Productivity Inequality and Efficiency in the mining sector: A Decomposition Analysis of Indonesia’s Provincial Economies

KATAOKA Mitsuhiko

Graduate School of Business, Rikkyo University, Tokyo, Japan

Address; 3-34-1Nishiikebukuro,Toshima-ku,Tokyo, Japan171-8501*Tel:+81-3-5705-8360; Email: mkataoka@rikkyo.ac.jp*

ORCID ID: 0000-0002-0752-454X

Abstract

In general, the mining sector contributes to the development of remote areas, which may not have taken place otherwise. As Indonesia has rich mineral deposits scattered throughout the country, productivity in mining operations is very important for regional development.

We measured the relative efficiency factors influencing interprovincial inequality in mining labor productivity in Indonesia for 1990–2010, by applying data envelopment analysis in the inequality decomposition analysis. We found that the efficiency component contributes negligibly to the narrowing interprovincial inequality in mining productivity, which means that most regions in Indonesia have similar relative efficiency in resource utilization and allocation. The reason for this may be the large-scale operations and exclusive mining rights of Indonesia’s mining firms, which means that these firms operate at nearly the maximum level and optimal scale.

In contrast, pure labor productivity contributes largely to the narrowing productivity inequality. The composition of yielding natural resources and the quality and size of mineral deposits are factors that have a major influence on pure labor productivity.

Keywords: interprovincial inequality decomposition, productivity, data envelopment analysis, efficiency, Indonesia

JEL classification code: O11, O18, R11, R12, R58

Acknowledgements

This study is supported by Grant-in-Aid for Scientific Research C (26380308) by the Japan Society for the Promotion of Science.

1. Introduction

The mining industry has some special characteristics that are not shared with many other sectors. Not a few mineral deposits occur in remote locations and their relative scarcity increases their prices that can cover the long distance transportation cost. The mining operations contributed to make export earning, attract foreign capital, provide infrastructure, , raise the tax revenues, create jobs, provide new skills for the labor force, and generate demands for local goods and service. Besides, the mining production is mostly on a large scale and is heavily mechanized, so that the industry is capital-intensive rather than labor-intensive. (Clarke et al 2013).

In the context of regional science, the role of mining activities receives great attention in regional development, because the mining sector, of which productivity is the higher than other sectors, contributes to the development of many remote areas, which may not have taken place otherwise. Therefore, several empirical studies examined the relationship between the mining sector and regional income in resource rich countries such as, Australia Chile, China, Indonesia, Peru, Russia, South Africa, the United States (Akita et al. 2011, Bas and Kunc 2009, Bhattacharyya and Resosudarmo 2015, Bosker and Krugell. 2008, Buccellato and Mickiewicz 2009, Donald 1987, Fatah 2008, Fleming and Measham. 2015, Ivanova 2014, Kresge and Seiver 1978, Loayza and Rigolini. 2016, Partridge and Lobao 2013, Reeson et al. 2012, Spiegel 2012).

The mining sector has made a very significant contribution to the Indonesian economy over the past several decades and will continue to do so for decades to come. According to a Fraser Institute survey, Indonesia is ranked amongst the top six countries in the world in terms of geological prospectively. Indonesia is the seventh largest producer of both gold and coal in the world and the second-largest gold producer in Asia.

Given Indonesia's rich mineral resources, the mining sector represents a large share of the gross domestic product (GDP) of many provinces, including that of East Kalimantan (41.6%), Riau (35.8%), Papua (33.3%), West Nusa Tenggara (27.4%), South Kalimantan (22.2%), and South Sumatra (21.1%), contributing approximately 8% to the national GDP (Central Bureau of Statistics 2010).

Although the nation increased employment and GDP in the mining sector in 1990–2010, the higher annual growth in employment (4.4%) relative to GDP growth (1.4%) resulted in negative growth of labor productivity (−2.9%). Due to the highly capital-intensive nature of this sector, in 2010, mining productivity (IDR 136 million) was much higher than non-mining productivity (IDR 19.2 million); therefore, the mining operations scattered across the nation may contribute to affecting the interprovincial economic imbalance and has been frequently questioned in the empirical research (Akita et al. 2011, Bhattacharyya and Resosudarmo 2015, Fatah 2008). Akita et al. (2011) analyzed structural changes from the mining to the manufacturing sector as determinants of Indonesia's interprovincial income inequality. Bhattacharyya and Resosudarmo (2015) examine the relations between growth in mining sector and reduction in poverty and inequality, using provincial panel data for 1977 – 2010. They found that growth in non-mining significantly reduces poverty and inequality while growth in mining appears to have no effect on the same due to the asymmetric forward and backward linkages of mining and non-mining sectors. Fatah (2008) uses a Social Accounting Matrix (SAM) to analyze the impact of the coal mining industry on the South Kalimantan Province's economic growth and environmental sustainability. The results show that the large-scale coal mining is more profitable economically than small-scale operations while the latter is more environmental friendly. However, to the best of our knowledge, very few studies examined the interregional difference in mining labor productivity, associated with efficiency factors.

