Efficiency of mining and quarrying industry of V4 countries: the impact of investments and selected indicators

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Mining and quarrying industry is considered as an important industry since it provides several important natural resources used in energy, manufacturing and other sectors. The efficiency of this industry is then recommended to be measured, evaluated and improved. In this article, we have measured the efficiency of mining and quarrying industry of Visegrad 4 countries. There is a gap in the research of mining and quarrying industry efficiency research in the Central and Eastern European region. We have used modern, widely used method – two-step data envelopment analysis. This method is considered as the most used method of evaluating the efficiency. In the first step, we calculated the efficiencies of countries during the period 2011-2015. The results show that the Slovak Republic is the most inefficient country. Then, using the double bootstrapped efficiencies, which diminish disadvantage of Data Envelopment Analysis (DEA) – determinacy, and then truncated regression, we calculated the regressors of efficiency explaining the model, we have proposed. The results of the model show that Gross investments in machinery and equipment, Gross investments in construction and alteration of buildings and Human Development Index (HDI) have a positive impact on efficiency. On the contrary, results have shown that there is still relatively small amount of inefficient investments. Results proved that there could be exogenous factors of explaining the efficiencies, in our case the HDI index.

Keywords: *Efficiency, DEA, Truncated regression, V4, mining and quarrying.*

JEL Classification*: D24 N57 Q32 Q33*

Introduction

The cooperation of Central European countries, grouped in the Visegrad Four (V4) was successful in many respects. The aim of research in this paper is to show that DEA can be used to help to measure the efficiency of mining and quarrying industry of Visegrad 4 countries. DEA is a well-known method which is used to evaluate the efficiency of decision-making units. This method is based on the use of linear programming. In this study, we focus on the evaluation of efficiency in mining industry using two step DEA approach. Based on the study of literature, we have found that truncated regression and Tobit regression are the most commonly used regressions in this sector, used in the second step of two – step DEA.

Several studies have examined the efficiency of mining sector at the industry level (Zheng and Bloch, 2014; Leško et al., 2006; Cehlár et al., 2014). Based on these studies, there is considerable debate about the efficiency of the mining sector (Connolly and Orsmond, 2011; Parham, 2013). Quarrying and mining have played an essential role in the development of economies during the main history of society. In recent years, it could be said, that improper allocation of safety input has prevailed in coal mines. From another point of view, coal mining has very strong impact on the environment by the air pollution emissions (Fugiel et al., 2017). Generally speaking, there are two main issues in research of coal mining. Firstly, the exploration of mining has often been limited by time-consuming methods of analysis. In addition, it generates information and specimens that support the advancement of geoscience and creates exposures that provide a resource for scientific study, education, training. The mining of coal could be determined as key industry sub sector. On the one hand, this sector has a great impact in terms of investment expenditures on the national economy. Coal mining is stimulated by overall industry growth in a very extensive way. It is needed to highlight that there are significant differences in the distribution of coal resources and their utilisation efficiency across regions. According to studies (Dubinski, 2013; Hodge, 2014; Gomes et al., 2014; Škvareková and Bakalár, 2011; Rybár et al., 2016), the competitiveness of mining does not depend only on the production, but also on the environment. Examination of the relationship between progress and competitiveness of mining industry in selected countries, applying bivariate correlation analysis of respective time series, resulted in pointing to the impact of mining on the competitiveness especially in countries with low or medium economic growth (Madzík et al. 2016).

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The paper briefly summarises the main points of the transformation of the mining and quarrying industry of V4 countries in the European context. Concluding remarks assess the opportunities for the mining industry of V4 in the future.

Methods and methodology

DEA and linear programming problems were introduced by Farrel (1957). DEA is a widely used method for measuring the efficiency, the most used method for explaining the efficiency is the two-step DEA method (Liu et al. 2013). There are several studies that have applied DEA to measure the efficiency of mining companies (Geissler et al., 2015; Tsolas, 2011). Kauppinen (2016) used DEA as a tool for evaluating the frequency of minerals appearing in the drillcores. Another study (Tong and Ding, 2008) had proved, using DEA, that 45 % of resources in China could be saved in coal mining. Sueyoshi et al. (2010) found, using three DEA efficiencies, that the operational and unified performance of coal-fired power plants in the regulated states is better than those in the deregulated states because the investment on coal-fired power plants in the regulated states can be utilized as a financial tool under the rate-of-return criterion of regulation. Fugiel et al. (2017) used DEA to assess the impact caused by mining and quarrying industry in European countries. Results showed that the highest gas emission was in mining and quarrying industry of Great Britain, and the lowest occurs in Bulgary. The environmental indices in all of the impact and damage categories in the mining and quarrying sectors were the highest in Great Britain, Poland, Germany and Norway.

