



An empirical analysis of total-factor productivity in 30 sub-sub-sectors of China's nonferrous metal industry

Liuguo Shao^{a,b,c}, Yingying He^{a,c}, Chao Feng^{a,c,*}, Shijing Zhang^a

^a School of Business, Central South University, No. 932, Lushan South Road, Yuelu District, Changsha 410083, PR China

^b Institute of Industrial Economics of Chinese Academy of Social Sciences, Beijing 100836, PR China

^c Institute of Metal Resources Strategy, Central South University, Changsha 410083, PR China

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ABSTRACT

Based on the panel data of 30 sub-sub-sectors of China's nonferrous metal industry from 2004 to 2013, this paper utilizes a global data envelopment analysis (DEA) to analyze the total-factor productivity (TFP) of China's nonferrous metal industry from both static and dynamic perspectives. We present the fluctuation of TFP in the nonferrous metal industry during 2004–2013 and analyze the key factors responsible for this fluctuation from the perspectives of production techniques, management and scale. The static analysis results show that the overall TFP of China's nonferrous metal industry is relatively low, and production inefficiency in the mining and smelting industries are two primary sources of this overall TFP inefficiency. There are significant differences among the 30 sub-sub-sectors in TFPs. During our sample period, some sub-sub-sectors experienced rapid growth in TFP, while others remained at a low level. The dynamic analysis results show differences in the key factors affecting the TFPs of three sub-sectors. Technical progress was the biggest contributor to the TFP growth in the nonferrous metal smelting sector, while the rapid increase in scale efficiency was the primary source of TFP growth in both the nonferrous metal mining sector and the pressing and processing sector.

1. Introduction

Nonferrous metals are important basic and strategic materials for the national economy, the defense industry, and people's daily lives in China. In recent years, the Chinese government has actively promoted the development of the nonferrous metal industry and has already achieved positive results. In 2014, the output of ten nonferrous metals¹ in China increased by 7.2% annually. The outputs of refined copper, primary aluminum, and zinc increased annually by 13.8%, 7.7%, and 7%, respectively. At the same time, the total volume of imports and exports of nonferrous metals rose by 12.1%, reaching \$177.16 billion (MIIT, 2015).

Although the above economic data sounds positive, further development of China's nonferrous metal industry must still face many problems. Firstly, despite constant breakthroughs in the smelting and processing technologies used in the nonferrous metal industry, and the implementation of many new projects that have adopted new technology, there are still an enormous number of backward production facilities. Local taxation, personnel placement and debt issues associated with shutting down uncompetitive enterprises present a challenge for local officers. This limits the choice of capacity exit channels.

As a result, the pressure of electrolytic aluminum overcapacity is still considerable (MIIT, 2015). Secondly, the scale of new projects is expanding. The number of smelting and processing enterprises has rapidly increased, reaching 7385 in 2014 with a growth rate of 6% from 2012 (NBS, 2015). Consequently, prices fall, as well as business income. In 2014, the total profit of China's nonferrous metal industry was ¥205.3 billion, down 1.5% from the previous year. More specifically, the total profit of commonly used nonferrous metal mining sectors and smelting sectors fell by 12.4% and 13.7%, respectively, compared to the previous year (MIIT, 2015). Moreover, despite the amount of attention paid to management, nonferrous metal enterprises often perform poorly when predicting market changes and coping with price shock. Hence, there is some confusion over the nonferrous metal industry's efficiency, whether sub-sectors of the industry make progress and what factors might influence efficiency in production. Furthermore, nonferrous metal resources vary in types; there are differences between the different stages of the industrial chain in regard to various resources concerning terms of technical features, demand characteristics, application fields, and product prices. Thus, further analysis is necessary from the perspective of sub-sub-sectors that have integrated into a full chain in the nonferrous metal industry.

* Corresponding author at: School of Business, Central South University, No. 932, Lushan South Road, Yuelu District, Changsha 410083, PR China.

E-mail address: littlefc@126.com (C. Feng).

¹ Including copper, primary aluminum, lead, zinc, nickel, tin, antimony, mercury, magnesium and titanium.

In terms of evaluating productivity, the traditional approach is to use single-factor productivity, like capital productivity or labor productivity, as a measurable indicator. However, the actual production process obviously requires a variety of elements (e.g., capital, labor, and land), as traditional single-factor productivity cannot measure the relationship between the single factor and other elements. Thus, the single-factor method cannot accurately reflect changes in productivity (Zhang et al., 2003). To better analyze the comprehensive level of productivity and its variations, scholars began to employ total-factor productivity (TFP) to measure an industry's productivity (Ma et al., 2002; Tu and Xiao, 2005; Li and Zhu, 2005; Zhang et al., 2010). TFP refers to the output efficiency generated by the combined effects of numerous inputs. Compared to the traditional single-factor productivity, TFP has a more comprehensive consideration of inputs and better reflects the overall efficiency of an economic system.

Regarding the TFP measuring methods, setting up production functions, and estimating the production function parameters, the related methods can be divided into two groups: the parameter method and the nonparametric method (Mahadevan, 2003). The former primarily includes the Solow residual method, the growth accounting method and the stochastic frontier analysis (SFA). The latter includes the index method and DEA. Efficiency is generally measured using either DEA or SFA. The DEA method calculates the efficiency value by constructing a nonparametric production frontier through linear programming methods. Thus, compared to SFA, the DEA has an advantage in that it does not require setting the functional form of the model in advance (Coelli, 1998). The DEA method is therefore more suitable for estimating the efficiency of multiple inputs and outputs. Moreover, DEA method can be divided into two types: the static and the dynamic DEA methods.

