ENTREPRENEURSHIP AND SUSTAINABILITY ISSUES
ISSN 2345-0282 (online) http://jssidoi.org/jesi/
2024 Volume 11 Number 3 (March)
http://doi.org/10.9770/jesi.2024.11.3(28)

Publisher
http://jssidoi.org/esc/home

PERFORMANCE MEASURING OF WOOD-PROCESSING MICROENTERPRISES THROUGH DATA ENVELOPMENT ANALYSIS: A CASE STUDY OF SLOVAKIA, POLAND, AND BULGARIA

Mariana Sedliačiková [1], Nikolay Neykov [2], Ján Dobrovič [3], Anna Šatanová [4], Mária Osvaldová [5], Mykola Palinchak [6]

[1,5]Technical University in Zvolen, Faculty of Wood Sciences and Technology, Department of Economics, Management and Business, Slovakia
[2]University of Forestry, Faculty of Ecology and Landscape Architecture, Department of Alternative Tourism, Bulgaria
[3,4]International School of Management Slovakia in Prešov, Slovakia
[6]Uzhorod National University, Faculty of International Economic Relations, Department of International Politics, Ukraine

E-mails: [1] sedliacikova@tuzvo.sk; [2] nneykov@ltu.bg; [3]dobrovic@ismpo.sk; [4]satanova@ismpo.sk; [5]xosvaldova@tuzvo.sk, [6]mykola.palinchak@uzhnu.edu.ua

Received 21 November 2023; accepted 11 March 2024; published 30 March 2024

Abstract. In the context of the role the wood-processing industry has in Slovakia, Poland, and Bulgaria, as an income provider in rural regions and contemporary challenges like inflation and intensive competition, there is a need to assess the performance of microenterprises using Data Envelopment Analysis (DEA), considering the crucial role these entities play in the regional economies. The aim is the creation of a more universally applicable DEA model for assessing the efficiency and performance of wood-processing microenterprises, taking into account the unique challenges and opportunities in Slovakia, Poland, and Bulgaria, defining the profile of optimal enterprise according to methodology in the current research, and indicating the leading problems in their performance. In their management, wood-processing enterprises respond to changes in the external environment, pursuing profit extraction in the competitive struggle. Comparisons with similar companies provide data on the economic efficiency of the sector and the gaps the enterprise needs to correct. Data from the Eurostat Structural Business Statistics were involved for 2011-2020. The current study used Data Envelopment Analysis (DEA), a nonparametric technique that allows enterprises to compare their efficiency frontiers and, from there, reveal their competitiveness. Thus, they can be arranged and measured, and the differences between the inputs and outputs of enterprises can be measured, as well as the efficiency. The results revealed that all the surveyed countries have a problem with the gross value added by a wood-processing micro-enterprise. Polish and Bulgarian enterprises have a problem with pure technical efficiency. Slovakian enterprises have excellent performance and can be used as a benchmark in optimizing the activities of Polish and Bulgarian enterprises.

Keywords: DEA; benchmarking; competitiveness; wood-processing industry; microenterprises

Reference to this paper should be made as follows: Sedliačiková, M., Neykov, N., Dobrovič, J., Šatanová, A., Osvaldová, M., Palinchak, M. 2024. Performance measuring of wood-processing microenterprises through Data Envelopment Analysis: A case study of Slovakia, Poland, and Bulgaria. *Entrepreneurship and Sustainability Issues*, 11(3), 408-422. http://doi.org/10.9770/jesi.2024.11.3(28)

JEL Classifications: C14, L73, L25

1. Introduction

Micro and small enterprises are among the main driving forces of the economy. The close connection between the entrepreneur and the strategic and stable development of his business is particularly prevalent in micro and small enterprises due to the great connection between personal survival and the company's performance. The

ISSN 2345-0282 (online) http://jssidoi.org/jesi/
2024 Volume 11 Number 3 (March)
http://doi.org/10.9770/jesi.2024.11.3(28)

forest industry uses resources from the forest regions of the countries. These regions are often not economically developed or rely mostly on forestry and related industries, mainly in wood-processing industry enterprises. Micro enterprises include employees of up to 9 persons. This creates the potential for using family business principles (Porfírio, 2020). This way, good performance in good economic efficiency provides welfare and better economic conditions to the local communities in the regions with developed wood-processing industries.

Micro enterprises function in an uncertain environment. The availability of sufficient information is vital to the performance level of the business activity (Kononiuk, 2022). It is challenging for micro and small enterprise entrepreneurs to get the necessary information to make the right decisions. Benchmarking, as an approach to compare different performance characteristics, can successfully support management decisions in many industrial enterprises (Zhang et al., 2017). It allows comparison with other enterprises and assessment of the state of a given enterprise relative to them. The wood processing industry includes the woodworking, furniture pulp, and paper industries, and the potential for comparison is interesting. The wood processing enterprises in the EU function in different environments, but they have many things in common. Comparison between different enterprises clarifies the possibility of using the best practices (Ruiz and Sirvent, 2016) for improvement. When comparing wood-processing enterprises between countries with Data Envelopment Analysis of the EU, it is possible to place an efficient frontier that can be used as a union target, regardless of the country specifics. DEA is a nonparametric mathematical methodology that includes many models in it. It was developed by Charnes et al. (1978) or the so-called CCR model, latterly complied by Banker et al. (1984) with their BCC model and developed in many directions by a lot of research until nowadays.

The current research is in line with studies like those of Guan et al. (2006), Baek and Lee (2009), Pastor and Aparicio (2010), Ruiz and Sirvent (2016), De et al. (2020), and others dedicated to benchmarking with DEA. This approach is quite suitable for performance measurement. Takouda et al. (2022) used DEA for performance analysis of financial inclusion in the West African Economic and Monetary Union's economies. Henriques et al. (2023) used Slack-based measurement of DEA to evaluate the performance of US and European exchange-traded funds. Ammirato et al. (2022) developed the performance measurement, further proposing innovative composite indicators to measure and control the performance of production processes. Tsolas (2020) measured performance differences between 62 precious metal mutual funds using weighted additive data envelopment analysis (DEA). Other authors like Dia et al. (2020), Neves et al. (2020), and Qayyum and Riaz (2018) used DEA for benchmarking and performance measurement in the banking sector in various ways, which proved the applicability of this approach. Horváthová et al. (2021) used DEA for benchmarking and performance measurement to provide necessary information for improving business performance. The current study provides an assessment through DEA efficiency scores of wood-processing micro-enterprises in Slovakia, Poland and Bulgaria and indicates the efficiency targets by comparing these three countries with the EU levels of efficiency as a benchmark. The study also evaluates the performance of wood-processing microenterprises in Slovakia, Poland, and Bulgaria across the research period. This article reveals the leading problems in their performance. The three countries were chosen to indicate the nature of the performance of two Central and one East European countries, which have had different genesiss in the last 10 years.

In this study, we gauge the enterprises' success in attaining managerial goals, utilizing their efficiency as a metric. The study's overarching question, formulated in alignment with its defined objectives, is: Can we discern the performance constraints of wood-processing enterprises in the examined Slovakia, Poland and Bulgaria through an assessment of efficiency?