In the first step of two-step DEA, we have to compute the efficiency scores using Cooper, Charnes, Rhodes (CCR) output oriented DEA model according to following input oriented model as a reciprocal value of 1/ϴ (Cooper et al., 2007).

We need n optimisations to find the solution. In each optimisation, we use the notation Decision-making unit DMUo , o =1, 2, ..., n, to denote DMUj. Then the optimal solution of the problem of obtaining weights for all inputs and outputs is the result of partial modelling using the following expression where u and v are variables, y is the amount of output and x is the input:

$$
\begin{aligned}
&\max_{u,v} \theta = \frac{u_1 y_{10} + u_2 y_{20} + \dots\dots\dots + u_s y_{so}}{v_1 x_{10} + v_2 x_{20} + \dots\dots\dots\dots + v_m x_{m0}} \\
&where \frac{u_1 y_{1j} + u_2 y_{2j} + \dots\dots\dots + u_s y_{sj}}{v_1 x_{1j} + v_2 x_{2j} + \dots\dots\dots\dots + v_m x_{mj}} \le 1;\ j = 1,2,\dots,n. \\
&v_1, v_2, \dots, v_m \ge 0 \\
&u_1, u_2, \dots, u_s \ge 0
\end{aligned} \tag{1}
$$

Then the linear model has the following form:

$$
\begin{aligned}
&\max_{u,v} \theta = \mu_1 y_{10} + \dots\dots\dots\dots + \mu_s y_{1s} \\
&where\, \upsilon_1 x_{10} + \dots\dots\dots\dots + \upsilon_m x_{m0} = 1 \\
&\mu_1 y_{1j} + \dots + \mu_s y_{sj} \le \upsilon_1 x_{1j} + \dots + \upsilon_m x_{mj},\ j = 1,2,\dots,n. \\
&\upsilon_1, \upsilon_2, \dots, \upsilon_m \ge 0 \\
&\mu_1, \mu_2, \dots, \mu_s \ge 0
\end{aligned} \tag{2}
$$

Where μ and υ are variables, weights of individual inputs and outputs.

„Let $v = \upsilon = \upsilon^*$, $u = \mu = \mu^*$ a $\theta = \theta^*$ is the optimal solution, then DMU_j is CCR effective if optimal $\theta^* = 1$ and there exists at least one optimal (u^*, v^*) satisfying the condition $u^*, v^* > 0$. Else DMU_j is CCR non-effective“ (Cooper et al. 2007).

In the second step, we need to use regression in order to check the influence of explanatory variables on efficiency. For this purpose, truncated regression and Tobit regression are often used. To get consistent estimates of regression model, we need to use method/algorithm proposed by Simar and Wilson (2007) which provides bias corrected DEA efficiencies suitable for the use in regression models by using the double bootstrap mechanism. Simar a Wilson (2007) suggested solving some of the problems of the two mentioned algorithms. The first algorithm does not take into account the distortion of data. Therefore we use the second, which is used disproportionately more often than the first.

Let $\mathscr{S}_n$ be the set of original data, *P* is set of productivity, *x* is set of inputs, *y* is set of outputs, *δ* efficiency values, *β* are regressors, *ε* is standard error, σ_ε is variance, *z* is explanatory variables set, number of "hats" – "^" above the variable means how many times the data were bootstrapped. The algorithm is expressed as follows:

1) Using $\mathscr{S}_n$ compute $\hat{\delta}_i = \hat{\delta}(x_i, y_i | \hat{P}) \forall i = 1,2,...,n$ using

   $\hat{\delta}_0 = \delta(x_0, y_0 | \hat{P}) = \max\{\theta > 0 | \theta y_0 \le Yq, x_0 \ge Xq, i'q = 1, q \in \Re^n_+\}$.