We measure the causal factors of interprovincial inequality in mining labor productivity in Indonesia for 1990–2010 by referring to Cheng and Li's (2006) inequality decomposition technique. We apply data envelopment analysis (DEA) to incorporate relative efficiency factors in the decomposition analysis.

2. Method and Data

Note that all exogenous variables and related endogenous variables used in this study are specific to the mining sector, assuming that each province uses factor inputs in the mining sector to produce the corresponding GDP.

2.1. DEA Application of Multiplicative Income Decomposition

DEA is a linear-programming method for assessing the relative efficiency of decision-making units (DMUs). DEA derives a surface called "frontier," which follows peak performers and envelops the remainder. The DEA model has two versions by assumption with different frontiers: (1) constant returns to scale (CRS) where all DMUs operate at the optimal scale and (2) variable returns to scale (VRS) where all DMUs operate at the maximum level.

Each DMU is assigned an efficiency score between zero and unity (efficient: score = 1; inefficient: score < 1). The VRS and CRS models measure the scores for pure technical efficiency (*pe*) and overall technical efficiency (*oe*), respectively. The ratio of *oe* to *pe* derives scale efficiency (*se*). The *pe* score helps assess the ability of a DMU to utilize a given resource, whereas the *se* score helps assess the optimality of the operation size (Coelli et al. 2005). We use the output-oriented model that maximizes the DMU's outputs and keeps inputs unchanged.

We treat a province as a DMU and use output-oriented CCR and BCC models in order to take into account given province-specific resource endowments and the presence of economies or diseconomies of scale in Indonesia's provinces. Suppose that each province *i* ($i = 1, ..., n$) uses *m* inputs X_{ij} ($j = 1, ... m$) to produce gross regional domestic products (GRDP) of the mining sector Y_i. In the output-oriented DEA model, Y_{si} and Y_{ei} are province i's projected output of GRDP without pure technical inefficiency and overall technical inefficiency, respectively. Our study use physical and human capital and labor as input variables.

Figure 1 depicts piecewise-linear frontiers assembled by four observed DMUs A–D. The diagonal passing through 0B represents the CRS frontier, whereas ABD represents the VRS frontier. All observed DMUs except C are efficient under VRS, and only a straight line passing through B is efficient under CRS. C1 and C2 are projected under VRS and CRS, respectively. Two projected output values Y_{si} and Y_{ei} are shows as are from actual output values Y of inefficient DMU C. Then, each of three score in province *i* is expressed as (oe = Y_i / Y_{si}), (pe = Y_i / Y_{ei}), and (se = Y_{ei} / Y_{si}).

We can run the following output-oriented DEA CCR model in the dual form to obtain the pe_{io} score of one of *n* province under evaluation, denoted as province io:

$$\begin{aligned}
&\mathrm{Max}_{\theta,z}\ \theta \\
&\text{s.t. } \theta \cdot Y_{10} \leq \Sigma^{n}_{i=1} z_i Y_i \\
&\Sigma^{n}_{i=1} z_i X_{ij} \leq X_{i0j}\ (j = 1, \ldots m) \\
&z_i \geq 0 \\
&\Sigma^{n}_{i=1} z_i = 1\ (i = 1, \ldots n),
\end{aligned} \tag{1}$$

where θ and z are decision variables. (1/θ) represents the pe_{io} score, which varies between zero and unity. z is an unknown optimal weight for each province and takes a non-negative value. Removing the last constraint, we obtain the oe_{i0} scores (Y_i / Y_{ei}) under CRS. Dividing *oe* by *pe*, we obtain the *se* score (Y_{si} / Y_{ei}). The relation of the three scores is expressed as follows:

$$oe_i = pe_i \cdot se_i \,. \tag{2}$$

Let L be the labor force; labor productivity is then expressed as $x_i\,(= Y_i / L_i)$. Below the frontier level, the labor productivity is decomposed as follows:

$$x_i = (Y_{ei} / L_i\,) \cdot pe_i \cdot se_i = x_{ei} \cdot oe_i \,, \tag{3}$$

where $x_e = (Y_e / L)$ indicates pure labor productivity, that is, labor productivity after eliminating the overall technical inefficiency. It is affected by the per capita level of factor inputs and technological progress.