2. Theoretical background

When comparing the wood-processing enterprises, the researchers used different methodologies and indicators as variables. Sedliačiková et al. (2016) analyzed the performance of wood-processing enterprises in financial controlling. For Performance Measurement Systems (PMS), the Key Performance Indicators (KPI) scale is very

ISSN 2345-0282 (online) http://jssidoi.org/jesi/
2024 Volume 11 Number 3 (March)
http://doi.org/10.9770/jesi.2024.11.3(28)

important (Hyránek et al., 2021; Mihalčová et al., 2021; Du et al., 2022; Ferreira and Silva, 2022; Bumba et al., 2023). The variables are based on a particular survey, which is valuable when a problem is profoundly studied in industrial enterprises. Michal et al. (2021) analyzed the performance of woodworking enterprises in the Czech Republic. They conducted a statistical comparative analysis of the Czech Republic and several other countries. It appeared that Poland is among the most effective countries in the sample. The authors used variables such as wooden raw materials for production and the final products in processed wood. Stojčić et al. (2019) investigated the effect of clustering on the wood-processing company's performance. They compared the EU28 members to Slovenia and Croatia. The variables in their methodology, which is parametric (a regression model), are unit costs, subsidiaries, market concentration, turnover, the productivity of labour, etc. The authors comment on the efficiency of the labour. They found that labour productivity is higher in clusters than in individual enterprises. This is a typical example of a parametric measure of labour efficiency by implementing ratios. When using parametric approaches, the variables are usually grouped according to the purpose of the estimation. In DEA this is not necessary. When using DEA, the usual variables are considered inputs and outputs. There is a practice that follows the main production inputs (Woodwell, 1998) in economics. One of the problems using DEA (called "pitfalls" by Dyson et al., 2002) is the so-called "rule of thumb" (Khezrimotlagh et al., 2021) that requires the number of the DMUs to be at least three times more than the sum of inputs and outputs. The outputs in many DEA studies also have many in common. Chen (2004), Hua et al. (2007) and Ning et al. (2018) used the total revenues along with other specific outputs according to their studies. Tsolas (2011) used the production quantity in natural units, such as tones. Some authors (De et al., 2020) use lean practices and sustainability-oriented innovations as outputs, but this is a particular case of DEA problem formulation. Many others (Baek and Lee, 2009) use trivial outputs as revenues and production value. Sedivka (2009) analyzed the technical efficiency of 203 sawmills in the Czech Republic. He used a parametric approach with a stochastic frontier and double logarithmic regression model for the Cobb-Douglas production function. The variables in the model are many and include direct costs, labour costs, the value of timber, and times for production operations. Sedivka (2009) found that direct costs and the value of soft timber hurt the efficiency of the investigated sawmills. Trigkas et al. (2012) used DEA to analyze the efficiency of 17 furniture and wood-processing enterprises. They implemented the causally related inputs like innovation costs and revenues (sales) as outputs. The study's results revealed higher efficiency after introducing innovations in their products and processes. Salehirad and Sowlati (2005) investigated the performance of 82 sawmills in Canadian British Columbia. They used an output-oriented DEA CCR model (Charnes et al., 1978). For inputs, the authors implemented some employees into the model logs and, as outputs, lumber and chips. This is a way to utilize the DEA model without considering expenditures or prices. Results of the study showed that the mills perform well in scale efficiency but have shortages in pure technical efficiency. The authors point to the low labour productivity as the main reason for this. For this reason, using naturally measured inputs/outputs in DEA, like m3, tones, and kilograms, can be very beneficial when assessing labour productivity. This is not possible when wood-processing enterprises produce different products. Sari et al. (2018) calculated the DEA efficiency of 10 furniture enterprises in Indonesia. They used labour as input as well as electricity and other costs. The productivity of labour appeared to be vital for the total efficiency level. Kovalčík (2020) used DEA for performance analysis of Slovak forestry in some forest regions in the country. He discovered that the efficiency of forestry hardly depends on outsourcing the forest activities. This interesting result involves the costs for services and outlines their role in efficiency. The same authors (Kovalčík, 2020) and Gutiérrez and Lozano (2020) made cross-country efficiency comparisons of forestry through the DEA. The research of Gutiérrez and Lozano covered 29 countries, including Bulgaria and Slovakia. Kovalčík analyzed 22 countries and covered indicators for entire forest sectors in each studied country. Korkmaz (2011) and Šporčić et al. (2009, 2014) used a nonparametric approach with CCR and BCC DEA to calculate the efficiency of forestry units at the level of enterprises. They combined inputs and outputs measured in value and quantities. This very beneficial property of the models is not always applicable in parametric techniques. Kropivšek and Grošelj (2019) analyzed by DEA the financial performance of sectors C16 "Manufacture of wood and of products of wood and cork, except furniture; manufacture of articles of straw and plaiting materials" and C31 "Manufacture of Furniture", through window analyses in which every sector is threatened as different DMU in each year. In the scientific literature, efficiency and competitiveness are considered common phenomena. Villaverde et al. (2020) directly associate efficiency with the competitiveness of wood enterprises and state entities. Lundmark (2021) used DEA and other approaches to estimate the competitiveness of Swedish forest regions. Charles and Zegarra (2014) and Martin et al. (2017) narrowly used DEA for competitiveness estimation.

ISSN 2345-0282 (online) http://jssidoi.org/jesi/
2024 Volume 11 Number 3 (March)
http://doi.org/10.9770/jesi.2024.11.3(28)

Summarizing some of the research based on the problem of forest-based industries and forestry as an actor in the wood supply chain in the current study provides a comparative table outlining some of the significant research gaps that can be addressed (Table 1).

Table 1. Comparative table of studies related to the problems of the present study

Study	Methodology	Observed indicator	Factors of influence	Application	Gaps
Stojčić et. al. (2019)	Regression-based	Labour productivity, Firm size, Sales revenues, Export propensity, Export performance, Wage premium, High growth firm	Unit labour costs (%), Unit material costs (%), Market concentration, Urbanization economies, Localization economies	Analysis of wood-processing clusters performance	There is no efficiency estimation and microenterprises analysis by different indicators
Michal et al. (2021)	"Black-calculation", various statistical indicators	Sales, value-added and income tax per one cubic metre, roundwood, chips and pulpwood	ROE, length of employment of the certification systems in the companies	Analysis of wood-processing enterprises in the whole NACE C16 sector	Lack of microenterprises distinguished analysis, efficiency is contextually measured
Kovalčík, M. (2018)	DEA CCR and BCC	Efficiency of forest enterprises	Inputs: Compensation of employees, fixed capital consumption, other taxes on production, interests, and rents paid Labour, material and overhead costs Outputs: Total output of the forestry, other subsidies on production and interest receivable	Efficiency of Slovak forestry in comparison to other European countries	There is not considered the specifics of the efficiency according to the enterprise size
Sari et al. (2018)	DEA CCR	Efficiency of small and medium-sized enterprises	Inputs: Labour, material and overhead cost Outputs: The amount of wood furniture produced in units, s	Assessing the efficiency of small and medium-sized wood-furniture enterprises: a case study	Lack of direction of enterprises to achieve improvements
Zhang et al. (2023)	DNSBM	Carbon emissions efficiency of China's provinces	Inputs: Labour, capital, energy per unit of output. Outputs: Wooden raw materials, wood-processing output, carbon emissions	Carbon Footprint Assessment and Efficiency Measurement of Wood Processing Industry Based on Life Cycle Assessment	Province level of analysis, no enterprise's recommendations

Source: own processing

Table 1 shows that the studies related to the issues of enterprises in the forest industry consider generalizing indicators for a sector or enterprises that do not lead to specific recommendations, with a high practical orientation. At the same time, micro-enterprises do not fall into the main focus of research, but they are leaders in the entrepreneurial ecosystem of the studied countries.

