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Earnings Drivers of Slovak Manufacturers: Efficiency Assessment of Innovation Management

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Abstract: In innovation management, it is crucial to know the incentives or factors that, in many cases, provide the fundamental drivers of earnings, competitive advantage and the sustainable growth of businesses while also measuring their effectiveness. The study deals with the evaluation of the efficiency of investments in innovations utilizing constant returns to scale models of small- and medium-sized industrial enterprises in Slovakia. It is industrial production that includes enterprises that are the creators of new products, the appliers of the latest knowledge of science, and the creators of innovations. The main objective of the study is to evaluate the effectiveness of invested finances in the innovation of small- and medium-sized production enterprises in Slovakia, as it is a very demanding and neglected role in management. The method to assess the efficacy that was used is called Data Envelopment Analysis. CCR-I also CCR-O models were run, where it was essential to determine the inputs and outputs. The indicators R&D expenditures and employee training costs were selected based on a detailed analysis of articles with similar issues. The final sample contained 132 manufacturing enterprises within industrial production that were classified according to the official Slovak categorization because of their relevance. We assessed the effectiveness of food producers, beverage manufacturers, textile and clothing manufacturers, manufacturers of rubber plastic products, metal manufacturers, PC, electronic and optical equipment manufacturers, machine and equipment manufacturers, and furniture manufacturers to identify the enterprises that own earnings drivers caused by innovation. It was detected that the most efficient units in the industrial production are the rubber plastic products manufacturers. The least effective units were found in beverage and furniture manufacturers.

Keywords: Data Envelopment Analysis; earnings; efficiency; innovation management; manufacturing enterprises

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1. Introduction

Innovation is the foundation of sustainable growth in the business [1,2] and innovative activity is an important source of competitiveness, economic growth, as well as the image of each country [3]. On the other hand, regardless of the amount of investment in innovation, there is no guarantee that it is spent efficiently. Therefore, it is necessary to innovate wisely and with focus. Such an activity requires an enterprise to continuously evaluate its ongoing innovation projects and use that data to decide whether to continue [4].

Unfortunately, a large number of enterprises are not concerned with measuring the performance of innovations despite their enormous importance in business development [5]. Experience and research show that senior management needs to show a long-term commitment to allocate resources for innovation to create a lasting organizational capacity [6].

It is a current, significant, but neglected area, as many research studies point to the absence of evaluating the effectiveness of innovation investments [7]. This fact led to the analysis of efficiency from invested finances in innovation activities producing companies in Slovakia. The main problem is the discrepancy between what the manager wants to achieve and what he does from investing in innovation, so it is necessary to continuously evaluate the activities and investments invested in the innovation projects to see if it makes sense to continue the action. On the other hand, management by risk is a global process and drives business process innovation [8]. The study explores the constant returns to scale model from the scope of data package analysis to determine the efficiency of invested funds in industrial production innovations [9].

Data Envelopment Analysis (DEA) is an approach that based on evaluating the performance of a set of similar entities called production units, referred to as "DMUs", that convert inputs to outputs. Currently, DEA analysis is increasingly being used to assess the performance of many different types of entities involved in many activities in different contexts across the world. Therefore, the possibilities of DEA are diverse and can be used in performance assessments within the public, private and third sectors [10].

Measuring the innovation performance of a selected sample through DEA analysis was based on the assumption that identifying sources of inefficiency and measuring the efficiency of production units is a necessary condition for increasing productivity. Performance assessment is an essential continuous tool for improvement for the business to remain competitive and play an important role in the global marketplace where competition is continuously growing [11]. Through performance evaluation, it is possible to identify weak and robust business processes, activities and operations; at the same time, it can better prepare the business to meet customer requirements and identify opportunities to improve the current status, create new products, services and processes.

A production unit (DMU) is a unit that produces certain outputs that result from the production of consumed inputs. In our case, these are industrial production enterprises, falling under the industrial production according to official Slovak classification.

Measuring the performance of innovation is currently discussed and topical issue, especially among researchers. They emphasize the importance of this measurement, especially at the company level, and point to the absence of the detection and evaluation of the impact of innovation. The trend is to manage innovation, but it is also essential to find out how effective it is.

The main objective of the study is to evaluate the effectiveness of invested finances in the innovation of small- and medium-sized production enterprises in Slovakia. Efficiency assessment and measurement is a neglected and challenging task for management today, and therefore, the purpose was to explore the possibilities and ways of measuring. At the same time, a similar publication has not yet been found in Slovakia, in which the authors deal with the evaluation of the efficiency of manufacturing enterprises using DEA analysis, and therefore the study can be considered beneficial.

The article consists of five parts. The first part introduction is focused on the issue of measuring the effectiveness of innovation, its current state and the need to measure the effect of invested resources on the activities of small- and medium-sized enterprises. In the next section, literature review, key publications and authors who deal with a similar issue are listed, and their article outputs have been a useful tool for processing. In the materials and methods section, the process of data collection and handling is elaborated, and the DEA analysis is used to assess efficiency. In the results, we provide a detailed overview of the innovation efficiency of individual enterprises in the respective manufacturing sectors, and in the last part of the discussion, we provide an overview and summary of the outputs, adding conclusions from the results. In Slovakia, a similar study has not been performed yet, and this fact has also been an incentive for the article.