2) Using the maximum likelihood method to estimate $\hat{\hat{\beta}}$ from β and $\hat{\sigma}_s$ from σ_s in truncated regression where $\hat{\delta}_i$ depends on z_i according to the formula $\hat{\delta}_i = z_i\beta + \xi \ge 1$ using $m < n$ observations where $\hat{\delta}_i > 1$.

3) Repeating the following four steps L₁-times to gain *n* sets of bootstrap estimates $B_i - \{\delta^*_{ib}\}_{b=1}^{L_1}$
   a) For every $i = 1,2,...,n$ choose ε_i from the distribution $N(0, \hat{\sigma}_s^2)$ left-truncation at $1 - z_i\beta$.
   b) Again for every $i = 1,2,...,n$, compute $\delta^*_i = z_i\hat{\beta} + \varepsilon_i$.
   c) Set $x^*_i = x_i, y^*_i = \frac{y_i\hat{\delta}_i}{\delta^*_i}$, for every $i = 1,2,...,n$.
   d) Compute $\hat{\delta}^*_i = \delta(x_i, y_i | \hat{P}^*)$, for every i = 1,2, …..n, where $\hat{P}^*$ is gained by the replacement of ***X,Y*** in $\hat{P} = \{(x, y | y \le Yq, x \ge Xq, i'q = 1, q \in \Re^n_+\}$ by the terms $Y^* = [y^*_1 ... y^*_n]$ and $X^* = [x^*_1 ... x^*_n]$.

4) For every $i = 1,2,...,n$, computing the bias-corrected estimator $\hat{\hat{\delta}}_i$ defined as $\hat{\hat{\delta}}_i = \hat{\delta}_i - \widehat{BIAS}(\hat{\delta}_i)$ using the bootstrap estimates from the set B_i gained in the step 3.d and the original estimate $\hat{\delta}_i$.

5) Using the method of maximum likelihood to calculate the truncated regression where $\hat{\hat{\delta}}_i$ depends on z_i to get the estimates $(\hat{\hat{\beta}}, \hat{\hat{\sigma}})$.

6) Repeating the following three steps L₂-times to gain the sets of bootstrap estimates $C = \{\hat{\beta}^*, \hat{\sigma}^*_s\}_{b=1}^{L_2}$:
   a) For every $i = 1,2,...,n$, choose ε_i from the distribution $N(0, \hat{\hat{\sigma}}^2)$ left-truncation at $1 - z_i\hat{\hat{\beta}}$.
   b) Again for every $i = 1,2,...,n$, compute $\delta^{**}_i = z_i\hat{\hat{\beta}} + \varepsilon_i$.
   c) Use the method of maximum likelihood to calculate to estimate the truncated regression of $\delta^{**}_i \sim z_i$ which yields to the estimates $(\hat{\hat{\beta}}^*, \hat{\hat{\sigma}}^*)$.

7) Use the bootstrap values in *C* and the original $\hat{\hat{\beta}}, \hat{\hat{\sigma}}$ to construct estimated confidence intervals for each element of β and for each σ_s (Simar a Wilson, 2007).

The truncated regression model will be used in the form of:

$$\delta_i = z_i\beta + \varepsilon_i, i = 1,...,n. \quad (3)$$

where δ_i is DEA efficiency score of selected DMU, z_i is set of explanatory variables, β are regression coefficients and ε_i is a standard error. If we use algorithm proposed by Simar a Wilson (2007) truncated regression model will have the following form:

$$\hat{\delta}_i^{BC} \approx z_i \beta + \varepsilon_i \quad \mathrm{i} = 1,2,......,\mathrm{n}, \\ \text{where}\, \varepsilon_\mathrm{i} \geq 1 - z_i\,\beta \ \text{ and}\, \varepsilon_\mathrm{i} \in \mathrm{N}\left(0, \sigma_s{}^2\right) \tag{4}$$

where $\hat{\delta}_i^{BC}$ is bias corrected efficiency using the second algorithm proposed by Simar and Wilson (2007).

Data will be truncated left to point 1, because output efficiencies are in interval 1 to infinity. The main point of this regression is that explanatory and dependent variables under this boundary are latent. Regression Tobit assumes that only explanatory variable is the latent one.

Our model will thus have the following form:

$$\hat{\delta}^{BC} = \beta_0 + HDI\beta_1 + GDP/10^4\beta_2 + GITng\beta_3 + \\ + GICnstr\beta_4 + GIMchnr\beta_5 + \varepsilon_i. \tag{5}$$

Variables, mentioned above will be described in the next section.