While existing literature employs various methodologies and indicators to assess the performance of wood-processing enterprises, there is a lack of standardization or consensus on the specific set of inputs and outputs

ISSN 2345-0282 (online) http://jssidoi.org/jesi/
2024 Volume 11 Number 3 (March)
http://doi.org/10.9770/jesi.2024.11.3(28)

considered in DEA analyses. Each study uses different combinations of inputs (such as labour and capital) and outputs (like total revenues and quantity of production) based on the context of their research. The research gap appears in establishing a standardized and comprehensive set of inputs and outputs tailored explicitly to the wood-processing microenterprises. The aim is to create a more universally applicable DEA model for assessing the efficiency and as a prerequisite for the performance of wood-processing microenterprises, considering the unique challenges and opportunities in Slovakia, Poland, and Bulgaria. By developing a standardized set of inputs and outputs, the research can contribute to the comparability and generalizability of DEA results across different enterprises.

3. Materials and methods

In the current research, the implemented methodology is based on the classical DEA models (CCR – Charnes, Cooper and Rhodes, and BCC – Banker, Charnes and Cooper) and some additional indicators that reveal different aspects of efficiency. In CCR models, the DMUs (Decision Making Units) are accepted without consideration of their scale, until in BCC models, the scale of each DMU is taken into account, and the model calculates the pure technical efficiency scores. The current study uses an in-put-oriented DEA model as it emphasizes improving efficiency by minimizing input usage while keeping outputs constant. This aligns with identifying areas like wages, personnel, or purchases of goods where microenterprises can enhance their performance by using resources more effectively.

Mathematical expressions of the DEA CCR input-oriented model are following (Charnes et al., 1978; Banker et al., 1984):

$$\min \theta$$

$$\sum_{j=1}^{n} \lambda_j x_{ij} \le \theta x_{i0} \qquad (1)$$

$$\sum_{j=1}^{n} \lambda_j y_{rj} \ge y_{i0}$$

$$\lambda_j \ge 0, \forall j$$

where λj are the individual scalars of each DMUj j϶[1, 25], x_{ij} are the amounts of inputs of type i϶[1, 3] in DMU j, xi0 is the amount of i-th input of DMU_0 being under efficiency estimation. The yrj are the outputs of type r in DMU_j, and the consequent yr_0 for the DMU_0 is being assessed. If the sum of lambdas (λ) equals unity (Σλ=1), then the model becomes BCC with variable returns to scale. The BCC efficiency is the pure technical efficiency (PTE), also called BCC or VRS (θ_{BCC}).

Estimating improvements in the inputs are made through well-established and explained slack literature (Banker, 1989). The expressions for that are the following:

$$\sum_{j=1}^{n} \lambda_j x_{ij} + s_i^- = \theta x_{i0}$$

$$\sum_{j=1}^{n} \lambda_j y_{rj} - s_j^+ \ge y_{i0} \qquad (2)$$

$$s_i^-, s_j^+ \ge 0$$

where s_i^- denotes the input slacks, s_j^+ denotes output slacks. If the input slack is not zero for DMU_0 than it can be subtracted from the input i and if any output slack is not zero it can be added to DMU's j output.
The scale efficiency (SE) is a combines the CCR and BCC efficiencies. It is a proportion of CCR efficiency in the BCC efficiency. The expression of SE is as follows (Bielik and Rajčániová, 2004):

$$SE=\theta_{CCR}/\theta_{BCC} \qquad (3)$$

ISSN 2345-0282 (online) http://jssidoi.org/jesi/
2024 Volume 11 Number 3 (March)
http://doi.org/10.9770/jesi.2024.11.3(28)

where θ_{CCR} is the constant returns to scale DEA efficiency of model CCR and θ_{BCC} is the constant returns to scale DEA efficiency of model BCC. If SE<1, the DMU_0 is scale inefficient. The returns to scale assessment in the current study is provided by the sum of lambdas following the research of Banker et al. (2011).

The selection of Bulgaria, Poland, and Slovakia is based on the economic significance of the wood-processing industry in these countries, the regional impact of microenterprises, the contemporary challenges they face, and the aim to create a universally applicable DEA model that considers unique challenges and opportunities in each country. The comparative analysis enhances the understanding of efficiency and performance in the wood-processing sector across different national contexts. These countries travelled their way after the economic system change in 1989. The analysis in the current research shows how the wood processing enterprises dial with the efficiency under contemporary conditions. The analysis is made using two different research lines, according to the formulation of the DEA problem. The first direction or line of research is benchmarking the Polish, Slovakian and Bulgarian microenterprises with those in other EU countries. The DMUs include the EU countries with their data for microenterprises in economic sector C16 "Manufacture of wood and of products of wood and cork, except furniture; manufacture of articles of straw and plaiting materials". In this way, the efficient EU microenterprises define the efficient frontier. The second direction is based on the efficient frontier defined by the years or windows (Jia and Yuan, 2017) of the best performance of microenterprises in each country. This analysis compares the microenterprises to their most efficient year during the research period.

Authors that investigate the efficiency of enterprises use different inputs and outputs. Kovalčík (2018) used compensation for employees' fixed capital consumption, other taxes on production, interests, and rents paid for the whole of Slovak forestry. Korkmaz implemented DEA with Capital, Production costs, Employee costs, Total amount of employees again for the entire set of enterprises. Sedivka (2009) used a set of variables close to those used in the current research but didn't use the DEA model. Some authors used labour and capital invested (Hua et al., 2007; Yang et al., 2016; Tsolas, 2011; Zhang and Xu, 2022; Ning et al., 2018). This practice follows the main production inputs (Woodwell, 1998) in economics. There are many approaches in inputs/outputs selection. Still, in the current research, the simplicity of interpretation and applicability in practice provoked the choice of variables used in the current study. The inputs for both lines of research are the following:

- Wages and Salaries per enterprise. When comparing microenterprises from different countries, excluding the national tax and social security features is valuable. That is why the Wages and Salaries data are more applicable than labour costs.
- Total Purchases of Goods and Services per enterprise. The value of these costs defines the risks for value added. Their reduction will ensure the capabilities of the microenterprises to be efficient.
- Number of persons employed per enterprise. This essential input reveals the productivity of labour in the post-estimation analysis.

For the output, Value Added at Factor Costs per enterprise is used. Whatever the microenterprises do, their ability to add value is the most important to them. That was the reason for choosing this indicator as the output. The final results of the comparison with DEA are the optimal values of the inputs and outputs. They are calculated by comparison with benchmarks. The benchmarks in the study are the following:

- The best performers of the EU countries (DMUs in this case). The efficient DMUs with $\theta=1$ and zero slacks are benchmarks for other DMUs with $\theta<1$. These benchmarks change every year according to the optimal lambdas.
- The average EU DMU. This benchmark, proposed in the current study, can compare the three countries with the average EU level. This is the standardized wood processing microenterprise involved in the study as a DMU.
- The best annual performance of the microenterprises separately in each country. Here, the DEA calculates an optimal solution of (1) and puts optimal lambdas to the years with the best performance. This benchmark compares the enterprises with themselves, not considering the performance of the European Union members. In this case the indexes are $j\in[1, 10]$ and $i\in[1, 3]$.