2. Literature Review

In the course of this study, we have analyzed similar articles by other authors. An analysis of the efficiency of innovations in the industrial production of enterprises in Slovakia through the DEA analysis has not been performed yet. Therefore, information was drawn from foreign authors. The article by [12] presents an empirical study using DEA to evaluate the R&D (research and development expenditures) performance of 31 firms and peripheral firms located in a science-based industrial park in Taiwan. They found that R&D performance was very different among the companies evaluated, although most companies are technically efficient. Besides, they discussed possible directions for inefficient businesses to improve their R&D performance. An essential issue in [13] is how to determine an effective decision regarding eco-technological innovation and its impact on sustainability. To discuss global issues at a global level, this study first focuses on measuring the performance of its operational and environmental performance and then pays attention to the damage. The economic concept suggests a level of change in unwanted outputs (e.g., CO_2) by increasing one unit of desired output (e.g., oil production). Data package analysis is used to assess the size of the damage. The proposed DEA assessment theoretically provide researchers and policymakers with information on how to invest in eco-technology innovations to reduce unwanted outcomes, thereby increasing the level of corporate or social sustainability. The subject focused on eco-innovation and analyzing its barriers was also studied by [14]. A study by [15] suggests a new use of the Data Envelopment Analysis to examine the sustainability of Japanese industries. Among the five measures, the UEI (Unified Efficiency Index) examines a degree of how each enterprise can effectively use its resources. The empirical results obtained from the proposed approach identified two critical consequences. One of the two effects is that the Japanese energy industry has long been under government regulation, so energy companies do not have corporate capability management at the level of other industries that compete in the global market. Another consequence is that technological innovation can more effectively improve the performance of the energy sector.

Other authors who investigated the effectiveness of innovations using DEA analysis: [16] in Performance Evaluation of R&D active firms; [17]: Evaluating the efficiency of airports using an integrated AHP/DEA-AR technique.

In addition to the basic models, there are other DEA analysis models. One of them is referred to as the SBM model designed by [18]. This model serves as a basis for defining super efficiency.

Analyses of publications were used to determine inputs and outputs to determine the effectiveness of business innovation (Table 1).

Table 1. Input and output factors of innovation for data envelopment analysis (DEA) analysis from similar studies.

Authors	Input	Output
[19]	R&D expenditures, cost of human capital	indicators for measuring knowledge transfer between countries
[12]	enterprise age, paid capital, R&D expenditures, number of R&D staff	annual sales, number of patents approved by the Authority
[15]	Paid capital Nature of work energy	Desired: Gross regional product Unwanted: CO_2, SO_2, water pollution, air pollution, chemical oxygen demand, ammonia
[16]	R&D expenditures	Annual sales, Net added value per employee (last 4 years)
[17]	Operational expenditure, Enterprise service capacity	Annual sales, Performance of provided services
[20]	Number of R&D staff	Number of patent applications published
[21]	R&D expenditures, cost of human capital and accumulated knowledge	Knowledge involved in commercialization
[22]	Number of R&D staff, R&D expenditures, Knowledge expenditures	Knowledge involved in commercialization Work done equivalent to R&D work activities

Nearly all authors dealing with similar issues are R&D as an essential input in determining the effectiveness of businesses, or regions or countries. R&D plays a crucial role in the innovation process. It is an investment in technology and future capabilities that transforms into new products, processes and services.

The aim of the DEA analysis is not only to determine the degree of effectiveness of the entities being audited but in particular to find target values for inputs and outputs for an inefficient unit. When these values are reached, the unit would have reached the efficiency threshold. Variable returns to scale can also be considered in the efficiency analysis. In this case, the CCR model needs to be rewritten to include a convex condition. Subsequently, it is referred to as the BCC model, according to the author of [23].

3. Materials and Methods

In our research paper, we created a database of small- and medium-sized 133 enterprises which, within the SK NACE classification, Section C, contains the following sub-groups: food production, beverage production, textile and clothing production, rubber, plastic, metal and metal construction, computer production electronic and optical products, manufacture of machinery, equipment, motor vehicles, semi-trailers, trailers and other means of transport, furniture production and other manufacturing. Small- and medium-sized enterprises are the predominant type of business units in all OECD (The Organization for Economic Co-operation and Development) economies and account for about two-thirds of total employment [24].

Therefore, the sample was not random, it was a deliberate or purposeful sample of manufacturing companies that must incorporate innovative activities into the production process, in which enterprises had to meet the following conditions:

1. Operate on the market for more than 3 years;
2. The subject of business is focused on industrial production;

3. In terms of size, they are classified as small- and medium-sized enterprises, which means that the total number of employees is greater than nine and does not exceed the upper limit of 250 employees. The sample size was carefully determined so that valid and general conclusions can be drawn [25,26]. Determining the appropriate sample size requires specific information on the issues under investigation within the analyzed group and also the sample subcategories require detailed analysis. The minimum number of DMUs (production units) was discussed by [27] and proposes a clear rule. Whether p is the number of inputs (2 inputs) and q is the number of outputs (1 output) used in the analysis, then the sample size (n) should meet:

$$\begin{gathered} n \geq max\,\{p.q,\ 3(p+g)\} \\ n \geq \max\,\{2,\ 9\} \\ n \geq 9 \end{gathered} \tag{1}$$

where:

n minimum sample size
p number of inputs
q number of outputs

The determination of the minimum number of DMUs is also addressed by [28], who were also inspired according to the abovementioned formula in their work; since we have one output and two inputs in the DEA analysis, the minimum size of DMUs will be nine in this case as well. The database of companies to which the questionnaire was sent consisted of three parts. The first part of the database was created based on the register of accounting units; the selection was based on the definition of SK NACE and the category specification. The aim was to select companies from each subcategory within the industrial production section. The main question of the survey was to evaluate the innovative efficiency of Slovak innovative enterprises. The total number of businesses surveyed was 11,838. The number of responses we received was 276, a return of 2.33% of the total number of enterprises surveyed. We attribute a low rate of return to the time-consuming questionnaire, or the company did not want to disclose its internal information, or the inquiry was considered irrelevant to a particular type of business. After the processing of the collected data, it was necessary to eliminate some of the enterprises, given that they did not provide complete information. Out of 276 enterprises, we had to remove 144 enterprises due to incomplete or incorrect data entry. To increase the reporting value of the output from the DEA analysis, we divided the companies into subcategories depending on the nature of the production, given that evaluating the efficiency of computer manufacturing companies is disproportionate to food or beverage companies. The minimum sample for DEA analysis is nine production units. We divided the companies into subcategories, according to Table 2.

Table 2. Classification of industrial production subcategories according to Slovak standard.