Data

We have collected data for the industry mining and quarrying from different databases. The major database, from which we collected data, was Eurostat (2017). The second database, from which we have obtained GDP of selected countries, was World Bank database (2017). The third source was a database of United Nations development program – Human development reports (2017) – index HDI.

We evaluated the efficiency of the mining and quarrying industry of V 4 countries – Slovakia, Czech Republic, Hungary and Poland throughout the years 2011 – 2015. As input variables (the lower value – the better value) we have chosen *Number of Enterprises*, *Number of persons employed* and *Average cost per employee (in thousand €).* On the contrary to inputs, we have chosen the following output variables: *Turnover or gross premium written* (in millions of €) and *Production value* (in millions of €).

Because we want to determinate the influence of the investments in this industry, we chose Gross investments in tangible goods (in millions of €) – *GITng,* Gross investments in construction and alteration of buildings (in millions of €) – *GICnstr*, Gross investments in machinery and equipment (in millions of €) – *GIMchnr* as the explanatory variables. Because we have to test the influence of some macroeconomic indicators on the efficiency of mining and quarrying industry, we decided to implement two of the most used indicators – Gross domestic product per capita in US dollars divided by 10^4 – $GDP/10^4$ and Human development index – *HDI.* Individual values are shown in Table 1.

In Table 1, differences between selected countries during the selected period from 2011 to 2015 can be observed. The highest number of enterprises was in Poland. The number of enterprises was declining in Hungary. This data set can be described from many points of view, so we remain other variables undescribed.

Tab. 1. Values of input, output and explanatory variables.

.	Country	Number of enterprises	Personnel	Average personnel costs	Turnover or gross premiums written	Production value	Gross operating surplus	HDI	$GDP/10^4$	GI in tangible goods	GI in construction and alteration of buildings	GI in machinery and equipment
2011	CR	333	35917	20.7	3769.6	3451.7	979.5	0.86	1.9764	433.2	118.1	289.5
	Hungary	469	4707	15.1	405.6	342.7	82.7	0.82	1.30258	72.4	42.3	26.9
	Poland	1785	176563	22.8	12472.9	13011	3893.9	0.83	1.25995	1297.4	518.2	719.2
	Slovakia	108	7286	15.7	499	497.9	191.2	0.83	1.66016	110.6	68.2	17.1
2012	CR	348	34607	22.1	3919.1	3711.4	1111.2	0.87	2.17175	521.3	171.2	330.6
	Hungary	459	4547	16.2	430.5	380.6	118.5	0.82	1.40489	78.7	39.7	37.9
	Poland	2014	174000	24.3	14728.9	15260	5380.6	0.83	1.38934	1703.3	631	1016.3
	Slovakia	138	7442	16.4	543.4	524.2	208.8	0.83	1.8186	50.6	22.6	13.3
2013	CR	359	34072	23	3602.2	3449.1	829.7	0.87	1.97299	452.7	208	215.2
	Hungary	448	4403	16.8	441.2	369.6	111.9	0.82	1.28343	42.9	19.4	23.3
	Poland	1944	175220	25	14495.6	15186	4680.4	0.84	1.31451	1919.3	795.6	1082.6
	Slovakia	125	7316	16.7	505.1	497.6	198.2	0.84	1.72746	36.8	12.2	9.9
2014	CR	363	33015	21.3	3401.5	2944.4	599.4	0.87	1.9916	391.7	173	202.7
	Hungary	448	4337	17	491.6	418.1	130	0.83	1.36136	40.4	10.5	29.1
	Poland	1657	171468	23.5	13781.1	13628.6	3816.4	0.84	1.37805	1825.4	927.1	863.1
	Slovakia	157	7407	16.8	527.2	528	200	0.84	1.81916	52.5	12.3	25.7
2015	CR	380	30854	19.9	2947.6	2614.9	542.6	0.87	1.97446	280	111.5	153.8
	Hungary	429	4298	17.4	447	387.4	99.3	0.83	1.4118	45.8	4.3	40.7
	Poland	1852	164037	24.4	12450.5	12982.6	3380.1	0.84	1.43419	2033.6	1133.5	851.8
	Slovakia	193	7137	17.3	567	533	206	0.84	1.85952	26.7	7	9.9

