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Article

Efficiency Analysis of East Asian Zinc Smelters and the Effects of Capacity and Bonus Zinc on Efficiency

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Abstract: Non-ferrous metals are widely used as basic materials in various industrial fields, and zinc is a metal that is produced and used next to iron, aluminum, and copper. In this study, DEA (data envelopment analysis) was applied to measure the efficiency of 43 zinc smelters in three countries in East Asia: Korea, China, and Japan. The constant returns to scale (CRS) and the variable returns to scale (VRS) models, and the slack-based measure (SBM) were used for the analysis. As a result of the efficiency analysis, there were three efficient zinc smelters in the CRS model, 14 in the VRS model and 14 in the SBM. The average efficiency was 0.458 based on the SBM, which indicates that there is room for improvement in efficiency. In addition, the average scale efficiency value was 0.689, showing the scale to be inefficient. Therefore, it can be seen that the labor cost and the energy cost must be brought to an appropriate level. The Tobit regression analysis was used to analyze the causes of efficiency. The greater the capacity and the larger amount of bonus Zn of the refinery, the higher the efficiency of the refinery.

Keywords: zinc smelter; East Asia; DEA; SBM; efficiency analysis; Tobit regression analysis

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1. Introduction

A nonferrous metal refers to a metal other than iron, such as lead (Pb), zinc, tin, nickel, aluminum, magnesium, gold, silver, and platinum. The nonferrous metal industry can be divided into the smelting and the processing industries. The nonferrous metal smelting industry refers to an industry that purchases nonferrous metal ores and conducts smelting and refining processes to produce metals with high purity in the form of ingots [1]. The non-ferrous metal processing industry is an industry that uses non-ferrous metal as a raw material to manufacture products through processes such as rolling, extrusion, casting, and forging. The non-ferrous metal processing industry creates various types of processing products such as plates, stands, chests, rods, tubes, etc. The non-ferrous metal industry is a capital-intensive equipment industry that requires a large amount of capital to construct a plant. In order to continuously produce stable quality products, a long-term accumulation of technology is required. These requirements of accumulated technology and large amount of capital are high barriers to entry for new entrants [2,3]. The domestic non-ferrous metal industry, including the smelting and processing industries, is relatively large in terms of its annual market value of $38 billion (based on the first non-ferrous metal manufacturing shipments in 2013) [1]. This is because the downstream industries of the nonferrous metal industry are widely dispersed, such as electricity, automobiles, machinery, chemicals and steel, and are widely used as basic materials in various industrial fields.

World trade in nonferrous metal products is centered around the London Metal Exchange (LME), and fluctuations in LME prices have a major impact on the performance of nonferrous metal smelting and processing companies [2]. LME prices are affected by various variables such as the demand for non-ferrous metals, the supply capacity of concentrates, speculative investment, changes in geopolitical conditions and the value of the dollar as a payment instrument. Zinc is the most commonly used metal in the world after iron, aluminum and copper. It is used with iron in industry to prevent the corrosion of iron (50%) and the manufacture of alloys (30%) including brass (zinc and copper alloys), battery material and other compounds (20%).

Table 1 shows the production volume for each region from 2012 to 2015. As you can see, zinc production worldwide is around 13,000 kt, and is increasing gradually. The region with the lowest production of zinc products is the Middle East, producing 103 kt per year from 2012 to 2015. The largest region is Asia, which increased by about 1500 kt from 7141 kt in 2012 to 8637 kt in 2015. In 2014, global zinc production is at 13,281 kt, of which zinc production in Asia is 8022 kt, accounting for 60.4% of global production. By country, China's production is the highest at 5675 kt, followed by Korea (901 kt), India (736 kt), Japan (584 kt) and other countries (126 kt). The production volume of China, Korea, and Japan, three East Asian countries, is 7160 kt, accounting for more than 50% of global production.

Table 1. Zinc production (2012–2015) (unit: kt).

Area	2012	2013	2014	2015
Africa	170	139	134	83
Asia	7141	7626	8022	8637
Europe	2094	2113	2215	2224
South America	599	653	619	635
Middle East	103	103	103	103
North America	1231	1230	1106	1186
Oceania	498	499	484	489
Russia	617	572	599	570
Total	12,454	12,935	13,281	13,927

Due to the recent slowdown in global economic growth, competition among zinc smelters in Asia, especially in the three East Asian countries (China, Japan and Korea) which produce 60% of the world's zinc products, is expected to be inevitable. Cost reduction and profit improvement through the efficiency of the smelters is important to secure an advantage in this competition. Therefore, we compare the efficiency of 43 smelters in three East Asian countries and identify the factors that affect efficiency in order to improve it. Capacity is an important factor for many companies in terms of scale efficiency, and bonus zinc is an indicator of the degree of excellence in the zinc production process. In this way, the zinc refinery industry treats these two factors as important for the performance of the company, but there is little research on the empirical effect on the efficiency. In this study, the efficiency of zinc smelters in three East Asian countries (China, Japan, Korea) was analyzed using data envelopment analysis (DEA). In order to improve inefficiency, we will identify two factors which are expected to affect efficiency, namely capacity and bonus zinc.

