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What determines the efficiency of Australian mining companies?*

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We examine the firm-specific determinants of technical efficiency in Australian mining companies using data envelopment analysis (DEA). To do so, we employ panel data sourced from individual mining companies listed on the Australian Securities Exchange (ASX) over the period 2010–2014. To ensure valid statistical inference in the presence of serial correlation between DEA efficiency scores, we apply Simar and Wilson's two-stage bootstrap method. We find that ownership concentration, firm size, firm age, product portfolio, product diversification and growth status significantly contribute to efficiency gains. However, other firm-specific factors, such as capacity utilisation, financial risk and overseas operations appear to have limited impact on the technical efficiency of mining firms.

Key words: bootstrap, data envelopment analysis, efficiency determinants, mining companies.

1. Introduction

The mining industry is one of the main pillars of the Australian economy, and it is usually given credit for preventing Australia slipping into recession during and after the global financial crisis of 2007–2008 (Garnett 2015). Over the past decade, improving Australian living standards is largely attributable to the mining boom (Downes *et al*. 2014). However, the recent downturn in commodity prices has raised concerns about the profitability of mining companies. This challenge has also highlighted the importance of improving the efficiency of this crucial sector to the economy. Consequently, many mining companies regard raising productivity as one of their main priorities (Lumley and McKee 2014).

Yet, we know little about the efficiency of Australian mining companies and what we do know is mostly restricted to performance at the industry level (see, inter alia, Syed *et al*. 2015; Zheng and Bloch 2014). Due to significant differences between individual companies in this sector, efficiency studies at the firm level are essential to complement industry-level analysis. As discussed

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by Hosseinzadeh *et al.* (2016), firm-level analysis has the advantage that it assists mangers and policymakers to make better informed decisions as to how to improve efficiency by identifying best practices and benchmarking across analogous firms.

To shed light on firm-level efficiency, and its determinants in the Australian mining sector, we apply second-stage bootstrap data envelopment analysis (DEA) proposed by Simar and Wilson (2007, 2011), using a panel of 34 companies over the period 2010 to 2014. The closest paper in the literature to ours is Hosseinzadeh *et al.* (2016). That study used DEA to identify changes in efficiency in individual Australian mining companies over the period 2008 to 2014. An important point of difference between this study and Hosseinzadeh *et al.* (2016) is that we focus on the determinants of technical efficiency by examining the relationship between DEA efficiency scores and firm-specific characteristics in the second-stage regression, whereas in their study, they did not investigate the effects of exogenous variables on firms' efficiency. In so doing, we contribute to a broader literature that has focused on examining the determinants of efficiency using a second-stage regression, rather than only measuring the efficiency levels of individual firms (see Byrnes *et al.* 1984 and Geissler *et al.* 2015 for examples of studies for mining companies). However, as discussed by Simar and Wilson (2007, 2011), the majority of these studies suffer from the existence of serial correlation and boundary problems in their second-stage regressions. We overcome this problem through using a second-stage double bootstrap procedure to ascertain statistical significance of efficiency drivers of mining companies in a nonparametric framework.

We contribute to the ongoing policy debate about efficiency in the Australian mining industry by addressing two major gaps in the literature. Our first contribution is to provide the first estimates of the firm-specific determinants of technical efficiency in Australian mining companies. Our second contribution is methodological. This is the first study to employ a second-stage double bootstrap procedure to ascertain statistical significance of the determinants of technical efficiency in mining companies using a nonparametric set-up. In so doing, we avoid common pitfalls associated with using Tobit or ordinary least squares in the second stage as detailed in Simar and Wilson (2007, 2011).

The rest of this study is organised as follows: Section 2 reviews the literature and highlights the gaps. Section 3 concisely discusses the methodology used to estimate technical efficiency and its determinants within a bootstrap DEA framework. Section 4 describes the inputs and outputs as well as variables used in the second-stage regression. Section 5 presents the empirical results. The paper ends with summary and concluding remarks in Section 6.

2. Existing literature

Existing studies on firm-level efficiency using DEA are numerous and cover a wide range of industries, including banking, education, tourism, agriculture, airports and manufacturing (e.g. Worthington and Lee 2008; O'Donnell 2010; Mugera 2013; Atici and Podinovski 2015; Corne 2015; Khan *et al.* 2015; Moradi-Motlagh *et al.* 2015; Rezitis and Kalantzi 2015; Min and Joo 2016). In contrast, studies of mining efficiency are relatively few in number (e.g. Byrnes *et al.* 1984; Thompson *et al.* 1995; Kulshreshtha and Parikh 2002; Fang *et al.* 2009; Tsolas 2011; Geissler *et al.* 2015) and most suffer from lack of statistical precision in their estimates. In a recent study, Hosseinzadeh *et al.* (2016) addressed this shortcoming in the Australian mining efficiency literature by applying the bootstrap procedure introduced by Simar and Wilson (1998). They examined the technical efficiency of 33 Australian mining firms over the period 2008–2014, representing 85 per cent of mining companies on the ASX, and found that most had improved their efficiency during the period studied. That study, however, did not examine the determinants of such efficiency gains over time.