Subcategory SK NACE-INDUSTRIAL PRODUCTION-SECTION "C"	Sample Size
10 food production	23
11 beverage production	14
13 textile production	8
14 manufacture of clothing	8
16 wood processing	3
22 manufacture of rubber and plastic products	9
24 manufacture and processing of metals	7
25 manufacture of metal structures	10
26 manufacture of computer electronic and optical products	17
28 manufacture of machinery and equipment	14
31 manufacture of furniture	15
33 repair and installation of machinery and equipment	4

Since the minimum number of units in the DEA analysis group is nine, we decided to consider one subcategory because of the homogeneity of production of some subcategories. These are subcategories, 13 and 14 for the manufacture of textiles and clothing and subcategories, and 24 and 25 for the manufacture and processing of metals and metal structures, respectively.

In 1978, the DEA was introduced for the first time and is now considered a simple and excellent methodology for modeling operational processes for performance evaluation. In the analysis, CCR input (input oriented model designed by [28]) and output model to analyze efficiency was applied, which is the most widely used among others but is not explicitly specified by the authors in which cases and under what conditions a particular model could be chosen for efficiency analysis [29]. The software used to evaluate efficiency was able to determine the optimal weights that change between individual production units. Therefore, the "weights" in the DEA analysis are derived from data instead of predetermined. Each DMU assigned an optimal set of weights with values that can vary from one DMU to another.

Linear programming is the basic methodology that makes the DEA model particularly powerful compared to alternative productivity tools [30]. The DEA can calculate the size and type of cost and resource savings that can be achieved by making each inefficient production unit as effective as the units that are most effective. Data Envelope Analysis is a method that allows you to compare and evaluate different data (businesses, employees, websites, marketing campaigns, etc.) based on their properties without making hasty assumptions about the importance or weight of properties [31]. The most interesting part of this technique is that it makes possible to compare multi-function data that has completely different units of measurement [32].

Measuring efficiency in production units and identifying sources of inefficiency is a prerequisite for improving the performance of any production unit in a competitive environment. The term productive unit refers to a unit that produces specific outputs by spending certain inputs.

The most common method of measuring efficiency is based on ratios. Their drawback is that they reflect only a few factors that affect the overall efficiency of a production unit.

For instance, if let us assume thta we have a group of n production units, DMU1, DMU2,..., DMUn. Each unit produces with inputs when consuming m inputs. The input matrix is written as follows: X = [x_ij, i = 1, 2, ... , m, j = 1,2, ... , n] and the output matrix Y = [y_ij, i = 1,2, ... , S, j = 1,2, ... , n]. Row q e. c. Xq and Yq of these matrices show the quantified inputs/outputs of DMUq. The rate of efficacy of such a unit can then generally be expressed as:

$$Ef_a = \frac{\sum_{i=1}^{S} u_i y_{iq}}{\sum_{j=1}^{m} v_j x_{jq}} \tag{2}$$

where:

Ef_a is effectiveness,
$v_j,\ j = 1,\ 2, \ldots,\ m$ is weight to j-th entry,
$u_{i,} i = 1,\ 2,\ \ldots,\ s$ is weight to i-th output,
$\sum_{i=1}^{S} u_i y_{iq}$ is weighted sum of outputs, and
$\sum_{j=1}^{m} v_j x_{jq}$ is weighted sum of inputs.

In DEA models n productive units, DMUs, are evaluated, where each DMU receives different inputs to produce different outputs. The essence of the DEA models in measuring the efficiency of a DMUq production unit is to maximize its efficiency. However, provided that the effectiveness of any other unit in the group may not be greater than 1. The models shall include all the characteristics considered, i.e., the weights of all inputs and outputs must be greater than zero. Such a model is defined as a linear dividing programming model. It is often called the primary CCR model [27]. The dual model is as follows:

$$
\begin{array}{ll}
\text{maximization} & z = u^T Y_q, \\
\text{to} & v^T X_q = 1, \\
 & u^T Y - v^T X \leq 0 \\
 & u \geq \in, \\
 & v \leq \in. \\
\text{minimization} & f = \theta - \in \left(e^T s^+ + e^T s^-\right), \\
\text{to} & Y\lambda - s^+ = Y_q, \\
 & X\lambda + s^- = \theta X_q, \\
 & \lambda, s^+, s^- \geq 0 = Y_q.
\end{array}
\tag{3}
$$

where:

$\lambda = (\ \lambda_1,\ \lambda_{2,} \ldots\ ,\ \lambda_n),\ \lambda \geq 0$ vector for individual production units,
s^+, s^- are vectors of additional input and output variables,
$e^T = (+, 1,\ \ldots,\ 1)$; $\in$ are constants greater than zero, and
$Y\lambda, X\lambda$ is a linear combination of inputs and outputs of units.

If the DMU is effective, then:

the value of variable θ is zero,
the values of all other variables s^+, s^- are equal to zero.

Thus, the DMUq is effective if the optimum value of the objective function of the minimization model is one. Otherwise, the unit is ineffective. The optimal amount of the target function f* indicates the degree of efficiency of the respective unit. The lower the rate, the less the unit is comparable to the rest of the group. In inefficient units, θ is less than one. This value points to the need for proportional input reduction for the DMUq to be effective. The advantage of the DEA model is that it recommends how the rated entity should change its behavior to achieve efficiency. Models of maximization and minimization are input-oriented-trying to figure out how to improve the input characteristics of a particular unit to become effective. There are also output-oriented models. If the function value is more significant than one, the unit is ineffective in the output model. The variable θ indicates the need for increased power to achieve efficiency. For optimal CCR modelling, objective function values should be inverted.

After analyzing the individual studies, the results were consulted with several experts in the field and the following were specified inputs and outputs suitable for processing the DEA analysis:

Input Factors

- The amount of R&D expenditures, including salaries of researchers for 2017.
- Amount of costs to finance training courses for employees to acquire new information for 2017.

Output factor

- Amount of sales for 2017 from sold products that were launched in the last 5 years.