2. Literature Review

DEA has been widely applied to research related to the relative efficiency measurement of companies, governments, public institutions, research institutes, banks, hospitals, and so on. For example, Ko and Kim (2014) [4] measured the efficiency of 91 retail stores located in Seoul, Korea using the DEA model. As a result, although the same business processes, IT systems, and employee education programs were available, the efficiency of each store was different, and it was found that the optimal number of products was the cause of the efficiency difference. Park and You (2013) [5] conducted an analysis of the efficiency of domestically listed pharmaceutical companies using the DEA model. As a result, listed pharmaceutical companies need to make efforts to improve production processes and the management environment to improve efficiency. Park et al. (2009) [6] evaluated the efficiency of 74 general hospitals over 500 hospital beds in Korea. As a result of analyzing the difference between efficient hospitals and inefficient hospitals, major differences were found in terms of their material cost, labor cost, number of operations, and outpatient revenues. In addition, it was found that hospitals located in Seoul in the form of a corporation and established over 50 years ago are efficient. Using the DEA model and the post-DEA model, Ju and Kim (2014) [7] compared the efficiency of 18 regional software convergence centers for the regional software growth support projects conducted in 2012. Tier analysis has identified the groups that can be benchmarked in real terms. Tobit analysis shows that the total number of software companies in the region and the total number of personnel in the regional software convergence center are factors affecting efficiency. Shin (2006) [8] conducted an analysis of efficiency and productivity for 10 national university hospitals in the fiscal years of 2001–2004. The efficiency was measured by human efficiency, profit efficiency, and hospitalization efficiency according to the input variables and the characteristics of the output variables. The average efficiency of hospitals has been declining in general, the number of the most efficient hospitals has decreased, the polarization of efficiency between hospitals has intensified, and the wastage of resources has been worsened. Productivity has risen, but this is due to the increase in the productivity of a few leading hospitals, and efficiency has declined. Yoon and Kim (2006) [9] analyzed the efficiency of the 200 top-ranked companies among listed companies on the Korea Stock Exchange. The more efficient the firm, the higher the effect of efficiency on stock prices compared to the inefficient firms. Yum and Shin (2013) [10] analyzed the efficiency of 46 university–industry cooperation groups of large-scale universities with more than 15,000 students enrolled in 2011. As a result, university–industry cooperation groups from provincial public universities showed efficiency. Lee and Han (2011) [11] conducted an efficiency evaluation of 527 public libraries in Korea using the DEA model. As a result, the average efficiency of public libraries was found to be very low, and the efficiency of public libraries established by the major cities and the capital regions was relatively high. Sohn and Choi (2014) [12] measured the relative efficiency using the DEA model in order to find out management measures to improve the efficiency and quality of the medical services of 72 nursing hospitals in 2012. The results indicated that hospitals with more hospitalized nursing homes and a lower turnover rate of nursing personnel and staff showed better efficiency and a higher quality of medical service.

There is little research on the efficiency of zinc smelters in domestic and overseas studies. Shao et al. (2016) [11] used a DEA to investigate the total-factor productivity (TFP) of China's nonferrous metal industry. They identified the fluctuation of TFP and the key factors for it in the nonferrous metal industry during 2004–2013. The result showed that the overall TFP of China's nonferrous metal industry is relatively low. It was also shown that the TFP growth in the smelting sector accounted for the technical progress. In the pressing and processing sector, however, scale efficiency was found to be the biggest source of TFP increase. Shao and Wang (2016) [12] studied the environmental efficiency of China's nonferrous metals industry production utilizing DEA. The result showed that the efficiency of the east area in the industry was larger than that of the other area. The average annual increase of the Malmquist Production Index was 4.4%. This indicted that the annual growth in productivity of the industry is relatively high. The major contributor to productivity growth was technological progress.

3. Method

3.1. DEA Models

There are two major ways to measure efficiency: parametric and nonparametric methods. DEA is a nonparametric method based on the concept of nonparametric efficiency measurement proposed by Farrell (1957) [13] and the concept of distance function of Shephard (1970) [14].