Data for the current study are delivered from the Eurostat database Structural Business Statistics, Industry by employment size class (EUSBS, 2023); Table 1 presents the wages and salaries per enterprise in the three studied countries and the average values for the other included as DMUs countries from the EU. They are 24

ENTREPRENEURSHIP AND SUSTAINABILITY ISSUES
ISSN 2345-0282 (online) http://jssidoi.org/jesi/
2024 Volume 11 Number 3 (March)
http://doi.org/10.9770/jesi.2024.11.3(28)

(denoted as EU24), because Ireland, Luxembourg and Malta are excluded from the analysis. They have many zero values and this misleads the results.

Table 2. Data for the DEA analysis

	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020
Wages and Salaries, thousands of EUR, per enterprise										
BG	3.19	3.59	3.85	4.39	4.95	5.42	5.57	6.29	6.65	6.89
PL	5.26	5.05	5.49	5.75	6.84	6.74	6.93	6.42	6.63	6.97
SK	1.60	1.34	1.42	2.01	2.12	2.16	1.94	2.58	2.98	2.73
EU24	19.83	19.77	18.74	18.57	19.42	19.58	19.42	19.13	20.61	21.68
Costs for goods and services, thousands of EUR, per enterprise										
BG	31.80	35.16	37.52	38.90	51.25	53.62	47.36	53.88	47.41	51.79
PL	64.96	72.75	77.25	57.66	61.18	57.11	55.97	85.67	87.86	78.20
SK	17.45	18.41	31.92	39.40	34.21	38.84	41.69	50.31	43.87	41.11
EU24	103.40	101.75	101.03	103.31	105.47	109.29	113.17	110.85	108.74	110.57
Persons employed, number per enterprise										
BG	3	3	3	3	3	3	3	3	3	3
PL	2	2	2	2	3	3	2	2	2	2
SK	1	1	1	1	1	1	1	1	1	1
EU24	2	2	2	2	2	2	2	2	2	2
Value added at factor cost, thousands of EUR, per enterprise										
BG	3.23	3.47	3.02	3.94	4.39	4.65	4.90	5.11	5.63	6.00
PL	6.08	6.94	6.30	7.45	5.69	5.74	3.36	9.11	10.63	9.05
SK	10.79	9.27	7.94	7.71	7.79	7.29	7.30	7.98	9.04	6.93
EU24	42.98	42.41	39.65	40.61	42.18	42.86	42.29	46.47	47.41	47.60

Source: EUSBS (2023)

The table illustrates an exceptionally high average level for the EU when compared to the surveyed countries. It is worth noting that Slovakia exhibits remarkably low wage costs, and in recent years, Bulgaria has been progressively approaching the levels observed in Poland. The overall trends are predominantly positive, except for the observed decline in recent years among Polish micro-enterprises.

The data in Table 1 indicate that costs for goods and services in Polish micro-enterprises closely align with the average EU24 level. Bulgarian enterprises, on the other hand, exhibit higher costs for goods and services compared to their Slovakian counterparts. Trends are notably positive for Bulgaria, Slovakia, and the EU24, while costs in Po-land demonstrate considerable instability. These fluctuations can potentially lead to a loss of efficiency for Bulgaria and Slovakia, though the impact on Polish enterprises remains unclear. As depicted in Table 2, Bulgaria leads in the number of persons employed among the studied countries. Bulgaria demonstrates a slight positive trend up to the EU24, while Poland experiences negative trends. Slovakia maintains a stable number of C16 microenterprises. Results further reveal that the output of the surveyed countries significantly lags behind the EU24 level, with Slovakia showing a negative trend. Bulgaria and the EU24 display positive and comparatively stable tendencies. Polish enterprises, although lacking a stable trend, exhibit a slightly positive trajectory. A comparison of input and output figures highlights the endangered efficiency in the surveyed countries, with a substantial difference from the EU24 level.

ENTREPRENEURSHIP AND SUSTAINABILITY ISSUES
ISSN 2345-0282 (online) http://jssidoi.org/jesi/
2024 Volume 11 Number 3 (March)
http://doi.org/10.9770/jesi.2024.11.3(28)

The software for the DEA analysis used in the current research is Stata Version 14.0.

4. Results and discussion

The initial outcome involves a static analysis of the efficiencies in the three countries. The benchmarks are set by the most efficient countries within the EU, with the EU24 serving as the benchmark for the average EU efficiency level. The EU24 represents the average DMU for EU 27 countries, excluding Ireland, Luxembourg, and Malta, due to their lack of records in the database, potentially distorting the results. Throughout the period, the best performers varied each year. Notably, the efficient countries, specifically C16 microenterprises within each country, averaged over the period, include the Czech Republic, Netherlands, and Sweden for BCC efficiency, and only the Netherlands for CCR efficiency. The outcomes of benchmarking the investigated countries against the average EU level (EU24) are summarized in Table 3.

Table 3. Average efficiency scores and their standard deviation – σ

	CCR	σ	BCC	σ	SE	σ
SK	0.79	0.15	0.89	0.09	0.89	0.10
PL	0.52	0.10	0.55	0.10	0.93	0.10
BG	0.49	0.08	0.56	0.06	0.88	0.13
EU24	0.74	0.04	0.76	0.03	0.98	0.03

Source: own research

The findings presented in Table 3 indicate that Slovakia demonstrates the highest technical efficiency (θCCR=0.79) among micro-enterprises in the C16 sector, followed by Poland (θCCR=0.52), while Bulgaria exhibits the lowest performance (θCCR=0.49). Slovakian enterprises outperform the average EU microenterprise, attributed to their remarkably high pure technical efficiency θBCC=0.89, surpassing the EU24 score by 0.13 points (θBCC=0.76). This outcome underscores the adeptness of Slovak enterprises in effectively converting costs of wages and goods and services into gross added value. However, the scale poses a challenge for Slovakian enterprises, as their scale efficiency (SE=0.89) is lower than that of the EU24 (SE=98). This indicator suggests that within the EU24, microenterprises in the C16 sector exhibit superior scale efficiency. Slovakian enterprises also exhibit less stable efficiency than the EU24, with standard deviations of σ=0.15 for CCR, σ=0.09 for BCC, and σ=0.10 for SE. Polish enterprises face challenges with pure technical efficiency, scoring θBCC=0.55, significantly below the EU24 benchmark (θBCC=0.76). Polish enterprises exhibit evenly unstable efficiency across all types, with a standard deviation of σ=0.10. Bulgarian enterprises grapple with very low scale efficiency (SE=0.88). An intriguing phenomenon arises, indicating that stable low efficiency scores are more problematic than instability itself. Bulgarian enterprises record the lowest technical efficiency scores (θCCR=0.49) alongside high stability, with σ=0.08 for CCR and σ=0.06 for BCC, signifying sustained low efficiency in pure technical and technical efficiency. Scale efficiency exhibits high instability (σ=0.13) coupled with low efficiency scores (SE=0.88). For all the countries, the efficiency scores annually are presented in Table 4.