The subject of the analysis was the innovation performance of individual companies. The number of enterprises of the final sample is 132 within industrial production. In order to ensure the homogeneity of the sample, which is a prerequisite for the DEA analysis, we subdivided the companies into other subcategories, while the number of enterprises in one category could not be less than nine as the minimum sample rule would not be met. For an efficiency assessment, we used the most commonly used CCR model, input and output oriented. Additionally, to ensure the relevance of the results, we identified extreme values that were removed from the analysis based on an outliers analysis.

Output-oriented model (CCR-O): model used in the case of an inefficient production unit propose an increase in the amount of output, while the amount of input remains the same.

Input oriented model (CCR-I): model used in the case of an inefficient production unit propose a reduction in the amount of input while maintaining the current amount of output.

An outlier is an observation far away from most or all other observations. It is possible to keep the outlier and treat it like any other data point, winsorize it or remove it. The winsorizing and removing introduce statistical bias and may undervalue the outlier, while keeping it and treating it like the other points may overvalue it and cause the estimate to vary drastically from the true population value [33]. As we prefer robust statistics, results of efficiency insensitive to outliers, we choose the third possibility to remove all outliers before running DEA based on the study being an outlier of [34]. We used Z-scores for detecting outliers for each analyzed subcategory from industrial production.

4. Results

The results of the methods used are the results of evaluating the effectiveness of invested funds in innovation incentives. To increase the relevance, manufacturing enterprises that participated in the survey are categorized according to the official Slovak NACE classification.

In the analyzed group are included the companies which, according to categorization, are food producers. Altogether, 23 such enterprises participated in the survey. Based on the outliers analysis, we managed to identify two extreme values: DMU 36 and DMU 38, which were removed prior to using the CCR-I model.

Based on the CCR performance analysis, the individual companies ranked on the basis of which enterprises can best use their resources to obtain the given outputs (Table 3).

Table 3. CCR method for assessing the effectiveness of food producers.

	CCR Model	
DMU	**Input**	**Output**
DMU18	0.2552	3.9183
DMU19	1	1
DMU20	0.095	10.5211
DMU21	0.0714	13.9977
DMU22	0.0276	36.2215
DMU23	0.0103	97.0227
DMU24	0.0872	11.4617
DMU25	0.0418	23.9433
DMU26	0.4609	2.1696
DMU27	0.682	1.4664
DMU28	1	1
DMU29	0.0024	416.5181
DMU30	0.2852	3.5066
DMU31	0.0388	25.7903
DMU32	0.3853	2.5952
DMU33	0.0024	408.8255
DMU34	0.094	10.6336
DMU35	0.0067	148.3912
DMU37	0.008	125.7298
DMU39	0.0658	15.1917
DMU40	1	1

At the same time, we found that there are three companies (DMU 19, DMU 28, DMU 40) within a given producer group that can be considered adequate in terms of input costs to support innovations producing specific outputs. The super CCR coefficient expresses the ratio to the effective unit (effective unit = 1). For example, DMU 27 does not use the full potential of its inputs and, while maintaining output, inputs should be reduced by approximately 32%. Effective units could achieve nearly 50% higher output at these inputs. In the DEA analysis, we identified R&D costs as one of the input values. The CCR-I method detects how inputs could be reduced, while the output is unchanged, trying to minimize inputs in this case. On the other hand, the CCR-O model works to maximize output with consistent inputs. For some DMUs (19, 28, 40) there was no change in value because in terms of output this value is considered to be an effective input. In other cases, it is proposed to eliminate the height of the entry. For example, for DMU 27, the original R&D cost is EUR 7620; the CCR-I aims to reduce this amount by EUR 2423.47, and the total R&D cost would be EUR 5196.53. This means that there are effective units in our database that can generate the same output at a lower input variable than the DMU 27.

Another input variable is the number of costs earmarked for training employees of the enterprise. The cost of employee training in the analysis is another input that encourages new information and ideas for employees. Using the CCR-I model, we assessed how efficiently the input is involved in the output. For the units that were identified as effective, t. j., their value is equal to one; it uses its inputs most efficiently concerning the outputs obtained. As in the previous case, for others, a reduction in CCR-I inputs is proposed. For example, the DMU 26 model suggests a decrease of EUR 5072.80 from the original EUR 5700 of training costs to EUR 2627.20.

In the case of the CCR-O, the reduction is not designed, as the inputs are not changing, but the outputs are. Subsequently, in the output analysis, in our case, the sales of products marketed in the last five years for 2017 need to be based on the output-oriented CCR-O model. The CCR-I target does not change in this case, there is only a change in the CCR-O model, assuming that the original input value is maintained, and output is maximized. For example, based on our database, an effective unit retaining the original DMU 32 inputs with an initial sale of EUR 1,434,883 could generate EUR 3,723,875.51.

Within the beverage division, we include producers of alcoholic beverages, beer, wine, producers of distilled alcoholic beverages, mineral water producers, and soft drinks. We included 14 enterprises, and the results of the business innovation performance assessment by DEA analysis are available in Table 4. In the analysis of outliers, the following production units were found with extreme values: DMU 46, DMU 47, and DMU 50. The DMA 49 production unit could not be included in the DEA analysis as its output was zero, and the investigation could not evaluate its effectiveness.

Table 4. CCR method for assessing the effectiveness of beverage manufacturers.

	CCR Model	
DMU	**Input**	**Output**
DMU41	0.541	1.8483
DMU42	0.4295	2.3283
DMU43	0.4069	2.4573
DMU44	0.2428	4.1187
DMU45	0.5481	1.8246
DMU48	0.09	11.1069
DMU51	1	1
DMU52	0.0173	57.939
DMU53	0.0778	12.8481
DMU54	1	1

Two effective units were identified: DMU 51 and DMU 54. For example, in DMU 41, an input-oriented CCR proposes a reduction in research and development costs of EUR 917.95 to EUR 1082.05. In the case of DMU 43, it intends to reduce the cost by up to EUR 4269.99 to EUR 2930.01. The new, reduced value of R&D costs explains the amount of input with which an efficient unit can achieve the same output.