DEA derives the most efficient DMUs (decision-making units) from all the DMUs to be evaluated and then calculates the relative efficiency of the individual DMU based on the efficient DMUs. DEA has two basic models of the CRS (constant returns to scale) model proposed by Charnes et al. (1978) [15] and the VRS (variable returns to scale) model developed by Banker et al. (1984) [16]. The CRS model is based on the assumption that the rate of output to input is unchanged at a constant, regardless of the input size. The CRS model can be formulated as follows:

$$\theta^{k*} = Min\theta^k$$

which is subject to

$$\theta^k x_m^k \ \geq \ \sum_{j-1}^{J} x_m^j \lambda^j (m = 1, 2, \ \ldots . \ M)$$

$$y_n^k \ \leq \ \sum_{j-1}^{J} y_n^j \lambda^j (n = 1, 2, \ \ldots . N)$$

$$\lambda^j \geq 0 \ (j = 1, 2, \ldots . \mathrm{J})$$

On the other hand, the VRS model assumes that the rate of output to input changes according to input size. In this case, by imposing the constraint of convexity ($\sum_{j=1}^{J} \lambda^j = 1$) on the linear programming model of the CRS model, the VRS model can be developed as the following:

$$\theta^{k*} = Min \ \theta^k$$

which is subject to

$$\theta^k x_m^k \ \geq \ \sum_{j-1}^{J} x_m^j \lambda^j (m = 1, 2, \ \ldots . \ M)$$

$$y_n^k \ \leq \sum_{j-1}^{J} y_n^j \lambda^j (n = 1, 2, \ \ldots . \ N)$$

$$\sum_{j=1}^{J} \lambda^j = 1$$

$$\lambda^j \geq 0 \ (j = 1, 2, \ldots . \mathrm{J})$$

Since the CRS model shows technological efficiency when it is in an optimal state in terms of scale, the scale efficiency (SE) can be deduced from the difference of the technological efficiency of these two models.

$$\mathrm{SE} = \frac{\theta^*(CRS)}{\theta^*(VRS)}$$

The CRS and VRS models of the DEA fall into the radial model category because the inefficient DMUs move in the direction of the origin to become efficient. The radial model has the disadvantage that the efficiency value is distorted because the efficiency value is measured as 1 despite the existence of the slacks of the input and output elements. To overcome this problem, Tone (2001) [17] proposed the SBM (slacks-based measure) by applying an average input/output efficiency improvement ratio. The average input improvement ratio is an average value of the amount of reduction of the M input factors and is independent of the unit, and the average output efficiency improvement ratio is an average value of the amount of increase of the N calculation elements and is independent of the unit.

The average input improvement ratio is as follows:

$$\frac{1}{M} \left(\sum_{m=1}^{M} \frac{x_m^k - s_m^-}{x_m^k} \right)$$

While the average output improvement ratio is as follows:

$$\frac{1}{N}\left(\sum_{n=1}^{N}\frac{y_n^k+s_n^+}{x_n^k}\right)$$

Improving the efficiency of the kth observation under the structure of the SBM model is the same as reducing the input and increasing the output within the production possibility set. Let the input slack indicate the input excess, and output slack be the shortage of output shortfall. After making the input and output slacks unitless, the efficiency is measured using the average of the input slack and the average of the output slack.

$$\theta_{SBM}^{k*}=\min_{\lambda,s^+,s^-}\left(\frac{1}{M}\sum_{m=1}^{M}\frac{x_m^k-s_m^-}{x_m^k}\right)/\left(\frac{1}{N}\sum_{n=1}^{N}\frac{y_n^k+s_n^+}{x_n^k}\right)$$

or

$$\theta_{SBM}^{k*}=\min_{\lambda,s^+,s^-}\left(1-\frac{1}{M}\sum_{m=1}^{M}\frac{s_m^-}{x_m^k}\right)/\left(1+\frac{1}{N}\sum_{n=1}^{N}\frac{s_n^+}{x_n^k}\right)$$

which is subject to

$$x_m^k=\sum_{j=1}^{J}x_m^j\lambda^j+s_m^-(m=1,2,\ldots,M)$$

$$y_n^k=\sum_{j=1}^{J}y_n^j\lambda^j+s_n^+(n=1,2,\ldots,N)$$

$$\sum_{j=1}^{J}\lambda^j=1$$

$$\lambda^j\geq 0(j=1,2,\ldots.,J)$$

$$s_m^-\geq 0(m=1,2,\ldots.,M)$$

$$s_n^+\geq 0(n=1,2,\ldots.,N)$$

Since the SBM does not need to move toward the origin in order to improve the efficiencies of the DMUs, it belongs to the category of a non-radial model. In addition, by measuring the inefficiency of slacks, it can have an advantage over the CRS model and the VRS model, which have slacks even if the efficiency score is equal to one.