Source: processed according to the data from Eurostat, World Bank and UN

Results

First of all, we need to compute individual efficiencies for the first step of DEA. We used the statistical program R to compute these efficiencies. We computed CCR output efficiency values. If the value is 1, then the country is CCR efficient, if not, it is inefficient. The higher absolute value, the more inefficient country. Then we computed bias corrected efficiency values, which are higher than CCR efficiency computed before. It is because the stochastic noise is included in these values. Last two columns show the lower and upper confidence intervals of efficiency, in which the true values of efficiency could be found with the level of significance 0.001. It means that the true values of efficiencies could be observed with probability 99.9 % in these intervals. These computations are necessary for the second step of DEA since they provide statistically consistent input to build up a regression model of mining and quarrying industry in selected countries. Table 2 describes the individual values connected with measured efficiency.

Tab. 2. Results of DEA computation.

Year	Country	CCR Output efficiency	Bias corrected efficiency	Lower Confidence Interval Boundary	Upper Confidence Interval Boundary
2011	Czech Republic	1	1.0692473	0.9559209	1.1309729
	Hungary	1.3151702	1.3607960	1.2702125	1.4053488
	Poland	1.0692083	1.0808806	1.0526527	1.0922272
	Slovakia	1.5693538	1.6719577	1.5482360	1.7744130
2012	Czech Republic	1	1.0731288	0.9510233	1.1461628
	Hungary	1.1968368	1.2433247	1.1656247	1.2889809
	Poland	1	1.0186181	0.9755845	1.0369914
	Slovakia	1.5225321	1.6219990	1.5035808	1.7213217
2013	Czech Republic	1.0594139	1.1320218	1.0213744	1.2045293
	Hungary	1.1311571	1.1681700	1.0883856	1.2040672
	Poland	1	1.0113365	0.9902035	1.0226377
	Slovakia	1.5767656	1.6798064	1.5566306	1.7826977
2014	Czech Republic	1.0991679	1.1552681	1.0513747	1.2112621
	Hungary	1	1.0325645	0.9619281	1.0648518
	Poland	1	1.0223635	0.9527091	1.0442913
	Slovakia	1.5044655	1.6026987	1.4864670	1.7007893
2015	Czech Republic	1.1854032	1.2432829	1.1286088	1.3010481
	Hungary	1.0897183	1.1263345	1.0507491	1.1623835
	Poland	1.1046795	1.1191017	1.0886541	1.1323808
	Slovakia	1.4255547	1.5151810	1.4123259	1.6045774

There was no country efficient in all years within the selected period. The Czech Republic was efficient in years 2011 and 2012, Poland was efficient in years 2012, 2013 and 2014, and Slovakia and Hungary were inefficient in the selected period. The higher number of CCR output efficiency, the more inefficient country, since we are using output oriented efficiency. Next column shows the values of double bootstrapped efficiencies, which means, that there is statistical bias incorporated. The most efficient, but still inefficient, were, according to bootstrapped efficiencies, Poland within the whole period, Hungary in the year 2014 and the Czech Republic in years 2011 and 2012. Using bootstrapped values, we can calculated and proposed a statistically consistent model. The worst values of efficiencies, according to the upper confidence interval, could occur in case of the Slovak Republic. Figure 1 graphically shows the distance from efficiency border in selected countries.

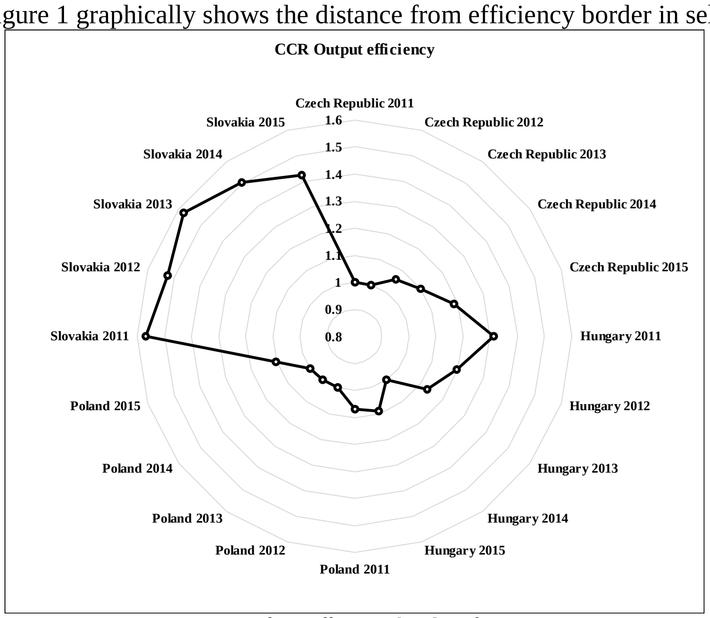

Fig. 1. Distance from efficiency border of V4 countries.