Another input variable is the cost of training the employees. In the first look at Table 4, we can see that the effective units are DMU 51 and DMU 54. There are significant differences between others. There are several reasons why there is such a strong suggestion of reducing staff training costs. Efficiency is determined by the amount of revenue that is the output variable of the model. However, income is influenced by several factors, due to the purpose of the final work focusing on the innovative capabilities of the company, the appropriate input variables were chosen to determine the efficiency of resources to support innovation concerning sales. The impact of other factors on sales was likely reflected. Assuming that the output variable is influenced by the inputs we choose, the effective units identified within that group can obtain the same outputs, while eliminating the cost of education. In the case of other units, it does not mean that they should automatically reduce the amount of these costs but consider how to make more effective use of the invested funds.

In the analysis of the CCR-O output, we identified the most significant differences in DMU 48 and DMU 53 production units. For example, if the DMU 41 production unit was effective, it could generate revenue of almost 85% higher on its inputs. For DMU 53, while maintaining inputs, sales could be almost 13 times higher.

The lower number of respondents and relatively homogeneous production, we included companies from divisions 13 and 14 in this group, i.e., in addition to textile producers, there are garment manufacturers in this group. The resulting innovations in the efficiency of individual manufacturers are available in Table 5. In determining outliers, we identified three production units that were not included in the analysis: DMU4, DMU5, and DMU11.

Table 5. CCR method for assessing the effectiveness of textile and clothing manufacturers.

	CCR Model	
DMU	**Input**	**Output**
DMU1	0.3676	2.7202
DMU2	1	1
DMU3	0.6125	1.6327
DMU6	0.0903	11.076
DMU7	0.0352	28.4246
DMU8	0.0185	54.1612
DMU9	0.414	2.4152
DMU10	0.0079	126.2523
DMU12	1	1
DMU13	0.0143	69.9671
DMU14	1	1
DMU15	0.0065	152.7538
DMU16	0.4578	2.1845

When analyzing the industrial sector focusing on the production of textiles and clothing, their research and development expenditures, and their staff training costs, we can say that among other categories, the category invests at least in inputs compared to others. Based on the analysis of CCR-I as effective units, we can consider DMU 2, DMU 12, and DMU 14. These efficient production units can deposit fewer resources than others at the same output level. For the DMU 1 to be effective, it would have to reduce the number of input variables by 64% when the output is unchanged. An efficient unit could generate nearly three times more revenue at these inputs. The DMU 3 production unit uses its inputs at 61% compared to, for example, DMU 12, which uses its inputs to 100%. An effective unit could achieve 63% more revenue with the same DMU 3 inputs.

In the analysis of CCR-O sales, a significant increase in revenue was found in DMU 8, DMU 10, and DMU 15 production units.

Other divisions include manufacturers of rubber and plastic products. The total number of units is nine, and its effectiveness is shown in Table 6. Extreme values were not identified after the outliers were analyzed and, therefore, all units examined were included in the DEA analysis.

Table 6. CCR method for assessing the effectiveness of manufacturers of rubber plastic products.

	CCR Model	
DMU	**Input**	**Output**
DMU84	0.0306	32.6602
DMU85	0.1932	5.1771
DMU86	0.0684	14.6217
DMU87	1	1
DMU88	0.003	338.4313
DMU89	1	1
DMU90	0.1372	7.2865
DMU91	1	1
DMU92	1	1

By using the DEA analysis of the CCR-I input-oriented model, we identified up to four effective production units, DMU 87, DMU 89, DMU 91, and DMU 92, out of nine. We can say that the manufacturers' innovations used to innovate in the enterprise are used effectively. In other cases, there is efficiency in terms of the resources that the units have, and there is potential for it to increase. For example, for DMU 85, its input value for research and development is EUR 350,000, and based on the model used, we found that an effective unit can achieve the same output at EUR 67,605.96. Within this production unit, the model proposes a reduction in training costs of EUR 7500 and an effective unit of EUR 1448.70. Of the total input efficiency, the production unit uses less than 20%. From the output point of view, this unit could reach sales with unchanged inputs more than five times higher.

In this case, we combined two divisions with homogeneous characters of production: Division 24, the manufacture and processing of metals; and 25, the manufacture of fabricated metal products, except machinery and equipment. The total number of participating enterprises in the survey was 17, and the results of the CCR analysis are available in Table 7. The DEA analysis using the CCR model was preceded by an outliers analysis which excluded one DMU 112 unit.

Table 7. CCR method for assessing the effectiveness of metal manufacturers.

	CCR Model	
DMU	**Input**	**Output**
DMU108	0.8438	1.1851
DMU109	0.5376	1.8601
DMU110	1	1
DMU111	0.0917	10.9059
DMU113	0.6689	1.495
DMU114	0.1402	7.1335
DMU115	1	1
DMU116	0.0965	10.3574
DMU117	0.6493	1.54
DMU118	0.5843	1.7115
DMU119	0.1694	5.9048
DMU120	1	1
DMU121	0.8514	1.1745
DMU122	0.1127	8.8769
DMU123	0.4327	2.3109
DMU124	0.2118	4.7221

Based on CCR-I analysis, we identified three effective units: DMU 110, DMU 115, and DMU120. At the same time, we found out the efficiency of using input variables in other units. The CCR-I model demonstrates the effectiveness of inputs for production units and allows them to be categorized into efficient and less efficient. For less effective, it suggests appropriate input reductions to increase their efficiency or points out at what inputs effective units could achieve the same output. For example, DMU 121 uses its inputs to 85%, so the analysis suggests a 15% reduction on unchanged outputs. Effective units would be able to gain 88% more revenue with the inputs. However, the highest level of inefficiency is the cost of training employees when entering variable, so production units should deal with the possibility of more efficient investment (another form of education, change of trainers, etc.)

Based on the revenue analysis using the CCR-O model, we found that the differences between the original and target sales are not very significant. In this case, it is necessary to reassess the investment of resources in this area or make changes in the provision of education.

Into this group, we include manufacturers of various communication devices, computers, electronic products as well as components for this type of products. The total number of respondents in the category was 17 enterprises. Only 11 companies could be included in the DEA analysis because of the outlier values (see in Table 8).