3.2. Date Collection and Variable Selection

The data used to analyze the efficiency and cause of the 43 zinc smelters (DMU) in East Asia was from the 2014 survey data of Wood Mackenzie, a global energy, metal and mining business consulting firm. The data includes sales, zinc manufacturing method, and various expenses of the zinc smelters. The selected DMUs, the zinc smelters in East Asia, are from 35 firms in China, six in Japan, and two in Korea.

In order to select input and output variables for efficiency analysis, we refer to the previous study of the steel industry, which is a similar industry, and the key management indices of the zinc smelters. Zinc smelters' key management indicators are raw material costs, utility costs, and maintenance costs. The selected input variables include labor, utility, maintenance, and raw material costs. Labor cost was used as an input variable in most previous studies of the steel industry, and the utility cost, raw material cost and maintenance cost were considered because they are key management indicators of the zinc smelters and a feature of the smelting industry. The output variables are sales and production volume. The sales revenue and production volume are selected because both sales revenue and production volume have been used as output variables in most prior studies, and sales revenue and production volume are key performance indices of the zinc smelters. (See Table 2).

Table 2. Descriptive statistics of input and output variables.

Classification	Input				Output	
	Labor Cost	**Utility Cost**	**Maintenance Cost**	**Material Cost**	**Revenue**	**Production Volume**
	1000 US$	**1000 US$**	**1000 US$**	**1000 US$**	**1000 US$**	**kt**
Max	39,735	177,917	77,431	519,682	730,805	548
Min	210	343	115	1282	903	1
Mean	11,781	42,290	17,433	151,654	112,401	120
Standard Deviation	7534	41,541	15,553	135,587	125,435	113

4. Results

4.1. Efficiency Analysis

The results of the analysis of the efficiency of 43 zinc smelters in East Asia are shown in Table 3. The first column in Table 3 represents the DMUs, and the second column shows the countries where the DMUs are located. The third column indicates the efficiency values by the CCR model, and refers to the total technical efficiency (TE). Efficient zinc smelters are found in the three places, and the remaining 40 zinc smelters are relatively inefficient DMUs. The average efficiency of the entire zinc smelter by the CCR model is 0.605. The fourth column shows the efficiency values from the BCC model. This implies the pure technical efficiency (PTE). In the BCC model, there are 14 efficient zinc smelters, and the remaining 29 smelters are inefficient DMUs. The average efficiency of all smelting companies by BCC model is shown as 0.878.

In the fifth column, SE values indicating scale efficiency are presented, and three zinc refineries (DMU14, DMU32, and DMU42) are effective in terms of scale, and the most scale inefficient zinc smelter is DMU19 (0.390). The cause of inefficiency comes from the comparison of SE and PTE. For example, for DMU35, SE (0.793) is larger than PTE (0.760). This means that the inefficiency of DMU35 is due to the inefficiency of pure cost. Therefore, DMU35 should try to improve its technology through R & D to be efficient. Conversely, for the DMU1, the PTE (0.888) is higher than SE (0.719). This means that to improve the efficiency, the inputs of labor cost and utility cost should reach appropriate levels.

In the eighth column, the efficiency values of the SBM model are shown. The number of efficient Zinc smelters is the same 14 DMUs as the BCC model, and the remaining 29 zinc smelters are relatively inefficient. The average efficiency of the entire zinc smelter is 0.458, indicating that there is room for improvement.

Reference groups are naturally generated as outputs of DEA algorithms and represent efficient DMUs. If a DMU k is efficient, it does not have a reference group. If DMU k is inefficient, then it has a reference group including at least one efficient DMU. In this case, the θ^{k*} of DMU k is determined relative to its reference group. In order for inefficient DMUs to become efficient DMUs, reference groups must be benchmarked to reduce or increase their input or output. Table 4 shows the lambda (λ) value of the input-based BCC model. The lambda (λ) value is the weight of the reference DMU at which the efficiency frontier of the inefficient focal DMU is represented by the ratio of the reference DMU. Reference group DMUs are relatively close to the efficiency frontier of the focal DMU, and therefore, the reference DMUs have similar characteristics to the focal DMU. For example, DMU4 (China), DMU14 (China), DMU32 (China), DMU41 (Japan) and DMU42 (Korea) are the reference groups for DMU1 (China). The reference frequency of a DMU is the number of times used for the evaluation of other DMUs.