2.2. Inequality Decomposition Method

Let μ_x, μ_{xe}, and μ_{oe} be the provincial mean values of labor productivity, $\mu_x\ [= (1 / n)\ \Sigma x_i]$, and its two multiplicative elements. The interprovincial inequality of labor productivity is measured by the Theil second index as follows:

$$T(x) = (1 / n)\ \Sigma^n_{i=1} \ln (\mu_x / x_i)\ [T(x) \geq 0], \tag{4}$$

where T represents the Theil second index.

Substituting Equation (3) into Equation (4) and multiplying the quotient inside the natural logarithm by $(\mu_{xe} \cdot \mu_{oe} / \mu_{xe} \cdot \mu_{oe})$ yields

$$\begin{aligned} T(x) &= (1 / n)\ \Sigma^n_{i=1} \ln\,[\mu_{xe} / xe_i \cdot \mu_{oe} / oe_i \cdot \mu_x / (\mu_{xe} \cdot \mu_{oe})] \\ &= (1 / n)\ \Sigma^n_{i=1} \ln\,(\mu_{xe} / xe_i) \\ &\quad + (1 / n)\ \Sigma^n_{i=1} \ln\,(\mu_{oe} / oe_i) + \ln\,[\mu_x / (\mu_{xe} \cdot \mu_{oe})], \end{aligned} \tag{5}$$

where the first and second additive terms on the right-hand side are strict Theil second indexes.[1] We rewrite Equation (5) as

---

[1] Theil indexes are distance functions that measure the divergence between the two shares. Their structure requires that the weights be given by the share in the numerator of variables inside the natural logarithm (Gisbert 2001). Quotients inside the natural logarithm of the first and second terms in Equation (5) are expressed as follows.

$$(\mu_{xe} / xe_i) = [(1 / n) / (xe_i / \Sigma xe_i)]$$

$$T(x) = T(xe) + T(oe) + \ln [\mu_x / (\mu_{xe} \cdot \mu_{oe})]. \quad (6)$$

We express the covariance of *xe* and *oe* [*cov(xe, oe)*] as follows:

$$cov(xe, oe) = (1 / n) \Sigma^n_{i=1} (xe_i - \mu_{xe}) (oe_i - \mu_{oe})$$
$$= \mu - \mu_{xe} \cdot \mu_{oe} . \quad (7)$$

Dividing both sides by ($\mu_{xe} \cdot \mu_{oe}$), we get

$$\mu / (\mu_{xe} \cdot \mu_{oe}) = cov(xe, oe) / (\mu_{xe} \cdot \mu_{oe}) + 1. \quad (8)$$

Substituting Equation (8) into Equation (6), we obtain

$$T(x) = T(xe) + T(oe) + \ln [cov(xe, oe) / (\mu_{xe} \cdot \mu_{oe}) + 1]$$
$$= T(xe) + T(oe) + I(xe, oe), \quad (9)$$

where $I(xe, oe) = \ln [cov(xe, oe) / (\mu_{xe} \cdot \mu_{oe}) + 1]$ is the interaction term that can be positive, negative, or zero if the element variables are correlated positively, correlated negatively, or not correlated.

We measure inequality decompositions in the *oe* score using Equation (2).

$$T(oe) = T(pe) + T(se) + I(pe, se) \quad (10)$$

2.3 Data

We use data on GDP and factor inputs (labor and physical capital) of the mining sector in 26 contiguous Indonesian provinces for the quinquennial period of 1990–2010.[2] The data on GDP and labor are from the *Statistical Yearbook of Indonesia* (Central Bureau of Statistics 1990–2010), and we estimate the provincial values of physical capital by using data from Kataoka and Wibowo (2014) and Yudanto et al. (2004).[3] All monetary values are expressed

---

$$(\mu_{oe} / oe_i) = [(1 / n) / (oe_i / \Sigma oe_i)]$$

Each term is weighted by the number of provinces $(1/n)$ and satisfies the Theil index property.

[2] Political reforms after the 1998 economic crisis increased the number of provinces from 27 to 34. Until now, no effort has been made to adjust historical data to account for these changes. Therefore, we consider only 26 provinces, aggregating data on the new and existing provinces for each year.

[3] These two studies present the aggregate physical capital estimates by province for 1990–2010 and national physical capital estimates by sector for 1960–2002, respectively. We employ exponential

in constant prices for the year 2000.