Table 4. Efficiency scores for each year of the research period

	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020
Poland										
CCR	0.46	0.56	0.50	0.67	0.46	0.50	0.29	0.52	0.64	0.56
BCC	0.50	0.59	0.50	0.77	0.46	0.50	0.44	0.52	0.70	0.56
SE	0.93	0.96	0.99	0.87	1.00	1.00	0.66	0.99	0.92	0.99

ISSN 2345-0282 (online) http://jssidoi.org/jesi/
2024 Volume 11 Number 3 (March)
http://doi.org/10.9770/jesi.2024.11.3(28)

Slovakia										
CCR	1.00	1.00	1.00	0.86	0.75	0.68	0.72	0.62	0.67	0.61
BCC	1.00	1.00	1.00	0.88	0.83	0.82	0.88	0.76	0.76	0.92
SE	1.00	1.00	1.00	0.98	0.89	0.83	0.82	0.82	0.89	0.66
Bulgaria										
CCR	0.33	0.42	0.44	0.55	0.45	0.47	0.56	0.47	0.59	0.62
BCC	0.55	0.52	0.61	0.59	0.45	0.47	0.57	0.52	0.65	0.63
SE	0.60	0.81	0.72	0.94	0.98	1.00	0.98	0.92	0.91	0.99
BCC-EU24	0.74	0.70	0.79	0.78	0.80	0.76	0.73	0.75	0.75	0.80
SE-EU24	1.00	1.00	0.98	0.99	0.99	0.97	0.97	0.89	0.98	0.99

Source: own research

The presented results provide a broad view of which DMUs are efficient without differentiating them into "strongly" and "weakly" efficient (see Cooper et al., 2007). Table 4 illustrates that Slovakian enterprises exhibited scale efficiency with SE=1 and BCC=1 in 2011, 2012, and 2013. However, both efficiencies experienced a decline after that. Despite these negative changes post-2012, pure technical efficiency surpassed the average EU level (EU24) in 2017 and 2020. The SE levels post-2012 were lower than those of the EU24, with an additional drop in scale efficiency in 2020. Throughout the period, C16 microenterprises in Slovakia made decisions aligned with their performance to pure technical efficiency in the EU, but not in scale. Slovakian microenterprises are working under increasing returns to scale with $\Sigma\lambda=0.83$ (according to the interpretation of Banker et al., 2011), indicating a positive trend.

In contrast, Polish enterprises achieved scale efficiency (SE=1) in 2015 and 2016. Fluctuations in 2014 and 2019 led to instability ($\sigma=0.10$), as presented in Table 3. The results of the comparison of annual performance and efficiencies are presented in Table 5. This is the second line of research, as was described before. Following the formula of Yang and Chang (2009), the number of windows is 10 (10 years with 1 year width of the window).

Table 5. Results of DEA analysis using time windows as benchmarks for each country

	Slovakia			Poland			Bulgaria		
	CCR	BCC	SE	CCR	BCC	SE	CCR	BCC	SE
2011	1.00	1.00	1.00	0.76	1.00	0.76	1.00	1.00	1.00
2012	1.00	1.00	1.00	0.86	1.00	0.86	0.98	0.99	0.99
2013	0.81	0.97	0.84	0.72	0.98	0.73	0.81	0.99	0.82
2014	0.70	0.90	0.77	1.00	1.00	1.00	0.95	0.99	0.96
2015	0.70	0.90	0.78	0.72	0.96	0.76	0.96	0.98	0.98
2016	0.67	0.91	0.73	0.78	1.00	0.78	0.94	0.96	0.98
2017	0.68	0.93	0.73	0.47	1.00	0.47	0.97	0.97	1.00
2018	0.71	0.90	0.80	0.89	1.00	0.89	0.91	0.96	0.96
2019	0.80	0.89	0.91	1.00	1.00	1.00	1.00	1.00	1.00
2020	0.65	0.94	0.69	0.95	1.00	0.95	1.00	1.00	1.00
Average	0.77	0.93	0.82	0.81	0.99	0.82	0.95	0.99	0.97
σ	0.12	0.04	0.10	0.15	0.01	0.15	0.05	0.02	0.05

Source: own research

Slovakia demonstrated efficiency in the initial two years, with its enterprises exhibiting strong alignment with European trends. During this period, both technical and pure technical efficiency were achieved, showcasing effective scale and production methods. However, a subsequent decline in efficiency set in, with scale efficiency falling behind pure technical efficiency. Poland consistently maintained pure technical efficiency in almost every year. However, the enterprises did not adapt their BCC efficiency to align with European standards.

Consequently, the management compared results to previous years rather than benchmarking against European enterprises in C16. Figure 6 illustrates the microenterprises' stability in technology and value-added maintenance when self-compared. Bulgarian enterprises adjusted their performance based on previous years, regaining efficiency in the last two years, mirroring their initial period's effectiveness. Like Poland, Bulgarian enterprises demonstrated independent management practices, deviating from European trends. As previously mentioned, the ultimate benefit of DEA benchmarking lies in optimizing input and output values. The research's recommendations are rooted in the methodological benchmarks, specifically the efficient countries and the average performer or microenterprise (EU24). The results, presented as input percentage changes, align with the input-oriented models. Table 6 delineates the necessary adjustments in input economies that the investigated countries should undertake to achieve benchmark performance.

Table 6. Improvements in inputs of each country's enterprises are necessary to achieve the optimal profile.

		Poland			Slovakia			Bulgaria		
Benchmark	Efficiency type	Wages and Salaries	Goods and Services	Number of Enterprises	Wages and Salaries	Goods and Services	Number of Enterprises	Wages and Salaries	Goods and Services	Persons Employed
Efficient countries in the EU	CCR	-48%	-48%	-48%	-17%	-36%	-26%	-47%	-47%	-66%
	BCC	-46%	-46%	-51%	-6%	-28%	-17%	-61%	-43%	-60%
EU24 - average performer	CCR	-25%	-25%	-25%	-7%	-13%	-3%	-24%	-24%	-43%
	BCC	-24%	-24%	-28%	17%	-6%	6%	-39%	-20%	-37%

Source: own research

Table 6 shows the main areas in which enterprises in the studied countries should make improvements to improve their efficiency. Results for Polish enterprises are similar to Michal et al. (2021) for the Polish wood-processing industry. Pure technical efficiency consistently falls below the EU24 level, indicating cost challenges. According to the Central Economic Development Agency models, enterprises in Poland should reduce the costs of wages and goods and services by 48% to reach efficient levels and 46% to achieve pure technical efficiency. Bulgaria is very close to Poland in this respect. Bulgaria lags significantly in terms of the need for improvements. Bulgarian enterprises must optimize pure technical efficiency according to the higher improvement requirements suggested in Table 6. The primary attention there should be paid to the number of personnel, it is necessary to make a 66% improvement in the number of people employed and 47% in wages and salaries. The models imply that staff leads in improving performance. In combination with the need to reduce labour costs, the present study hypothesizes low labour productivity in enterprises in these countries. As revealed by Kropivšek and Grošelj (2019), Slovakian enterprises demonstrate high efficiency. Slovakian enterprises have modest requirements for economies, with a 28% reduction in costs for goods and services for pure technical efficiency. A 17% improvement in wages and salaries is necessary for CCR efficiency, 36% in costs for goods and services, and 26% in persons employed. Positive values in Table 6, when benchmarked against the EU24 average enterprise, indicate a better comparative position. Challenges arise concerning scale (see Table 3), but Slovakian enterprises are better than the Bulgarian ones. Slovakian wood-processing microenterprises can serve as benchmarks for the average EU enterprise in wages and salaries, which can be hypothesized to be a result of improved internal processes (see Malá et al., 2017) and despite the tax burden (see Gombár et al., 2022).