Table 8. CCR method for assessing the effectiveness of PC, electronic and optical equipment manufacturers.

	CCR Model	
DMU	**Input**	**Output**
DMU127	0.3992	2.5049
DMU128	0.1979	5.0533
DMU129	0.0897	11.1426
DMU130	0.201	4.9757
DMU131	0.3074	3.2534
DMU133	0.0601	16.6481
DMU134	1	1
DMU136	1	1
DMU137	1	1
DMU138	0.3552	2.8151
DMU140	0.0779	12.8311

We identified three effective units: DMU 134, DMU 136, and DMU 137. These units use their inputs at 100%, which gives them 100% output. Based on the input-oriented CCR-I model, possible reductions were found in inefficient units. The DMU 131 proposes an almost 70% reduction in input, which does not use its input resources efficiently, but if it uses its inputs in terms of efficiency, not only 30%, it could achieve three times higher revenues.

In the categorization of industrial production within the SK NACE, we analyzed 14 enterprises belonging to the division of machinery and equipment production. It includes the production of machines that can be used for general purposes, possibly unique, as well as metal forming and agricultural and forestry machinery. DMU 143 and DMU 152 units were removed based on an outliers analysis.

The DEA analysis identified three effective units: DMU 145, DMU 148, and DMU 154 (Table 9). Other units propose to reduce inputs at unchanged outputs or increase output at constant inputs, depending on the type of CCR (input/output) model. For DMU 142, it suggests reducing input by 10% while maintaining output. The unit uses the potential of invested funds in its inputs to achieve higher revenues of 90%. An effective unit would, however, earn almost 11% more income from these inputs. With unchanged inputs, DMU 142 has sales of EUR 577,000, but if it had used its resources effectively, the revenue would have been EUR 638,981.48. If we focused on DMU 151, which should reduce its input by 80%, or effective units, they could generate the same revenue at 20% of the original inputs of this production unit.

Table 9. CCR method for assessing the effectiveness of machine and equipment manufacturers.

	CCR Model	
DMU	**Input**	**Output**
DMU142	0.903	1.1074
DMU144	0.2741	3.6486
DMU145	1	1
DMU146	0.5655	1.7684
DMU147	0.3456	2.8933
DMU148	1	1
DMU149	0.2338	4.2767
DMU150	0.8987	1.1127
DMU151	0.197	5.0757
DMU153	0.3329	3.004
DMU154	1	1
DMU155	0.2994	3.3398

Part of the industrial production is the furniture production division, which also includes the manufacture of any material. The number of enterprises participating in the survey under this division is 15. By analyzing outliers for extreme values, five production units were removed. DEA analysis followed with CCR-I and CCR-O models.

We identified two effective DMU 100 and DMU 106 units (Table 10). Other units could use their input resources more efficiently. For example, a DMU 103 unit should reduce its inputs by 44% for the consistent output to be effective, or even if it increases sales by almost 80% for unchanged inputs. Compared to efficient units that use their inputs to 100%, the DMU 104 production unit uses 12% of inputs. Therefore, it would have to reduce its inputs by almost 73% with the output unchanged, and as input levels would remain, then the unit would have to produce eight times more revenue than current.

Table 10. CCR method for assessing the effectiveness of furniture manufacturers.

	CCR Model	
DMU	**Input**	**Output**
DMU93	0.1829	5.4663
DMU94	0.3195	3.1304
DMU95	0.1489	6.7158
DMU96	0.1436	6.9652
DMU100	1	1
DMU101	0.1702	5.8763
DMU102	0.3468	2.8832
DMU103	0.558	1.792
DMU104	0.1244	8.036
DMU106	1	1

5. Discussion

After analyzing the research articles dealing with the evaluation of innovation efficiency using the Data Envelopment Analysis tool, we chose two input variables, R&D expenditures and employee training costs, for 2018. The output variable was the 2018 sales value of the products listed on the market for the past five years. Subsequently, we divided the total number of enterprises 132 by division to increase the reporting value of the analyzed data. We used input CCR-I, as well as the output CCR-O model of DEA analysis, to evaluate efficiency. The result was a proposal to reduce the number of inputs with consistent output or increase the output with unchanged inputs. This type of analysis shows how effectively the funds used by the individual enterprises in the analysis group are used. If the result indicates that the company should reduce its inputs by, for example, 67% (see Figure 1), this does not mean that it should do so, but there is an enterprise in the group of analyzed enterprises that can get the same output at inputs lower by 50%. Above all, businesses should lead them to reassess what they are investing in, ask whether the type of education they provide to their employees is ideal, whether there is a better option, a better trainer, training, technology, procedures and tried to achieve better results.