Table 3. Efficiencies of zinc smelters in East Asia in 2014. DMU: decision-making units; PTE: pure technical efficiency; SE: scale efficiency; SBM: slacks-based measure.

DMU	**Countries**	**CRS**	**VRS**	**Scale**	**Cause of Inefficiency**		**SBM**
		TE	**PTE**	**SE(TE/PTE)**	**PTE**	**SE**	
1	China	0.639	0.888	0.719		●	0.145
2	China	0.533	0.853	0.624		●	0.283
3	China	0.494	0.787	0.628		●	0.131
4	China	0.982	1.000	0.982		●	1.000
5	China	0.638	0.835	0.764		●	0.540
6	China	0.600	0.847	0.708		●	0.529
7	China	0.589	1.000	0.589		●	1.000
8	China	0.397	0.817	0.486		●	0.245
9	China	0.558	0.918	0.607		●	0.171
10	China	0.468	0.825	0.567		●	0.286
11	China	0.547	0.829	0.660		●	0.095
12	China	0.546	0.810	0.674		●	0.154
13	China	0.469	0.875	0.536		●	0.004
14	China	1.000	1.000	1.000			1.000
15	China	0.413	0.769	0.537		●	0.118
16	China	0.809	1.000	0.809		●	1.000
17	China	0.356	0.732	0.486		●	0.121
18	China	0.681	0.867	0.786		●	0.181
19	China	0.248	0.636	0.390		●	0.028
20	China	0.331	0.787	0.420		●	0.079
21	China	0.519	0.966	0.536		●	0.328
22	China	0.872	1.000	0.872		●	1.000
23	China	0.824	1.000	0.824		●	1.000
24	China	0.467	0.970	0.481		●	0.346
25	China	0.617	1.000	0.617		●	1.000
26	China	0.455	0.786	0.579		●	0.174
27	China	0.290	0.710	0.409		●	0.043
28	China	0.448	0.768	0.583		●	0.140
29	China	0.345	0.793	0.435		●	0.205
30	China	0.476	0.894	0.532		●	0.057
31	China	0.827	1.000	0.827		●	1.000
32	China	1.000	1.000	1.000			1.000
33	China	0.507	0.769	0.658		●	0.042
34	China	0.623	1.000	0.623		●	1.000
35	China	0.603	0.760	0.793	●		0.476
36	Japan	0.579	0.797	0.726		●	0.207
37	Japan	0.696	0.832	0.837	●		0.209
38	Japan	0.369	0.720	0.512		●	0.096
39	Japan	0.649	0.909	0.713		●	0.261
40	Japan	0.908	1.000	0.908		●	1.000
41	Japan	0.737	1.000	0.737		●	1.000
42	Korea	1.000	1.000	1.000			1.000
43	Korea	0.892	1.000	0.892		●	1.000
Average		**0.605**	**0.878**	**0.689**	**PTE**	**2**	**0.458**
Efficient DMUs		**3**	**14**	**3**	**SE**	**38**	**14**

Note: Where "●" is placed indicates the cause of inefficiency.

Table 4. The reference DMUs and lambda values of the BCC model.

DMU	**Countries**	**BCC**	**Reference DMU(λ)**	**Frequency of References**
		Efficiency		
1	China	0.888	D4(0.186), D14(0.366), D32(0.408), D41(0.131) D42(0316)	

Table 4. *Cont.*

DMU	Countries	BCC	Reference DMU(λ)	Frequency of References
		Efficiency		
2	China	0.853	D4(0.306), D14(0.023), D32(0.069), D41(0.323), D42(0.346)	
3	China	0.787	D4(0.202), D32(0.414), D41(0.032), D42(0.518)	
4	China	1.000		13
5	China	0.835	D7(0.141), D22(0.005), D31(0.134), D40(0494), D42(0.225)	
6	China	0.847	D31(0.391), D32(0.108), D40(0.418), D41(0.076), D43(0.114)	
7	China	1.000		8
8	China	0.817	D7(0.249), D40(0.302), D41(0.132), D42(0.316)	
9	China	0.918	D14(0.079), D22(0.066), D41(0.519), D42(0.334)	
10	China	0.825	D4(0.104), D7(0.219), D34(0.129), D41(0.152), D42(0.525)	
11	China	0.829	D4(0.239), D14(0.256), D42(0.504)	
12	China	0.810	D4(0.651), D14(0.348)	
13	China	0.875	D14(0.077), D22(0.397), D41(0.525)	
14	China	1.000		19
15	China	0.769	D14(0.132), D22(0.057), D41(0.366), D42(0.445)	
16	China	1.000		
17	China	0.732	D4(0.115), D14(0.138), D41(0.280), D42(0.467)	