3. Empirical Results

Table 1 shows the summary results of the efficiency analysis for 1990 and 2010. The higher mean and minimum values of both *pe* and *se* scores indicate that the mining sector for majority of the provinces utilized given factor inputs at nearly the maximum level and allocated factor inputs at nearly the optimal scale. This increase in both values for the period suggests that there was improvement in their abilities of resource utilization and allocation.

Table 2 displays the numbers of provinces by returns to scale (RTS).[4] The provinces exhibiting CRS increased from nine to 21 for the period, by decreasing provinces exhibiting IRS (from seven to five) and DRS (from 10 to zero). For the period, many scale-inefficient provinces could have adjusted their size of operation to gain efficiency. This suggests that the mining sector could have managed to prevent being subjected to business-unfriendly regulations and deal with the financial constraints.

Table 3 shows the interprovincial inequality decomposition in mining labor productivity for the quinquennial years of 1990–2010. The productivity inequalities, which largely declined from 1.808 to 0.852, are determined by pure labor productivity that is affected by non-efficiency factors, that is, per worker level of physical capital and technology. Unlike in many other sectors, the mining sector relies heavily on the quality and size of the natural capital stock. Therefore, one major factor that influences pure labor productivity relates to the composition of yielding natural resources and quality and size of mineral deposits.

In contrast, the efficiency component remains negligible simply because almost all provinces' mining sectors operate nearly at the maximum level and optimal scale. One

---

extrapolation for the missing years. For the estimation, we use the uniform capital-output ratio of the mining sector across provinces, assuming the indifferent profit-maximizing behaviour of the corresponding firms across provinces.

[4] A province is scale efficient if it operates at CRS. A scale-inefficient province takes the form of either increasing returns to scale (IRS) or decreasing returns to scale (DRS). IRS is due to their small size of operation, which may be essential to enhance their efficiency by increasing their scale of operations. The reverse is also true for DRS (Coelli et al. 2005).

possible reason for high efficiency could be that Indonesia’s mines are operated by the large-scale, domestic (state-owned or private) and multinational firms with rich skilled labor and high level of technology. Besides, these firms are generally given exclusive mining rights and consequently monopolize the operations at the assigned mining site. Because of the aforementioned reasons, mining firms can utilize factor inputs nearly at the maximum level and adjust the operation size to the optimal scale as regional monopolies.

The inequality in the overall technical efficiency can be further decomposed; however, we do not report the decomposition results as they are minor.

4. Conclusion

Applying the inequality decompositions to Indonesia’s mining sector for 1990–2010, we found that the narrowing interprovincial productivity inequality is determined by pure labor productivity. One major factor that influences pure labor productivity relates to the composition of yielding natural resources and quality and size of mineral deposits. In contrast, the efficiency component is negligible; that is, the relative efficiency in resource utilization and allocation is mostly similar throughout the country. This may be because Indonesia’s mining firms generally operate on a large scale and are given exclusive mining rights; that is, the firms operate nearly at the maximum level and at the optimal scale.

We measured the relative efficiency of each province’s performance in each quinquennial year for the period, but did not measure the efficiency change over time. This limitation relates to our potential extension. Further, another growing concern in Indonesia is the negative growth of the mining productivity for the last decade. The DEA-based Malmquist productivity index measures the productivity change over time and can be multiplicatively decomposed into two components: efficiency change and frontier shift (technical change). This potential extension could contribute to further discussions and understanding of policy implications.

References

Akita, T., Kurniawan, P.A., Miyata, S.: Structural changes and regional income inequality in Indonesia: A bidimensional decomposition analysis. Asian Econ. J. 25, 55–77 (2011)

Donald, A. R. 1987. An Export-Base Analysis of Louisiana's Petroleum Driven Economy. Annals of Regional Science, 21(1), 65.

Bas, T. G., Kunc, M.H., 2009. National Systems of Innovations and Natural Resources Clusters: Evidence from Copper Mining Industry Patents. European Planning Studies, 17(12), 1861-79.

Bhattacharyya, S., Resosudarmo, B.P., 2015. Growth, Growth Accelerations, and the Poor: Lessons from Indonesia. World Development 66, 154-165

Bosker, M., Krugell, W., 2008. Regional Income Evolution in South Africa after Apartheid." Journal of Regional Science, 48(3), 493-523.

