested with a link test [74] that is called the Pregibon test [75] for model specification. According to this test, the dependent variable is regressed to fitted values of the initial fractional regression and to squared fitted values. If the squared values are significant, the test failed. The test revealed that the model is an unspecified p-value of the squared fitted variable, which is 0.006. After the test, only the ENTNUM variable remained in the model. The results are presented in Table 6.

Table 6. Results of the cross-sectional analysis with two types of fractional regression by models (4) and (5) for single variable ENTNUM—number of enterprises in the interval; 1–49 persons employed.

Covariate	CCR-Dependent Coefficients in Each Model		BCC-Dependent Coefficients in Each Model	
	Probit	Logit	Probit	Logit
ENTNUM	0.00003 *	0.0000634 *	0.0000267	0.0000594

* Statistically significant at α = 0.05.

The results reveal that the number of enterprises positively influences the CCR efficiency. It does not influence the pure technical efficiency. The marginal effect of the number of enterprises is 0.01, which means that one more micro or small wood-processing enterprise will probably improve the efficiency of the existing ones by 10%.

The fractional regression analysis of the whole C16 economic sector in the EU was performed in order to better understand and improve the analysis, and to highlight the specifics of the micro and small wood-processing enterprises. The results are presented in Table 7.

Table 7. Results of the cross-sectional analysis with two types of fractional regression by models (4) and (5) for the whole C16 sector in the EU.

Covariate	CCR-Dependent Coefficients in Each Model		BCC-Dependent Coefficients in Each Model	
	Probit	Logit	Probit	Logit
GDP	−0.000	−0.000	−0.000	−0.000
HICP	−0.023	−0.050	−0.077	−0.200
IVP	0.013	0.028 *	0.053	0.121 *
ENTNUM	−0.000	−0.000	−0.000	−0.000

* Statistically significant at α = 0.05.

The results provided in Table 7 reveal that the regressions with BCC as a dependent variable were correctly specified. According to the results obtained for the CCR efficiency, none of the selected variables were significant. This means that the scale of the enterprises in the whole C16 does not depend on the level of the economy, inflation, and competition in a particular moment. These are interesting results that reveal that the scale of the enterprises depends mostly on decisions that are not related to the macroeconomic conditions in each of the countries. The quality part of the efficiency is related to the pure technical part or BCC. The results for that efficiency reveal that the investments per person, IVPs, are statistically significant variables. Nothing influences the optimality of resource allocation better than investments. They are vital for micro and small wood-processing enterprises, but they do not influence them. IVPs are factors for all the sectors despite the micro and small enterprises. The enterprises should develop internal determinants like management quality and human resources, on the one hand, that can be a result of appropriate behavioural aspects [75]. On the other hand, it is right alternative for the production process [76–78]. The marginal effects of the IVP variable in the two models are calculated according to Ramalho et al. [76]. The estimated marginal effect of IVP in the probit model is 0.021, and in the logit model it is 0.02. These values mean that with one percent higher investments per person employed in the sector, the efficiency of the micro and small wood-processing enterprises rises by about 2%. This result reveals the importance of the investments. The results in Table 7 provide information for the main direction of the development set up by the medium-sized and big enterprises. This means that technologies are not in the focus of the entrepreneurs of small businesses in C16. Other authors [44,58] revealed that investments in the form of direct foreign investments can improve efficiency; however, these investments can be made in mid-sized and big enterprises. The results provided in Tables 5 and 7 show that the small and micro wood-processing enterprises are vulnerable. The results are interesting in the fact that the macroeconomic conditions do not have any effect on the C16 efficiency. This can support a hypothesis that the European woodworking sector is quite closed in its efficiency factors. Most of the hypotheses in the current research failed with the exception of H3 for the IVP influence. Proving this hypothesis reveals that the overall improvement and the strategic orientation of the wood-based sector is technologically determined. The micro and small enterprises, with their capacity adaptation, will probably accumulate capital for investments.

4. Conclusions

In this study, the total and pure technical efficiency of the micro and small wood-processing enterprises in the EU was determined using DEA and a fractional regression analysis. The results showed that the enterprises are efficient mainly due to their scale. Pure technical efficiency, which is the result of optimality in the distribution of resources, is a problem for a large number of enterprises. Four hypotheses were put forward, of which only one was proven. Hypotheses H1, H2, and H3 were not confirmed by the empirical study for the micro and small enterprises. Businesses with a small volume of sales can be very efficient, with Cypriot businesses being a typical example of this. At the same time, the research found that there are micro and small wood-processing enterprises in the EU that are sustainably efficient in terms of both pure technical and scale efficiency. Hypothesis H4 was proven for the micro and small enterprises. The H3 was proven for the whole C16. The investments are vital for micro and small wood-processing enterprises, but they do not rely on them. They use process improvements regarding the scale, but not the cutting-edge technologies that can improve pure technical efficiency. The investments in the sector push forward the technological improvement of the production processes and from there, economic efficiency. The results from the fractional regression analysis revealed that technologies in C16 were influenced by investments but the scale was not influenced. This is a very significant contribution resulting from the empirical analysis in this study. The regression with BCC as a variable revealed that for the period from 2015 to 2020, the enterprises in C16 tried to improve the technology and optimal resource allocation. The current study also revealed that there is an interval of the revenues per employee showing that the efficiency is maximised. For the EU, this interval should be between 70,000 EUR and 100,000 EUR. This is quite beneficial for industrial practice because it can be accepted as a threshold to switch between managerial measures for efficiency improvement and investments. The current study is limited to the implementation of CCR and BCC DEA models. Numerical results are based on data for the C16 economic sector under the investigated period. Fractional regression included four contextual variables. Further research is needed to clarify the influence of other external factors. Directions for future research can be complemented with a comparison between micro/small and large enterprises. The substantial difference, if it exists, between factors for efficiency in small and bigger companies will be clarified. The main limitation of the survey is that the achieved results are presented in a sample of woodworking enterprises operating only in the selected countries. The results are valid for the selected variables. Further research should include an efficiency analysis of different variables and the scale of enterprises. Future directions of research can also include regression analyses to further outline the differences between small and large enterprises within the wood-based sector in the EU.

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