Figure 1 clearly shows that the most distant country from efficiency border is Slovakia. It means that, within the level of input, it produces the less output from selected countries of V4. The Czech Republic is more distant from efficiency border with every next year. On the contrary, Hungary is performing better than in 2011. From Figure 1, a trend of efficiency changes within the period selected is clearly observable. Table 3 shows the results from truncated regression of model we proposed.

Tab. 3. Model results.

	Dependent variable: CCR output efficiency
	Truncated regression
Intercept	10.1106866^{***}
	(0.0001)
HDI	-11.9918098^{***}
	(0.0009)
$GDP/10^4$	0.7358147^{**}
	(0.002)
GITng	0.0129091^{**}
	(0.001)
GICnstr	-0.0119270^{**}
	(0.004)
GIMchnr	-0.0149598^{***}
	(0.0005)
Sigma	0.043^{***}
	(0.0001)
Observations	20
Log Likelihood	28.817
R^2	0.6405
Note:	$^{*}p<0.05. ^{**}p<0.01. ^{***}p<0.001$

The results of the computation show that we can consider all the explanatory variables as statistically significant. R^2 of the model is 0.6405, which means that model explains 64% of the variability of the dependent variable. Variables *HDI, GICnstr, GIMchnr* have expected/positive effect on efficiency, which means that higher value of these variables, the lower value of inefficiency, which is, in fact, a better state. On the contrary to this finding, variables *$GDP/10^4$* and *GITng* have a negative/unexpected effect on efficiency.

Discussion

In this section, we can compose and discuss truncated regression model. Our model has, according to the results of our computation, the following form:

$$\widehat{\delta}_i^{\,BC} = 10.1107 - 11.9918 HDI + \frac{0.7358 GDP}{10^4} + 0.0129 GITng - 0.0119 GICnstr - 0.0150 GIMchnr + \varepsilon_i$$

We will mainly discuss the unexpected effects of two variables, i.e. GDP per capita and Gross Investments in tangible goods. GDP of selected countries is mostly orientated and gained from different sectors. The share of GDP is declining in the case of mining and quarrying industry. Politics of the European Union are mostly focused on research of new “greener” approaches in the energy sector (Fugiel et al., 2017). Moreover, the heavy industry of coal mining, for example, is standing apart, since this industry is considered as environmentally not friendly. These facts could be the reason, why the GDP per capita is not a suitable indicator for explaining the efficiency in selected industry.

It is also necessary to discuss, why the Gross investments in tangible goods have negative effect on efficiency in the industry of mining and quarrying. This could be explained by the fact that after the year 1989, there was privatisation of some state owned companies. New for-profit oriented stakeholders were aiming at the highest profits, so they are not likely to invest. As we consider, that state-owned companies, as well as privately-owned companies, were, and maybe they still are, in need of high capital investments - governments had to invest high amount of capital in these companies. Since the Gross investment is just the sum of particular types of investments, our model has proven that there are some particular types of investments which are inefficient in this industry. However, in the case of investments in machinery and construction of buildings, these investments have a positive impact.