Buccellato, T., Mickiewicz, T.: Oil and gas: A blessing for the few: Hydrocarbons and inequality within regions in Russia. Eur. Asia Stud. 61, 385–407 (2009)

Central Bureau of Statistics: Statistical Yearbook of Indonesia. Biro Pusat Statistik, Jakarta (1990–2010)

Cheng, Y-S., Li, S-K.: Income inequality and efficiency: A decomposition approach and applications to China. Econ. Lett. 91, 8–14 (2006)

Clarke, C.G, Dickenson J P, Gould W.T.S, Mather S., Mansell R, 2013 A Geography of the Third World, Routledge

Coelli, T.J., Prasada, R., Battese, G.E.: An Introduction to Efficiency and Productivity Analysis 2nd Edition. Kluwer Academic Publishers, Boston (2005)

Gisbert, G.F.J.: On factor decomposition of cross-country income inequality: Some extensions and qualifications. Econ. Lett. 70, 303–309 (2001)

Fatah, L., 2008. The Impacts of Coal Mining on the Economy and Environment of South Kalimantan Province, Indonesia. ASEAN Economic Bulletin 25, 85-98

Fleming, D. A., Thomas G. M., 2015. "Income Inequality across Australian Regions During the Mining Boom: 2001–11." Australian Geographer, 46(2), 203-16.

Ivanova, G., 2014. "The Mining Industry in Queensland, Australia: Some Regional Development Issues." Resources Policy, 39, 101-14.

Kresge, D. T., Seiver, D. A, 1978. "Planning for a Resource-Rich Region: The Case of Alaska." American Economic Review, 68(2), 99.

Kataoka, M., Wibowo, K.: Spatial allocation policy of public investment in the pre- and post-decentralization period in Indonesia and Japan. In: Fahmi, M., Yusuf, A.A., Purnagunawan, Y., Resosudarmo, B.P., Priyarsono, D.S. (eds.) Indonesian Regional Science Association Book Series: Government and Communities: Sharing Indonesia’s Common Goals, pp. 193–213. IRSA, Indonesia (2014)

Loayza, N., Rigolini J., 2016. "The Local Impact of Mining on Poverty and Inequality: Evidence from the Commodity Boom in Peru." World Development, 84, 219-34.

Partridge, M.D., Betz, M.R., Lobao, L., 2013. Natural Resource Curse and Poverty in Appalachian America. American Journal of Agricultural Economics 95, 449-456

Reeson, A.F., Measham, T.G., Hosking, K., 2012. Mining activity, income inequality and gender in regional Australia. Australian Journal of Agricultural & Resource Economics 56, 302-313

Spiegel, S.J., 2012. Governance Institutions, Resource Rights Regimes, and the Informal Mining Sector: Regulatory Complexities in Indonesia. World Development 40, 189-205

Yudanto, N., Wicaksono, G., Ariantoro, E., Reina Sari, A.: Capital stock in Indonesia: Measurement and validity test. Irving Fisher Committee Bulletin. 20, 183–98 (2005)

Figure 1. Summary results of the efficiency analysis

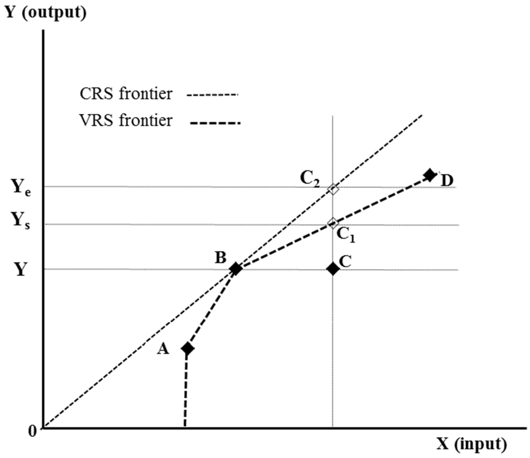

Table 1. Summary results of the efficiency analysis

	oe		*pe*		*se*	
	1990	2010	1990	2010	1990	2010
No. of efficient provinces	6	17	12	22	9	21
Mean values	0.9881	0.9994	0.9947	0.9998	0.9936	0.9997
Minimum values	0.9580	0.9960	0.9630	0.9970	0.9620	0.9970

Table 2. Number of provinces by returns to scale

	Sample size	IRS	CRS	DRS
No. of provinces in 1990	26	7	9	10
No. of provinces in 2010	26	5	21	0

Note: IRS, Increasing return to scale; CRS, Constant return to scale; DRS, Decreasing return to scale.

Table 3. Inequality decomposition of labor productivity

	T(*x*)	T(*xe*)	T(*oe*)	I(*xe*, *oe*)
1990	1.808	1.797	0.000	0.011
1995	1.511	1.508	0.000	0.003
2000	1.334	1.332	0.000	0.002
2005	1.124	1.123	0.000	0.001
2010	0.852	0.852	0.000	0.001