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Analyzing the efficiency performance of major Australian mining companies using bootstrap data envelopment analysis

Ahmad Hosseinzadeh [a], Russell Smyth [b,*], Abbas Valadkhani [a], Viet Le [a]

[a] Department of Accounting, Economics and Finance, Swinburne University of Technology, VIC 3122, Australia
[b] Department of Economics, Monash University, VIC 3800, Australia

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We identify the balance of efficiency gains and losses for 33 Australian mining firms over the period 2008–2014 using bootstrap data envelopment analysis (DEA). We ascertain which companies climbed the efficiency ladder and which companies slipped back in efficiency over time. We find that mining companies involved in metal processing or mining services have been more efficient than those involved in exploration and extraction activities. Assuming variable returns to scale (VRS), on average, we find that mining firms could improve their performance between a minimum of 17% in 2010 and a maximum of 34% in 2008, relative to the best practice performers. We find that, overall, most mining companies became more efficient over time, with the top performers generally maintaining a ranking in the top third of companies in terms of efficiency throughout the period.

1. Introduction

The mining industry plays an important role in the Australian economy. Following the millennium mining boom, the Australian mining sector has experienced considerable growth in terms of employment, investment, export and revenue (Connolly and Orsmond, 2011). The mining sector is normally attributed with having safeguarded the Australian economy from the deleterious effects of the global financial crisis (GFC). At the same time, over the last few years prices for exports, particularly for iron ore, oil and coal, have stabilized or fallen, primarily reflecting slower economic growth in China. Australia's mining sector is now moving from the construction phase, which creates considerable employment, to the operation phase, which requires much fewer workers (Garnett, 2015). How the mining sector responds to these challenges, which carries broader implications for the Australian economy as a whole, will depend on the efficiency performance of its largest companies.

Several studies have examined the efficiency performance of the Australian mining sector at the industry level (Syed et al., 2015; Topp et al., 2008; Zheng and Bloch, 2014). Based on these studies, there is considerable debate about the efficiency of the mining sector in Australia (see Connolly and Orsmond, 2011; Connolly and Gustafsson, 2013; Parham, 2013; Productivity Commission, 2015). However, no studies examine the efficiency of the Australian mining industry at the individual firm level. Our main contribution is to examine efficiency in the Australian mining sector at the firm level.

There are several advantages in considering efficiency at the firm level. First, with firm level data we can focus on a smaller, but more homogeneous, group of companies. Our sample consists of 33 mining companies that, together, account for more than 85% of the total market capitalization in the metals and mining industry. Second, with firm level analysis we can specify both production inputs and outputs more accurately. In sector studies, involving heterogeneous firms with a substantially different mix of inputs and outputs, such a targeted specification becomes difficult. Third, firm level analysis enables us to identify best practice and benchmark across comparable companies. Fourth, sector level studies show average figures that mask firm-specific efficiency levels. In contrast, firm-level efficiency analysis enables us to assess the performance of individual firms against the frontier.

Finally, by focusing on firm level efficiency we can decompose the sources of inefficiency into pure technical inefficiency and scale inefficiency. Pure technical inefficiency indicates that the firm's

* Corresponding author.
E-mail addresses: ahosseinzadeh@swin.edu.au (A. Hosseinzadeh), russell.smyth@monash.edu (R. Smyth), abbas@swin.edu.au (A. Valadkhani), clle@swin.edu.au (V. Le).

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performance gap against the corresponding frontier can be directly measured through variable returns to scale (VRS) models. Scale inefficiency indicates the degree to which the firm does not operate on its optimal scale. Constant returns to scale (CRS) efficiency reflects the effect of both scale and pure technical (in)efficiencies. A comparison of efficiency results derived from CRS and VRS models can reveal whether the source of inefficiency in mining firms results from pure technical inefficiency or whether it reflects the effects of operating beyond an optimal scale.

Our specific contributions in this study include the following: (i) to identify the efficiency gaps in Australian mining firms using bootstrap data envelopment analysis (DEA); (ii) to examine how the efficiency of individual mining firms have changed between 2008 and 2014; (iii) to divide the 33 companies into those involved with exploration and extraction activities (27 companies) and those involved with metal processing or mining services (six companies) and examine how bootstrap efficiency models describe their performance over time; and (iv) to examine which companies involved with exploration and extraction activities and with metal processing or mining services climbed the efficiency ladder and which companies slipped back in terms of efficiency over time.[1]

The remainder of the paper proceeds as follows. In Section 2 we provide a review of empirical studies using frontier methods in the mining sector, particularly those for Australia. Section 3 describes DEA and the bootstrapping procedure used in our study. Section 4 presents a description of the data. Section 5 presents the empirical results and discusses the efficiency performance of individual mining firms. Section 6 concludes the paper.