Makridou et al. (2016) examined the efficiency of energy intensive industries in period 2000 to 2009 in selected 23 European Union countries. They found, that in the case of the mining industry, using Malmquist productivity index which is composed of two components – efficiency change and productivity change, the total productivity factor growth change was mainly caused by technology change, not by efficiency change. This fact is important because it proves our considerations, that there is a need for technology improvement. This research also strongly pointed to the fact, that manufacturing and mining sectors present higher inefficiencies and stronger scale effect than in other sectors. It means that policy makers should give priority to improving the energy efficiency performance of these sectors more than in the other energy intensive sectors. Hosseinzadeh et al. (2016) found that most of the mining companies in Australia are within the selected period performing better, so it would be appropriate to deeply check what changes had taken part in Australia and implement some of these policy changes in our region. They also pointed to the fact, that research in the field of efficiency evaluation in the mining industry is limited, so this contribution is highly original, and there are just a few contributions to compare this study with. San Cristóbal and Biezma (2006) measured the linkages of the mining and quarrying industry in the European Union and determined if any of the industry subsectors can be considered key sectors. They found that three sub-sectors can be considered key sectors: the mining of coal and lignite and extraction of peat in Germany; mining of metal ores in Sweden, and other mining and quarrying in Austria, Denmark and Spain. These sectors are more stimulated by overall industry growth than other sectors and have greater impacts in terms of investment expenditures on the national economy than other sectors. The values of the forward and backward linkages show that the mining and quarrying is an industry that would be stimulated by an increase in a regional economy's production more than other sectors, while an increase in the mining and quarrying industry's output would not stimulate this regional economy more than an increase in other sectors. Vuori et al. (2008) compiled the available 2007 production data from public authorities and industrial enterprises in Finland to produce an overall view of production and volumes, as well as better the understanding of the profoundly positive downstream economic effects of secure access to such natural resources. Total metallic ore associated extraction in 2007 was ca. 7 Mt, of which ca. 4 Mt was ore and ca. 3 Mt was gangue. In terms of ore extraction, Finland's biggest mining operations were the Kemi chromite mine at 1.6 Mt (Outokumpu Chrome Oy) and the Pyhäsalmi copper-zinc mine at 1.4 Mt (Inmet Mining Corp./Pyhäsalmi Mine Oy). Industrial mineral production in 2007 amounted to 16.3 Mt out of total extraction of 24.8 Mt. The leading products were calcite and dolomite (4.4 Mt), apatite concentrate (830 kt) and talc (535 kt). Investment in industrial mineral mining reached €35 million - the highest level in the observed 13-year period. Production figures for granite have remained at around 600 kt, while soapstone production has almost doubled since 2002 to around 200 kt. The production of rock aggregates increased steadily from ca. 90 Mt in 2000 to ca. 110 Mt in 2007. Peat resources are scattered throughout Finland, but the production is concentrated in the regions of Ostrobothnia, Satakunta, Central Finland and North-Savo. Most peat (90 %) is burned for energy, but environmental and horticultural peat types now comprise 6-7 % of production. The annual energy production has varied between 17,000 and 27,000 GWh in recent years (ca. 20-32 Mm^3). The geothermal primary energy utilisation in Finland show marked increase in recent years. In a study by Armsworth et al. (2010) businesses from a variety of sectors demonstrated a clear interest in managing their impacts on, and exploiting opportunities created by, ecosystem services and biodiversity. To achieve this, businesses are asking diverse ecological research questions, but publications in leading applied ecology journals and research council funding reveal limited evidence of direct engagement with businesses. This represents a missed opportunity for ecological research findings to see the more widespread application.

Conclusion

Our research shows that there are inequalities in the efficiency of mining and quarrying industry between the selected countries of V4. The worst results were observed in Slovakia. We have bootstrapped the efficiencies and then calculated the model using the truncated regression. The model shows that higher investments, except the investments in tangible goods, have a positive impact on the efficiency of selected countries. Some of the buildings and machinery used in the V4 countries are "out-of-date", so procuring of new equipment and remediation of buildings should have a positive impact on the efficiency of this industry. These investments are very important because they are improving and encouraging the competitiveness of V4 countries not only in the EU market. The other fact is that raising investments in the tangible goods is according to the results of our model not improving the efficiency. The data assume that the amount of investments in the tangible goods is higher than in the case of buildings and machinery. As we consider, that the value of investments in tangible goods is composed of the sum of investments in machinery, investments in buildings, construction and some other investments (not shown in Eurostat), these implicate, that there could be inefficiency in other types of investments. So this "unknown" part of investments should be put under examination in the future. This research is strongly original, since measuring, evaluating and explaining the efficiency of industry Mining and quarrying is completely missing not just in the case of V4, but also in some other countries. According to the results, there could be exogenous factors for explaining the efficiencies, for example, the HDI index in our case, which has been proven to be a good indicator of explaining the efficiency in this industry. The research is likely to be an opening of the discussion to improve the efficiency of mining and quarrying industry by improving the efficiency of particular economical processes.

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