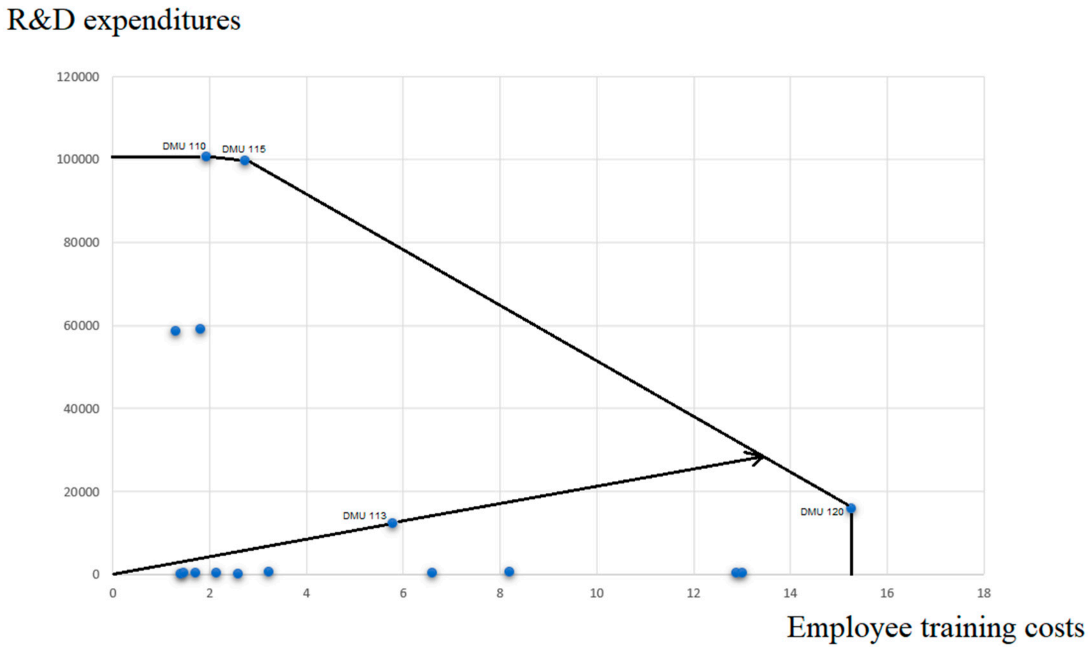

Figure 1. Evaluation of the Efficiency of Metal Manufacturers.

We identified the most efficient units in the industrial production of the rubber plastic products manufacturers Division, where we found four effective units. On the other hand, the least effective units were found in beverage and furniture manufacturers. The differences in the effective use of inputs—the costs of research and development and the costs of education, which are essential in promoting enterprise innovation—are substantial. Obviously, in some sectors, research on employee development and training will play a more important role than others.

In terms of R&D expenditures, business leaders often want to know what others are doing. To what extent do other companies invest in R&D. Leaders want to see the level of costs in absolute terms and also the percentage of income. Research and development expenditures are expected to be somewhat linked to increased business innovation and revenue and profit growth. Research and development costs are an essential source of future growth, innovation, and if they are well managed and realized as well as profit. Whether it is a pharmaceutical company that can invest millions of dollars in research to try to discover a breakthrough cancer drug or technology company that is developing a new line of hardware, R&D is the existing resource not only for a thriving economy but also for an economically prosperous company (Table 11).

The study has its limitations that need to be noted, such as the subjective of the survey. Besides, the other limitation is the absence of comparable quality indicators of R&D and employee education, the lack of information on the structure of R&D and employee training, its results, intensity, duration and ensuring the complete homogeneity and comparability of enterprises. Additionally, the amount of revenue is influenced by several factors (advertising, price programs, supplier–customer agreements, market share, seasonal changes, customer preferences, business management, competitive advantage, etc.), not only by the two chosen inputs. Depending on the industrial products division, the inputs we selected may have some or all of a more significant impact on some of them (computer production-food production). In addition, there may be a time mismatch as research and development costs can be reflected in sales later.

Table 11. Share in industry revenue for 2017 according to R&D expenditures and employee training costs.

Industry	Expenditure Share (R&D and Education) in Revenue 2018
food production	1.36%
beverage production	2.18%
manufacture of textiles and clothing	1.46%
manufacture of rubber and plastic products	2.43%
manufacture and processing of metals and metal structures	4.08%
manufacture of computer electronic and optical products	5.84%
manufacture of machinery and equipment	4.11%
manufacture of furniture	2.47%

6. Conclusions

The main aim of the study was to evaluate the effectiveness of invested finances in the innovation of small- and medium-sized production enterprises in Slovakia. R&D expenditures and employee training costs were input factors in efficiency assessment of innovation management. We identified the number of the most effective Slovak manufacturer in industrial production. These ones from the industrial production of the rubber plastic products manufacturers create their own earnings drivers based on efficiency innovation management.

To eliminate shortcomings, the focus should be on improving the quality, structure, and timeliness of the reported data and incorporating business collaboration that would regularly report the required data, since businesses do not report the inputs we address. Based on the data obtained, more accurate analysis of the data package could be created. As a result, it would be possible to determine the development of the technical efficiency of individual companies.

In addition to the abovementioned DEA analysis, another disadvantage is the deterministic approach and the high degree of subjectivity, which is based on an individual decision—the analyst's decision—on which inputs and outputs to choose in the analysis. DEA analysis still has a margin for statistical significance of indicators. This type of analysis is undergoing continuous development, but there is a presumption of linking econometrics and data package analysis.

Despite the lack of analysis, we conducted the study as a methodological basis for further investigation, possibly supplementing other indicators, or specifying the input variables of the data set or for comparing individual enterprises in a given product sector. Another possible step to deeper insights should gain by either using a meta-DEA frontier or implementing Malmquist indexes. The former should help identified which sector pushes the innovation frontier in Slovakia and which sector invests less fund for more innovation, while the later should help understand how innovation evolves over time as well as provide additional results that illustrate which factor (R&D or training of employees) is more influential in innovation based on slack values.