The results presented, addressed the research question, and identified directions for improvement of wood-processing micro-enterprises in Slovakia, Poland, and Bulgaria through DEA benchmarking. This validates the applicability of research methodologies such as those employed by Baek and Lee (2009), Pastor and Aparicio (2010), Ruiz and Sirvent (2016), and Zhang et al. (2017). The study also emphasizes the potential of enterprises based on past performance, emphasizing the difference between average efficiency levels and their best years. Optimizing implicit costs like taxes, as suggested by Dobrovič et al. (2016) and Korauš et al. (2021), would enhance competitiveness in international markets. These conclusions align with the findings of Trigkas et al. (2012), who analyze efficiency variation and identify development opportunities for both low-efficiency and efficient DMUs. In conclusion, the study reveals that Polish enterprises have significant potential for increasing labour productivity, while Bulgarian enterprises have a lower potential. During the research period, Bulgarian enter-prises did not significantly change their capabilities. Implementing the economies outlined in Table 5 would help them achieve their best, although this achievement may not be substantially different from EU benchmarks. The introduction of digitalization (Šimberová et al., 2022) and risk assessment (Kollmann et al., 2023) in their activities provides tools for improving the efficiency, competitiveness, and sustainability, in line with studies dedicated to the wood-processing industry (Kovalčík, 2020; Gutiérrez and Lozano, 2020; Sari et al., 2018; Šporčić et al., 2014).

Conclusions

The empirical study and its findings underscore the suitability of DEA as a methodology for benchmarking and guiding strategies to enhance competitiveness. It furnishes insights into a company's positioning relative to competitors, similar organizations, or its historical performance. The examination of initiatives across the three countries yielded markedly disparate results. Regarding the defined research question, it can be affirmed that the initial suspicion of Slovakian enterprises operating similarly to those in Bulgaria or Poland was not substantiated. All surveyed countries face challenges related to the gross value added of micro-enterprises in sector C16. Polish and Bulgarian enterprises encounter issues with pure economic efficiency, as evident from the marginal disparities in the economies required for overall technical efficiency. A significant hurdle for Polish and Bulgarian companies lies in labour productivity, with a notable distinction – Polish enterprises exhibit substantial potential for improvement, unlike their Bulgarian counterparts. Regarding resource utilization, Slovak enterprises demonstrated exceptional performance, positioning them as potential benchmarks for the average C16 European micro-enterprise rather than the other way around. Unlike Slovakian counterparts, Polish and Bulgarian enterprises can select their benchmark, opting for either the top-performing or average EU enterprises.

The proposed and implemented here approach for defining the optimal future development in the current research is easy to understand and used like a landmark by entrepreneurs The limitations of the study include potential challenges in data availability and quality, the subjective nature of variable selection, difficulty in capturing the dynamic and diverse nature of wood-processing microenterprises, and the inability to fully account for external factors and macroeconomic trends in the proposed comprehensive DEA analysis. The current research is limited to DEA-based efficiency scores estimation of the wood-processing micro-enterprises in the investigated countries. The DEA approach in the current study is implemented in a deterministic way after the nature of the methodology. Further research is needed to identify the leading factors that influence economic efficiency in these countries and the problem with the uncertainty of the empirical data, which deserves particular attention. Thus, their differences will reveal how enterprises in each country focus on the critical factors to improve their performance.

References

Ammirato, S., Fattoruso, G., & Violi, A. (2022). Parsimonious AHP-DEA Integrated Approach for Efficiency Evaluation of Production Processes. *J. Risk Financial Manag*., 15, 293. https://doi.org/10.3390/jrfm15070293

Baek, C., & Lee, J. D. (2009). The relevance of DEA benchmarking information and the least-distance measure. *Mathematical and Computer Modelling*, 49(1), 265-275. https://doi.org/10.1016/j.mcm.2008.08.007

Banker, R. D., Charnes, A., & Cooper, W. W. (1984). Some Models for Estimating Technical and Scale Inefficiencies in Data Envelopment Analysis. *Management Science*, 30(9). 1078-1092. https://doi.org/10.1287/mnsc.30.9.1078

Banker, R. D., Charnes, A., Cooper, W. W., Swarts, J., & Thomas, D. (1989). An introduction to data envelopment analysis with some of its models and their uses. *Research In Governmental and Nonprofit Accounting*, 5(1), 125-163.

Banker, R.D., Cooper, W.W., Seiford, L.M., Zhu, J. (2011). Returns to Scale in DEA. In: Cooper, W., Seiford, L., Zhu, J. (eds) Handbook on Data Envelopment Analysis. International Series in Operations Research & Management Science, vol 164. Springer, Boston, MA. https://doi.org/10.1007/978-1-4419-6151-8_2

Bielik, P., & Rajčániová, M. (2004). Scale efficiency of agricultural enterprises in Slovakia. *Agricultural Economics*, 50(8), 331-335. https://doi.org/10.17221/5211-AGRICECON

Bumba, A., Gomes, M., Jesus, C., & Lima, R. M. (2023). KPI tree - a hierarchical relationship structure of key performance indicators for value streams. *Production Engineering Archives*, 29(2), 175-185. https://doi.org/10.30657/pea.2023.29.21

Charnes, A., Cooper, W. W., & Rhodes, E. (1978). Measuring the efficiency of decision-making units. *European Journal of Operational Research*, 2(6), 429-444. https://doi.org/10.1016/0377-2217(78)90138-8

Charles, V., & Zegarra, L. F. (2014). Measuring regional competitiveness through data envelopment analysis: a Peruvian case. *Expert Systems with Applications*, 41(11), 5371-5381. https://doi.org/10.1016/j.eswa.2014.03.003

Chen, Y. (2004). Ranking efficient units in DEA. *Omega*, 32(3), 213-219. https://doi.org/10.1016/j.omega.2003.11.001

Cooper, W. W., Seiford, L. M., Tone, K., & Zhu, J. (2007). Some models and measures for evaluating performances with DEA: past accomplishments and future prospects. *Journal of Productivity Analysis*, 28, 151-163. https://doi.org/10.1007/s11123-007-0056-4

De, D., Chowdhury, S., Dey, P. K., & Ghosh, S. K. (2020). Impact of lean and sustainability-oriented innovation on the sustainability performance of small and medium-sized enterprises: a data envelopment analysis-based framework. *International Journal of Production Economics*, 219, 416-430. https://doi.org/10.1016/j.ijpe.2018.07.003

Dia M, Golmohammadi A, & Takouda PM. (2020). Relative Efficiency of Canadian Banks: A Three-Stage Network Bootstrap DEA. *Journal of Risk and Financial Management*, 13(4), 68. https://doi.org/10.3390/jrfm13040068

Dobrovič, J., Korauš, A. & Dančišinová, L. (2016). Sustainable economic development of Slovakia: factors determining optimal tax collection. *Journal of Security and Sustainability Issues*, 5(4), 533-544. https://doi.org/10.9770/jssi.2016.5.4(7)

Du, Y.C., Wang, R.X., & Li, M.W. (2022). Measurement and Evaluation of Corporate Governance Ability of Mixed-ownership Reform Enterprises: Evidence from China. *Transformations in Business & Economics*, Vol. 21, No 2 (56), pp.233-254.