Table 4. *Cont.*

DMU	Countries	BCC Efficiency	Reference DMU(λ)	Frequency of References
18	China	0.867	D4(0.032), D14(0.475), D42(0.493)	
19	China	0.636	D14(0.376), D22(0.229), D41(0.395)	
20	China	0.787	D7(0.158), D40(0.488), D41(0.178), D42(0.174)	
21	China	0.966	D7(0.430), D34(0.267), D42(0.302)	
22	China	1.000		10
23	China	1.000		
24	China	0.970	D7(0.528), D34(0.384), D42(0.087)	
25	China	1.000		
26	China	0.786	D4(0.209), D14(0.006), D42(0.784)	
27	China	0.710	D7(0.219), D14(0.077), D22(0.295), D41(0.345), D42(0.282)	
28	China	0.768	D4(0.126), D14(0.198), D41(0.176), D42(0.498)	
29	China	0.793	D4(0.016), D14(0.015), D41(0.792), D42(0.176)	
30	China	0.894	D7(0.019), D40(0.226), D41(0.617), D42(0.136)	
31	China	1.000		2
32	China	1.000		
33	China	0.769	D4(0.548), D14(0.452)	
34	China	1.000		2
35	China	0.760	D14(0.025), D22(0.059), D41(0.221), D42(0.694)	

Table 4. *Cont.*

DMU	Countries	BCC Efficiency	Reference DMU(λ)	Frequency of References
36	Japan	0.797	D14(0.335), D22(0.117), D41(0.355), D42(0.192)	
37	Japan	0.832	D14(0.353), D22(0.481), D42(0.166)	
38	Japan	0.720	D14(0.303), D22(0.060), D41(0.636)	
39	Japan	0.909	D4(0.262), D14(0.036), D41(0.317), D42(0.383)	
40	Japan	1.000		5
41	Japan	1.000		20
42	Korea	1.000		23
43	Korea	1.000		1

4.2. Causal Analysis

Through the DEA, the relative efficiency of the DMU can be measured and the target value to become an efficient DMU can be given for the inefficient DMU. However, in order to improve the efficiency of the inefficient DMU, it is necessary to identify the factors that affect the efficiency. Since the efficiency value is limited to a value greater than 0 and less than 1, the Tobit regression analysis is used. In this study, the production capacity of zinc smelters and the amount of additional zinc, called bonus zinc, were selected as the determinants of the efficiency of the East Asian zinc smelters. According to the study of Wei et al. [13] on China's technology and scale efficiency of nonferrous metal firms, efficiency increases with larger production capacity. Thus, the production capacity of zinc smelters can affect their efficiency. The amount of additional zinc extracted represents the excess amount of zinc compared to the expected zinc content at the time of purchase of zinc ore, and are dependent on the proprietary method or skills of the smelters. That is, when the same amount of raw material is purchased, the more products can be produced with a higher zinc extraction rate, and the more efficient the smelter will be expected to be. Therefore, the bonus zinc was considered to be a determinant of the efficiency.

The Tobit regression model can mostly be utilized where dependent variables have only a limited range of values. The efficient score has values between zero and one. Therefore, the Tobit regression model is used in the study. In this study, the dependent variable is the efficient score generated by DEA.

A higher production capacity does not necessarily mean that it is efficient. Scale inefficiency occurs in two situations: one is when the current capacity is lacking, and the other is when the current capacity has passed the optimal point. In addition, higher bonus Zn does not necessarily mean that it is efficient. This is because, if the production cost of bonus Zn is greater than the cost of producing ordinary Zn, the zinc production efficiency of the company may be low. Thus, in our study, we examined both the sign and the magnitude of the causality between production capacity, bonus zinc, and efficiency. Table 5 shows the results of the Tobit regression analysis. The production capacity of zinc smelters and bonus zinc are found to be significant at a 1% significance level. From the coefficients of the Tobit model, it is shown that the production capacity of the zinc smelter and the additional zinc have a positive relationship with the efficiency. This indicates that as the production capacity of the zinc smelter and the amount of bonus zinc increases, the efficiency of the zinc smelter becomes higher. In addition, this causality explains that companies with the ability to produce more zinc—that is, companies that have accumulated more know-how in the production of bonus Zn—are also more efficient in the production of total zinc.

Table 5. Results of the Tobit regression analysis.