The static DEA models include the CCR model based on constant returns to scale (CRS), and the BCC model based on variable returns to scale (VRS). The results estimated through static methods represent the value of the decision-making units' (DMUs) efficiency. Thus, we can see the comparison of the results and changes to each DMU's efficiency with the time series. After the DEA was proposed by Charnes et al. (1978) and gradually gained popularity, many scholars utilized the static DEA model for empirical research of TFP in China's metal industry (Ma et al., 2002; Zhao and Hao, 2003; Jiao et al., 2007; Zheng and Chai, 2010). However, we need to be clear that, despite their merits, there are still some flaws in the static methods. Because the results calculated using static methods only show the TFP of each DMU, they cannot reveal the factors for changes in each DMU's efficiency, and static methods therefore fail to provide effective guidance for production in practice.

The dynamic DEA models contain the DEA-Malmquist and DEA-Malmquist-Luenberger index. The results estimated using dynamic methods represent the trend of efficiency over time. According to a study by Färe et al. (1994), the Malmquist index can be decomposed into technical changes, pure technical efficiency changes, and scale efficiency changes. The three components above refer to the technical progress, management level and productive scale in practical production. Many scholars then analyzed TFP changes in many industries using the dynamic DEA models (Shunsuke and Shinji, 2004; Wang and Yan, 2007; Wei et al., 2007; Li and Hu, 2008; Wang and Zhu, 2011; He et al., 2012; Wei et al., 2013; Li and Lin, 2015). However, the dynamic DEA models depict both changes to and the decomposition of TFP through constructing a production technology set based on the data of a single cross section of the DMU. Ultimately, the evaluation results will lack robustness and generate false technical progress, which conflicts with the actual production. Therefore, there are certain limitations in the dynamic methods.

Most studies only measure the TFP using static or dynamic methods; both have some limitations. To overcome the defects of inconsistent results between static and dynamic methods due to single-phase production sets (Wang et al., 2014), this study adopts the global

DEA and directional distance function (DDF), which calculate the TFP efficiency indicators on the basis of input and output data in all phases. This enables us to measure and analyze the TFP of China's nonferrous metal industry from 2004 to 2013 and present the industry's current status. Furthermore, we have calculated technical change, pure technical efficiency and scale efficiency using the global Malmquist-Luenberger index (GML) decomposition method. Next, we analyzed the impact on TFP of China's nonferrous metal industry from the perspectives of technical progress, management levels and production scale.

The primary purpose of this study is to reveal the differences between upstream, medium-stream and downstream aspects of the nonferrous metal industry by calculating and analyzing its TFP and offering insight into its development. Additionally, in order to analyze the major factors of changing the TFP using the "static-dynamic" method from the perspectives of technical progress, management levels, and productive scale, we can identify the potential for improving the TFP and provide corresponding advice. We look forward to providing evidence and guidance for the establishment of a nonferrous metal industrial policy system.

2. Methods and materials

According to this article's purpose, the calculations are to be undertaken based on the global DEA method, and the corresponding analysis is to be discussed from both the static and dynamic perspectives. Therefore, before introducing our empirical DEA models, Section 2.1 first presents a brief introduction to the global DEA method. The static and dynamic models utilized in this paper are then introduced in Sections 2.2 and 2.3.

2.1. Concept of the global DEA method

To illustrate the concept of the global DEA method, two definitions of benchmark technology are essential, i.e., contemporaneous and global benchmark technologies (Oh, 2010). Let (x, y, b) represent, respectively, inputs, desirable outputs, and undesirable outputs. $P(x)$ represents the production possibility set (PPS).

A contemporaneous benchmark technology is defined as:

$$P^t(x^t) = \{(y^t, b^t) | x^t \text{ can produce } (y^t, b^t)\} \quad (1)$$

where $t = 1, \dots, T$. The contemporaneous benchmark technology constructs a reference production set at time t . This PPS is generated from the observations only at time t (Tulkens and Eeckaut, 1995).

A global benchmark technology is defined as:

$$P^G = P^1 \cup P^2 \cup \dots \cup P^T \quad (2)$$

This global benchmark technology envelops all contemporaneous benchmark technologies by establishing a single reference PPS from the panel data on the inputs and outputs of the relevant DMUs (Pastor and Lovell, 2005).

2.2. The static model

According to Chung et al. (1997), productivity with undesirable outputs can be obtained by applying the DDF approach. In this study, the DDF can be defined as $\bar{D}_0(x, y, b; g) = \sup\{\beta : (y, b) + \beta g \in P(x)\}$. Here, g is the directional vector. Subsequently, the DDF can be further calculated by solving the following linear programming problems:

$$\bar{D}_0(x, y, b; g | CRS) = \max \beta \quad (3)$$

$$\sum_{k=1}^K z_k x_{kn} \leq x_{kn}, \quad n = 1, \dots, N,$$

$$\sum_{k=1}^K z_k y_{km} \geq (1 + \beta) y_{km}, \quad m = 1, \dots, M,$$

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