2. Literature review

DEA and SFA are the two major methods to estimate technical efficiency. The main advantage of DEA is that it does not require any pre-defined functional form. Cooper et al. (2006 p.2) characterize DEA as an approach that “does not require the user to prescribe weights to be attached to each input and output, as in the usual index number approaches, and it also does not require prescribing the functional forms that are needed in statistical regression approaches to these topics.” A drawback of DEA is that it does not take into account statistical noise resulting from measurement errors. This shortcoming however, can be addressed using a bootstrap procedure proposed by Simar and Wilson (1998) to obtain bias corrected DEA estimates.

DEA has been successfully applied to measure efficiency of firms in a wide range of fields including cement, energy, finance, insurance and manufacturing (see Charoenrat and Harvie, 2014; Chen et al., 2013; Eller et al., 2011; Riccardi et al., 2012; Sueyoshi and Goto, 2012; Wang et al., 2013; Wanke and Barros, 2016; Wijesiri et al., 2015). While the literature that measures the efficiency of mining firms is limited, most of the studies that have focused on the mining sector have also applied DEA (see e.g. Byrnes et al., 1984; Fang et al., 2009; Geissler et al., 2015; Kulshreshtha and Parikh, 2002; Thompson et al., 1995; Tsolas, 2011). Most of these studies have used DEA to measure the (in)efficiency of specific firms relative to best performers in the sector or compare the relative efficiency performance of different types of mines or ownership forms.

Byrnes et al. (1984), Thompson et al. (1995) and Tsolas (2011) all apply DEA to examine different aspects of efficiency in Illinois strip mines. Byrnes et al. (1984) found that Illinois strip mines were fairly efficient, relative to each other, and that the major source of inefficiency was due to deviations from the optimal scale of production. Thompson et al. (1995) reformulated the data set of Byrnes et al. (1984) and applied DEA to derive profit ratios. Tsolas (2011) applied DEA to measure the environmental efficiency of Illinois strip mines and found them to be inefficient.

Of studies that have applied DEA to measure efficiency of mines outside the US, Fang et al. (2009) found that Chinese coal mines were relatively less efficient than their US counterparts. Kulshreshtha and Parikh (2002) found that opencast mines were less efficient than underground mines in India and that the efficiency of opencast mines declined over time. Geissler et al. (2015) applied DEA to measure the efficiency of global phosphate rock mining companies and found that publicly-listed mining companies were generally more efficient than state-owned mining companies.

Compared to DEA, SFA has the advantage that it takes into account statistical noise resulting from measurement errors or random noise. The downside, however, compared with DEA, is that SFA requires a larger sample size and the specification of a well-defined functional form a priori (see Geissler et al., 2015). Given the small number of firms ($n = 33$) in each year and the use of multiple inputs by each firm in the production of a mix of outputs as well as the lack of a well-defined functional form, we prefer DEA over SFA. It should be noted the SFA approach cannot handle small samples and or the simultaneous use of several inputs in the production of several outputs. As a result, we cannot utilize random parameters within the SFA framework.

The existing literature that has applied SFA to measure efficiency of mining firms is relatively limited (see eg. Koop and Tole, 2008; Tsolas, 2010). Koop and Tole (2008) apply SFA to examine the environmental performance of global gold mining firms and find that most firms are inefficient. Tsolas (2010) applies both DEA and SFA to examine the efficiency of Greek bauxite mining firms. Tsolas (2010) found that both methods suggested that most firms were inefficient and that the major source of inefficiency was deviations from the optimal scale of production, echoing the earlier findings by Byrnes et al. (1984) for Illinois strip mines.

In the Australian context, all existing studies for the mining sector have focused on productivity growth at the industry level (see e.g. Asafu-Adjaye and Mahadevan, 2003; Topp et al., 2008; Zheng and Bloch, 2014). To the best of our knowledge, there are no studies that have used firm level data to investigate the efficiency of Australian mining firms. This is a gap in the literature that we seek to address in the current study.

3. Methodology

We use DEA to estimate the technical efficiency of Australian mining firms. We prefer DEA over SFA given the limitations of the latter and that a methodology which does not require a functional form is desirable in this context. Each mining company uses multiple inputs to generate multiple outputs. In order to form a production function, one needs to aggregate outputs, and determine whether the chosen output mix is optimal, given output prices and input costs. As discussed above, one needs to choose the most suitable functional form if using

Table 1
Data description (in thousands of Australian dollars).

Variables	Mean	Std. deviation	Minimum	Maximum
Output variables				
Operating revenue ($Q1$)	5,007,930	14,901,259	2942	78,325,635
Other revenue excluding interest incomes ($Q2$)	121,689	502,497	1	4,452,830
Input variables				
Employee benefits (L)	546,528	1,705,413	457	10,145,785
Non-current assets (K)	7,066,467	22,935,811	16,839	137,100,000
Intermediate inputs (INT)	2,693,169	7,251,021	3406	40,389,362

[1] Due to its higher discrimination power, only the results of the bootstrap CRS efficiency models are presented for the two sub-groups.