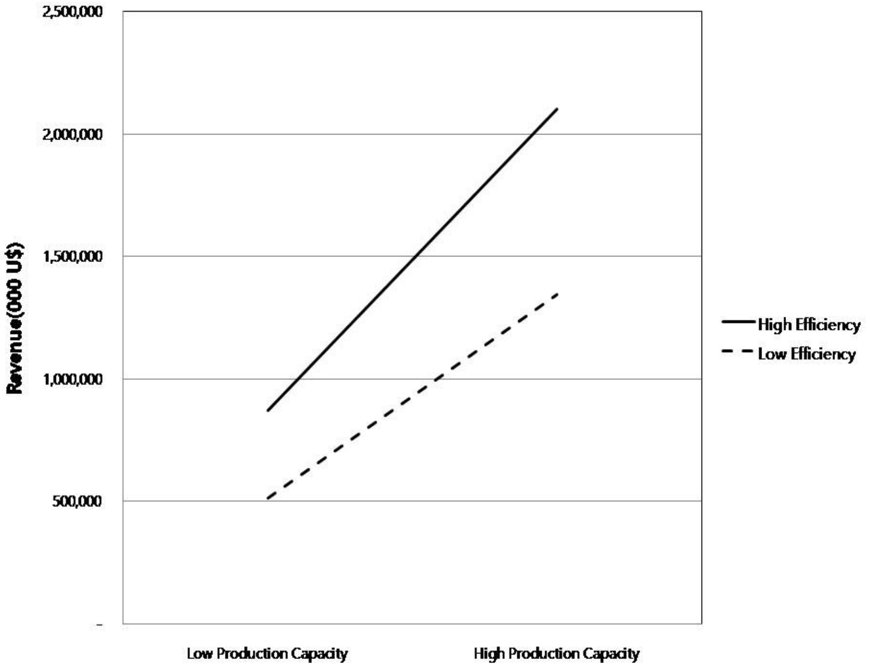
Classification	Coefficient	Standard Deviation	*z* value	Pr (>∣*z*∣)
Intercept	0.2425	0.0786	3.0830	0.002049 **
Capacity	0.0007	0.0002	3.0400	0.002368 **
Bonus Zn	0.0216	0.0057	3.7710	0.000163 ***
Adg. R^2				0.1656

Note:. **: 0.05; ***: 0.01.

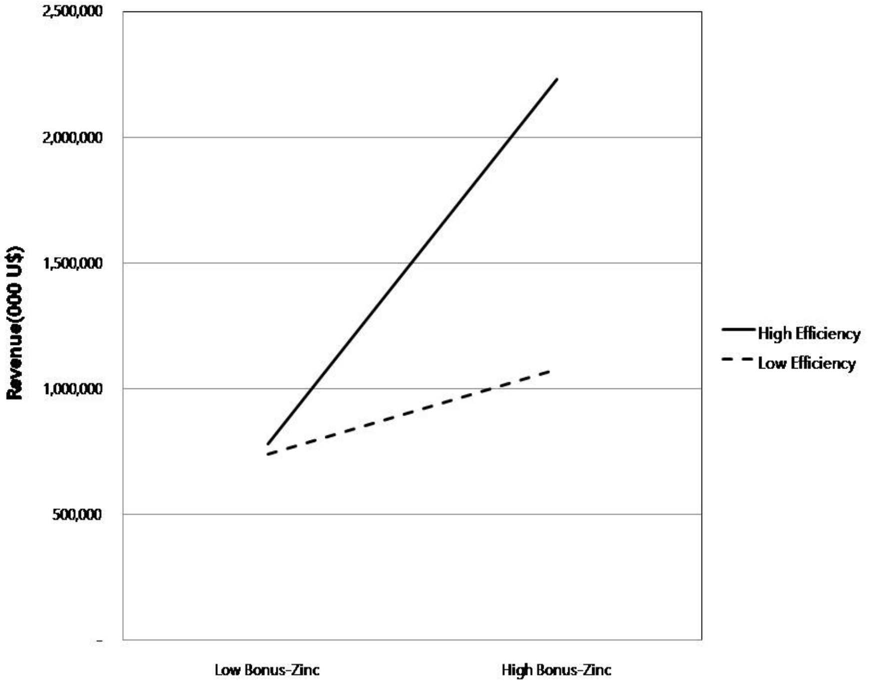
4.3. Performance Analysis

In this study, we analyzed the effect of efficiency in relation to production capacity/bonus zinc and revenue. For the analysis, two groups were classified into high and low according to the production capacity of the zinc smelter. Figure 1a shows the effect of production capacity on sales revenue by efficiency level. As can be seen from the figure, the difference in sales is larger according to the efficiency group when the production capacity is larger than the difference in sales due to the efficiency group when the production capacity is small. That is, it can be seen that there is an effect of efficiency. Regardless of the difference in production capacity, we can see that the sales performance of the high-efficiency group is higher. Therefore, it can be seen that efficiency has an important effect on the increase of sales. This is consistent with the results of Ping Wei et al. [13], because the efficiency of the scale is maximized when the production capacity is large and the efficiency is high.