EUSBS. (2023). Industry by employment size class (NACE Rev. 2, B-E). [Data set]. Statistical Office of the European Communities. https://ec.europa.eu/eurostat/databrowser/view/SBS_SC_IND_R2/default/table?lang=e

Ferreira, A. C., & Silva A. (2022). Supplier selection and procurement in SMEs: insights from the literature on key criteria and purchasing strategies. *Engineering Management in Production and Services*, 14(4), 47-60. https://doi.org/10.2478/emj-2022-0030

Gombár, M., Korauš, A., Vagaská, A., & Tóth, Š. (2022). Analytical View on the Sustainable Development of Tax and Customs Administration in the Context of Selected Groups of the Population of the Slovak Republic. *Sustainability*, 14, 1891. https://doi.org/10.3390/su14031891

Guan, J. C., Yam, R. C., Mok, C. K., & Ma, N. (2006). A study of the relationship between competitiveness and technological innovation capability based on DEA models. *European Journal of Operational Research*, 170(3), 971-986. https://doi.org/10.1016/j.ejor.2004.07.054

Gutiérrez, E., & Lozano, S. (2020). Cross-country comparison of the efficiency of the European forest sector and second stage DEA approach. *Annals of Operations Research*, 314(2), 471-496. https://doi.org/10.1007/s10479-020-03756-9

Henriques, C.O., Neves, M.E., Conceição, J.A., & Vieira, E.S. (2023) Performance of US and European Exchange Traded Funds: A Base Point-Slack-Based Measure Approach. *J. Risk Financial Manag.*, 16, 130. https://doi.org/10.3390/jrfm16020130

Horváthová, J., Mokrišová, M., & Vrábliková, M. (2021). Benchmarking—A Way of Finding Risk Factors in Business Performance. *J. Risk Financial Manag*., 14, 221. https://doi.org/10.3390/jrfm14050221

Hua, Z., Bian, Y., & Liang, L. (2007). Eco-efficiency analysis of paper mills along the Huai River: An extended DEA approach. *Omega*, 35, 578-587. http://doi.org/10.1016/j.omega.2005.11.001

Hyránek, E., Kowalska-Sudykam., Mišota, B., Ondrejmišková, I., & Kapko, M. (2021). Verification of the Performance Model in Selected Companies in the Mining Industry. *Acta Montanistica Slovaca*, 26(3), 415-426. https://doi.org/10.46544/AMS.v26i3.03

Jia, T., & Yuan, H. (2017). The application of DEA (Data Envelopment Analysis) window analysis in the assessment of influence on operational efficiencies after the establishment of branched hospitals. *BMC Health Services Research*, 17(1), 1-8. http://doi.org/10.1186/s12913-017-2203-6

Khezrimotlagh, D., Cook, W. D., & Zhu, J. (2021). Number of performance measures versus number of decision-making units in DEA. *Annals of Operations Research*, 303(1-2), 529-562. https://doi.org/10.1007/s10479-019-03411-y

Kollmann, J., Straková, J., Korauš, A., Palinchak, & M., Černák, F. (2023). Enterprise risk analysis in an engineering company with a focus on custom manufacturing. *Entrepreneurship and Sustainability Issues*, 10(3), 362-382. http://doi.org/10.9770/jesi.2023.10.3(24)

Kononiuk, A. (2022). Determinants of Foresight Maturity in SME Enterprises of Poland. *Foresight and STI Governance*, 16(1), 69-81. http://doi.org/10.17323/2500-2597.2022.1.69.81

Kovalčík, M. (2020). Profitability and Efficiency of Forest Contractors in Slovakia—Comparison of Mountain and Lowland Regions. *Forests*, 11(4), 370. http://doi.org/doi:10.3390/f11040370

Kovalčík, M. (2018). Efficiency of the Slovak forestry in comparison to other European countries: An application of Data Envelopment Analysis. *Central European Forestry Journal*, 64(1), 46-54. https://doi.org/10.1515/forj-2017-0026

Korkmaz, E. (2011) Measuring the productive efficiency of forest enterprises in the Mediterranean Region of Turkey using data envelopment analysis. *African Journal of Agricultural Research*, 2011, 6(19), 4522-4532. https://doi.org/10.5897/AJAR11.1002

Korauš, A., Gombár, M., Vagaská, A., Šišulák, S. & Černák, F. (2021) Secondary Energy Sources and Their Optimization in the Context of the Tax Gap on Petrol and Diesel. *Energies*, 14, 4121. https://doi.org/10.3390/en14144121

Kropivšek, J., & Grošelj, P. (2019). Long-term financial analysis of the Slovenian wood industry using DEA. *Drvna Industrija*, 70(1),. https://doi.org/10.5552/drvind.2019.1810

Malá, D., Sedliačiková, M., Kaščáková, A., Benčíková, D., Vavrová, K., & Bikár, M. (2017). Green Logistics in Slovak Small and Medium Wood-Processing Enterprises. *BioResources*, 12(3), 5155-5173. https://doi.org/10.15376/biores.12.3.5155-5173

Mihalčová, B., Korauš, A., Prokopenko, O., Hvastová, J., Freňáková, M., Gallo, P., & Beáta, B. (2021). Effective Management Tools for Solving the Problem of Poverty in Relation to Food Waste in Context of Integrated Management of Energy. *Energies*, 14, 4245. https://doi.org/10.3390/en14144245

Michal, J., Březina, D., Šafařík, D., & Babuka, R. (2021). Sustainable Development Model of Performance of Woodworking Enterprises in the Czech Republic. *Forests*, 12(6), 672. https://doi.org/10.3390/f12060672

Neves, M.E.D., Gouveia, M.D.C., & Proença, C.A.N. (2020). C.A.N. European Bank's Performance and Efficiency. *J. Risk Financial Manag.*, 13, 67. https://doi.org/10.3390/jrfm13040067

Ning, Y., Liu, Z., Ning, Z., & Zhang, H. (2018). Measuring Eco-Efficiency of State-Owned Forestry Enterprises in Northeast China. *Forests*, 9(8), 455. https://doi.org/10.3390/f9080455

Pastor, J. T., & Aparicio, J. (2010). The relevance of DEA benchmarking information and the least-distance measure: comment. *Mathematical and Computer Modelling*, 52(1-2), 397-399. https://doi.org/10.1016/j.mcm.2010.03.010

Porfírio, J. A., Felício, J. A., & Carrilho, T. (2020). Family business succession: Analysis of the drivers of success based on entrepreneurship theory. *Journal of Business Research*, 115, 250-257. https://doi.org/10.1016/j.jbusres.2019.11.054