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References

1. Smith, A.; Stirling, A. Innovation, sustainability and democracy: An analysis of grassroots contributions. *J. Self-Gover. Manag. Econ.* **2018**, *6*, 64–97. [CrossRef]
2. Szkutnik, W.; Szkutnik, W. Socio-economic convergence in models of endogeneous economic growth. *Ekon. Manaz. Spektrum* **2018**, *12*, 1–14. [CrossRef]
3. Janoskova, K.; Kral, P. An In-Depth analysis of the summary Innovation Index in the V4 countries. *J. Compet.* **2019**, *11*, 68–83. [CrossRef]
4. Janoskova, K.; Krizanova, A. Comparison of selected internationally recognized brand valuation methods. *Oecon. Copernic.* **2017**, *8*, 99. [CrossRef]
5. Skarzynski, P.; Gibson, R. *Innovation to the Core: A Blueprint for Transforming the Way Your Company Innovates*; Harvard Business Press: Boston, MA, USA, 2008.
6. Davila, T.; Epstein, M.; Shelton, R. *Making Innovation Work: How to Manage It, Measure It, and Profit from It*; Pearson FT Press: Upper Saddle River, NJ, USA, 2012.
7. Balcerzak, A.P.; Kliestik, T.; Streimikiene, D.; Smrcka, L. Non-parametric approach to measuring the efficiency of banking sectors in European Union Countries. *Acta Polytech. Hung.* **2017**, *14*, 51–70. [CrossRef]
8. Olah, J.; Kovacs, S.; Virglerova, Z.; Lakner, Z.; Popp, J. Analysis and comparison of economic and financial risk sources in SMEs of the Visegrad Group and Serbia. *Sustainability* **2019**, *11*, 1853. [CrossRef]
9. Ljungholm, D.P. Sharing economy, regulatory arbitrage, and urban governance: How city space shapes economic growth and innovation. *Geopolit. Hist. Int. Relat.* **2018**, *10*, 174–180. [CrossRef]
10. Cooper, W.W.; Seiford, L.M.; Zhu, J. *Data Envelopment Analysis: History, Models, and Interpretations*; Springer: Basel, Switzerland, 2011; pp. 1–39.
11. Moravcikova, D.; Krizanova, A.; Kliestikova, J.; Rypakova, M. Green marketing as the source of the competitive advantage of the business. *Sustainability* **2017**, *9*, 2218. [CrossRef]
12. Chen, C.T.; Chien, C.F.; Lin, M.H.; Wang, J.T. Using DEA to evaluate R&D performance of the computers and peripherals firms in Taiwan. *Int. J. Bus.* **2004**, *9*, 347–359.
13. Sueyoshi, T. Damages to return with a possible occurrence of eco-technology innovation measured by DEA environmental assessment. *J. Econ. Struct.* **2017**, *6*, 7. [CrossRef]
14. Hrabynskyi, I.; Horin, N.; Ukrayinets, L. Barriers and drivers to eco-innovation: Comparative analysis of Germany, Poland and Ukraine. *Ekon. Manaz. Spektrum* **2017**, *11*, 13–24. [CrossRef]
15. Sueyoshi, T.; Yuan, Y.; Goto, M. A literature study for DEA applied to energy and environment. *Energy Econ.* **2017**, *62*, 104–124. [CrossRef]
16. Khoshnevis, P.; Teirlinck, P. Performance evaluation of R&D active firms. *Socio-Econ. Plan. Sci.* **2018**, *61*, 16–28. [CrossRef]
17. Lai, P.L.; Potter, A.; Beynon, M.; Beresford, A. Evaluating the efficiency performance of airports using an integrated AHP/DEA-AR technique. *Transp. Policy* **2015**, *42*, 75–85. [CrossRef]
18. Tone, K. A slacks-based measure of efficiency in data envelopment analysis. *Eur. J. Oper. Res.* **2001**, *130*, 498–509. [CrossRef]
19. Kalapouti, K.; Petridis, K.; Malesios, C.; Dey, P.K. Measuring efficiency of innovation using combined Data Envelopment Analysis and Structural Equation Modeling: Empirical study in EU regions. *Ann. Oper. Res.* **2017**, 1–24. [CrossRef]
20. Abbasi, F.; Hajihoseini, H.; Haukka, S. Use of virtual index for measuring efficiency of innovation systems: A cross-country study. *Int. J. Technol. Man. Sustain. Devel.* **2011**, *9*, 195–212. [CrossRef]
21. Kalapouti, K.; Varsakelis, N.C. Intra and inter: Regional knowledge spillovers in European Union. *J. Technol. Transf.* **2015**, *40*, 760–781. [CrossRef]
22. Guan, J.; Kaihua, C. Modeling the relative efficiency of national innovation systems. *Res. Policy* **2012**, *41*, 102–115. [CrossRef]
23. Banker, R.D.; Charnes, A.; Cooper, W.W. Some models for estimating technical and scale inefficiencies in data envelopment analysis. *Manag. Sci.* **1984**, *30*, 1078–1092. [CrossRef]
24. Dvorsky, J.; Popp, J.; Virglerova, Z.; Kovacs, S.; Olah, J. Assessing the importance of market risk and its sources in the SME of the Visegrad Group and Serbia. *Adv. Decis. Sci.* **2018**, *22*, 1–22.
25. Saunders, M.; Lewis, P.; Thornhill, A. *Research Methods for Business Students*; Pearson Education Limited: Harlow, UK, 2012.

26. Singh, A.S.; Masuku, M.B. Sampling techniques & determination of sample size in applied statistics research: An overview. *Int. J. Econ. Commer. Manag.* **2014**, *2*, 1–22.
27. Charnes, A.; Cooper, W.W.; Rhodes, E. Measuring the efficiency of decision making units. *Eur. J. Oper. Res.* **1978**, *2*, 429–444. [CrossRef]
28. Cano, J.A.; Campo, E.A.; Baena, J.J. Application of DEA in international market selection for the export of goods. *DYNA* **2017**, *84*, 376–382. [CrossRef]
29. Soleimani-Damaneh, M.; Zarepisheh, M. Shannon's entropy for combining the efficiency results of different DEA models: Method and application. *Expert Syst. Appl.* **2009**, *36*, 5146–5150. [CrossRef]
30. Sherman, H.D.; Zhu, J. *Service Productivity Management: Improving Service Performance Using Data Envelopment Analysis (DEA)*; Springer: Berlin/Heidelberg, Germany, 2006; pp. 1–157. [CrossRef]
31. Duran, P.; Kammerlander, N.; Van Essen, M.; Zellweger, T. Doing more with less: Innovation input and output in family firms. *Acad. Manag. J.* **2016**, *59*, 1224–1264. [CrossRef]
32. Rizwanullah, M. Data Envelopment Analysis with LINGO modeling for technical educational group of an organization. *Int. J. Data Envel. Anal.* **2016**, *4*, 917–927.
33. Ghosh, D.; Vogt, A. Outliers: An evaluation of methodologies. In Proceedings of the Joint Statistical Meetings, San Diego, CA, USA, 28 July–2 August 2012; pp. 3455–3460.
34. Svabova, L.; Durica, M. Being an outlier: A company non-prosperity sign? *Equilib. Q. J. Econ. Econ. Policy* **2019**, *14*, 359–375. [CrossRef]