Figure 1b shows the effect of the bonus zinc scale on sales revenue according to the level of efficiency. As can be seen in the figure, when the size of the bonus zinc is small, the sales revenue difference according to the efficiency level does not appear to be large. This shows that, no matter how high the efficiency is, the ability to extract additional zinc has an important impact on sales. In other words, companies need to have the ability to obtain additional zinc in order to increase sales. On the other hand, when the size of the bonus zinc is large, it can be seen that there is a large difference in sales depending on the efficiency. That is, as in the case of the production capacity, it can be seen that there exists an effect of efficiency. In addition, the group with low efficiency shows that the increase in sales is relatively gradual even if the size of the additional zinc is increased. This means that even if the company has the ability or skill to extract a lot of additional zinc, if the overall efficiency of the operation is low, it cannot necessarily be linked to sales increases [18–20].



(**a**) Relationship between production capacity and revenue.



(**b**) Relationship between bonus zinc and revenue.

Figure 1. The effect of efficiency.

5. Conclusions

Competition among smelters in Asia, particularly in East Asia (China, Japan, and Korea), where more than 50% of the world's zinc products are produced, is expected to be inevitable as global economic growth slows. Therefore, the improvement of profit through the efficiency of companies is becoming more important. The purpose of this study is to compare and analyze the efficiency of 43 zinc smelting plants in East Asia in 2014 using the DEA model and to propose an efficiency-improvement plan.

As a result of the analysis, it is found that there are 14 efficient zinc smelters, and the average efficiency of the entire zinc smelter is 0.458 in SBM, which shows that there is a large difference between high-efficiency companies and low-efficiency companies. From the scale inefficiency perspective, also, among the 40 inefficient companies, 38 companies exhibited inefficiency caused by scale inefficiency. Only two out of the 40 inefficient firms showed that their cause of inefficiency was from pure technological inefficiency. Thus, most inefficient firms are more likely to need to adjust their input size rather than needing technological improvements. Based on this, the potential improvement targets of the inefficient zinc smelters are derived, suggesting the direction of efficiency improvement. As the benchmark for efficiency improvement, zinc smelters in Korea were the most referenced.

We also analyzed the effect of two key performance indices of zinc smelters, the production capacity and bonus zinc, on the efficiency of zinc smelting firms. As a result of the analysis, both the capacity and the bonus zinc have a positive influence on the efficiency at the significance level of 1%. This means that the greater the zinc production capacity and the more zinc is extracted from the raw material, the higher the expected efficiency. In other words, in order to become an efficient zinc smelter, it is necessary to secure cost advantages through economies of scale, and efforts should be made to improve the bonus zinc extraction rate through technological development.

On the other hand, there is an effect of efficiency on the relationship between production capacity/bonus zinc and sales revenue. The result shows that the difference of sales revenues between different levels of efficiency at a large production capacity is larger than the difference in sales by the efficiency level at a small production capacity. Thus, it can be concluded that efficiency is an important factor for sales revenue increases, especially for the case of large production capacities. The result supports the result of Ping Wei et al. [13] that the efficiency of a zinc smelter can be affected by production capacity.

It is also known that, in the case where the amount of the bonus zinc obtained is small, the difference of sales revenue between the two groups with different efficiency levels is not particularly large. This means that, in this case, the ability to extract bonus zinc is a more important factor than the efficiency for sales revenue. That is, if firms are in this situation, they should make efforts to improve their ability to obtain bonus zinc to increase sales revenue. On the other hand, in the case where the bonus zinc extracted is large, there is a large difference of sales volume depending on the efficiency level. This means that, in this case, the effect of bonus zinc on sales revenue can be affected by the efficiency of the firms. Thus, it is important to improve the ability of extracting bonus zinc as well as the efficiency if firms are in this condition. Moreover, when the firms show low efficiency, the sales revenue increase does not appear to be particularly large even if the amount of the bonus zinc is increased. This implies that even if the firm retains the technology or skills to obtain more bonus zinc, the sales revenue might not be increased enough if the efficiency of the firm is low.

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