Qayyum, A., & Riaz, K. (2018). Incorporating Credit Quality in Bank Efficiency Measurements: A Directional Distance Function Approach. *J. Risk Financial Manag.*, 11, 78. https://doi.org/10.3390/jrfm11040078

Ruiz, J. L., & Sirvent, I. (2016). Common benchmarking and ranking of units with DEA. *Omega*, 65, 1-9. https://doi.org/10.1016/j.omega.2015.11.007

Salehirad, N., & Sowlati, T. (2005). Performance analysis of primary wood producers in British Columbia using data envelopment analysis. *Canadian Journal of Forest Research*, 35(2), 285-294. https://doi.org/10.1139/x04-154

Sari, D., Handayani, N., Ulkhaq, M., Budiawan, W., Maharani, D., & Ardi, F. (2018). A data envelopment analysis approach for assessing the efficiency of small and medium-sized wood-furniture enterprises: A case study. [conference paper]. In MATEC Web of Conferences, 30-31 August 2018, Conference proceedings (Vol. 204, pp. 1015). https://doi.org/10.1051/matecconf/201820401015

Sedivka, P. (2009). Estimation of technical efficiency in production technologies of Czech sawmills. Drvna Industrija, 60(4), 197-207.

Sedliačiková, M., Hajdúchová, I., Krištofík, P., & Viszlai, I., Gaff, M. (2016). Improving the performance of small and medium wood-processing enterprises. *BioResources*, 11(1), 439-450. https://doi.org/10.15376/biores.11.1.439-450

Šimberová, I., Korauš, A., Schüller, D., Smolíkova, L., Straková, J. & Váchal, J. (2022). Threats and Opportunities in Digital Transformation in SMEs from the Perspective of Sustainability: A Case Study in the Czech Republic. *Sustainability*, 14(6), 3628. https://doi.org/10.3390/su14063628

Šporčić, M., Martinič, I., Landekič, M., & Lovrič, M. (2009). Measuring Efficiency of Organizational Units in Forestry by Nonparamet-ric Model. *Croatian Journal of Forest Engineering*, 30(1), 1-13. https://doi.org/10.5552/crojfe

Šporčić, M., & Landekič, M. (2014). Nonparametric Model for Business Performance Evaluation in Forestry. In Awrejcewicz, J. (Ed.), Computational and Numerical Simulations, IntechOpen, London, UK. https://doi.org/10.5772/57042

Stojčić, N., Anić, I. D., & Aralica, Z. (2019). Do firms in clusters perform better? Lessons from wood-processing industries in new EU member states. *Forest Policy and Economics*, 109, 102043. https://doi.org/10.1016/j.forpol.2019.102043

Straková, J., Korauš, A., Váchal, J., Pollák, F., Černák, F., Talíř, M. & Kollmann, J. (2021). Sustainable Development Economics of Enterprises in the Services Sector Based on Effective Management of Value Streams. *Sustainability*, 13(16), 8978. http://dx.doi.org/10.3390/su13168978

Takouda, P.M., Dia, M., & Ouattara, A. (2022). Financial Inclusion in West African Economic and Monetary Union's Economies: Performance Analysis Using Data Envelopment Analysis. *J. Risk Financial Manag*., 15, 605. https://doi.org/10.3390/jrfm15120605

Trigkas, M., Papadopoulos, I., & Karagouni, G. (2012). Economic efficiency of wood and furniture innovation system. *European Journal of Innovation Management*, 15(2), 150-176. https://doi.org/10.1108/14601061211220959

Tsolas, I. E. (2011). Performance assessment of mining operations using nonparametric production analysis: A bootstrapping approach in DEA. *Resources Policy*, 36(2), 159-167. https://doi.org/10.1016/j.resourpol.2010.10.003

Tsolas, I.E. (2020) The Determinants of the Performance of Precious Metal Mutual Funds. *J. Risk Financial Manag*., 13, 286. https://doi.org/10.3390/jrfm13110286

Villaverde, D. B., Paredes, A. P., & de los Ángeles, J. A. C. (2020). Assessment of innovation factors that impact competitiveness in the Mexican state entities through DEA analysis. Strategy, *Technology & Society*, 10(1).

Woodwell, J. C. (1998). A simulation model to illustrate feedback among resource consumption, production, and factors of production in ecological-economic systems. *Ecological Modelling*, 112(2-3), 227-248. https://doi.org/10.1016/S0304-3800(98)00080-5

Yang, H., Yuan, T., Zhang, X., & Li, S. (2016). A Decade Trend of Total Factor Productivity of Key State-Owned Forestry Enterprises in China. *Forests*, 7(5), 97. https://doi.org/10.3390/f7050097

Yang, H. H., & Chang, C. Y. (2009). Using DEA window analysis to measure efficiencies of Taiwan's integrated telecommunication firms. *Telecommunications Policy*, 33(1-2), 98-108. https://doi.org/10.1016/j.telpol.2008.11.001

Zhang, D., Nasir, H., & Haas, C. T. (2017). Development of an internal benchmarking and metrics model for industrial construction enterprises for productivity improvement. *Canadian Journal of Civil Engineering*, 44(7), 518-529. https://doi.org/10.1139/cjce-2016-0274

Zhang, X., Xu, D. (2022). Assessing the eco-efficiency of complex forestry enterprises using LCA/time-series DEA methodology. *Ecological Indicators*, 142, 109166 https://doi.org/10.1016/j.ecolind.2022.109166

Funding: This research was supported by the projects, which have received funding from the Scientific grant agency of the Ministry of Education, Science, Research and Sport of the Slovak Republic and the Slovak Academy of Sciences Grant Agreement Numbers 1/0011/24 and 1/0093/23 and from the Slovak Research and Development Agency Grant Agreement Numbers APVV-20-0004, APVV-21-0051, APVV-22-0238.

Author Contributions: All authors contributed equally; they have read and agreed to the published version of the manuscript.

Mariana SEDLIAČIKOVÁ is a Professor of Business Economics and Management at The Faculty of Wood Sciences and Technology, Technical University in Zvolen
ORCID ID: https://orcid.org/0000-0002-4460-2818

Nikolay NEYKOV is an Associate Professor at the University of Forestry, Bulgaria, Faculty of Ecology and Landscape Architecture
Department of Alternative Tourism

ORCID ID: https://orcid.org/0000-0002-8602-5254

Ján DOBROVIČ is the Associated Professor of Management at The College of International Business ISM Slovakia in Prešov
ORCID ID: https://orcid.org/0000-0002-0637-106X

Anna ŠATANOVÁ is a Professor of Business Economics and Management at The College of International Business ISM Slovakia in Prešov
ORCID ID: https://orcid.org/0000-0001-6770-7236

Mária OSVALDOVÁ, is the PhD. student at Technical University in Zvolen, Faculty of Wood Sciences and Technology, Department of Economics, Management and Business, Slovakia
ORCID ID: https://orcid.org/0000-0003-3184-7282

Mykola PALINCHAK is a Professor of Political Sciences at The Faculty of International Economic Relations of Uzhhorod National University**,** Ukraine
ORCID ID: https://orcid.org/0000-0002-9990-5314