The trend in the literature on efficiency studies is to move away from merely measuring efficiency towards examining its determinants in a second-stage regression (e.g. Pasiouras 2008; Delis and Papanikolaou 2009; Assaf *et al.* 2012; Chortareas *et al.* 2012; Çelen 2013; Doumpos and Cohen 2014; Mugera and Nyambane 2015; Wijesiri *et al.* 2015). This said, there are few studies that examine the determinants of efficiency in mining companies. Byrnes *et al.* (1984) examined determinants of efficiency in Illinois strip mines and found that inefficient mines are relatively older, have higher labour–output ratios and single, rather than multiple coal steams. In a more recent study, Geissler *et al.* (2015) investigated the efficiency performance of the world's leading companies in phosphate rock mining and reported no difference between the efficiency of large and small firms. They also did not find a significant difference between the efficiency of state and privately owned firms.

Due to the existence of serial correlation between DEA efficiency scores, studies that regress efficiency estimates on exogenous factors in a two-stage procedure are invalid (Simar and Wilson 2007, 2011). To the best of our knowledge, none of the prior mining efficiency studies have applied the second-stage bootstrap suggested by Simar and Wilson (2007) and, therefore, potentially suffer from serial correlation, boundary problem and lack of coherent description of the data generating process (DGP) as discussed by Simar and Wilson (2011).

3. Methodology

DEA is a nonparametric frontier technique used to estimate the relative technical efficiency of Decision Making Units (DMUs) in multiple input and output environments. An advantage of DEA is that it does not require any particular functional form to relate inputs to outputs. Suppose there are n DMUs, each transforming a vector of inputs x to a vector of outputs y. Assuming constant returns to scale (CRS), an output-oriented DEA can be formulated as:

$$\hat{\theta}_k = \max\{\theta > 0\ |\theta y_k \leq \sum_{i=1}^{n} \gamma_i\, y_i,\ x_k \geq \sum_{i=1}^{n} \gamma_i x_i, \gamma_i \geq 0, i = 1, \ldots, n\}, \qquad (1)$$

Where $\hat{\theta}_k$ indicates that the DMU is technically efficient, while it is inefficient if $\hat{\theta}_k \geq 1$. It should be noted that DEA is a deterministic method, which does not take into account statistical noise and errors. To overcome this shortcoming, Simar and Wilson (1998) proposed a bootstrap procedure which allows us to examine statistical properties of the estimated DEA scores. We use their approach with 2000 iterations to obtain bias-corrected efficiency estimates for 34 Australian mining firms. The technical details of this procedure are discussed in Simar and Wilson (1998).

The Tobit model is often used to regress DEA efficiency scores on firm-specific determinants in a second-stage regression. Simar and Wilson (2007) criticised the use of Tobit in the second stage as the serial correlation may bias the estimated parameters. They proposed an alternative approach using a bootstrap truncated regression:

$$\hat{\theta}_i = z_i\beta + \varepsilon_i, \quad i = 1, \ldots, n, \qquad (2)$$

where z_i is a vector of firm-specific variables relative to firm i. The aim is to estimate the coefficient vector β and generate the stochastic error term ε_i for each individual firm.

We use the second algorithm suggested by Simar and Wilson (2007) to estimate Equation (2) with B = 2000 bootstrap iterations, which can be summarised as follows:

1. Estimate the technical efficiency score $\hat{\theta}_i$ for each firm using (1);
2. Obtain an estimate $\hat{\beta}$ of β and $\hat{\sigma}_\varepsilon$ of σ_ε in the truncated regression of $\hat{\theta}_i$ on Z_i using the maximum-likelihood method when $\hat{\theta}_i > 1$;
3. Repeat the next four steps B times to obtain $\{\hat{\theta}^*_{ib},\ b = 1, \ldots, B\}$:

   a. Draw ε_i from the $N\left(0, \hat{\sigma}^2_\varepsilon\right)$ distribution with left truncation at $\left(1 - z_i\hat{\beta}\right)$ for $i = 1, \ldots, n$.
   b. Calculate $\theta^*_i = z_i\hat{\beta} + \varepsilon_i$ for each firm.
   c. Set $x^*_i = x_i,\ y^*_i = y_i\hat{\theta}_i/\theta^*_i$ for all $i = 1, \ldots, n$.
   d. Compute $\hat{\theta}^*_i$ for all firms by replacing x_i and y_i in (1) with x^*_i and y^*_i.

4. For each firm, calculate the bias-corrected $\hat{\hat{\theta}}_i = \hat{\theta}_i - \left(\frac{1}{B}\sum_{b=1}^{B} \hat{\theta}^*_{ib} - \hat{\theta}_i\right)$;
5. Estimate the truncated regression of $\hat{\hat{\theta}}_i$ on z_i using the maximum-likelihood method to obtain $\left(\hat{\hat{\beta}}, \hat{\hat{\sigma}}\right)$;

6. Loop over the next three steps B times to provide $\left(\hat{\hat{\beta}}_b^*, \hat{\hat{\sigma}}_b^*, b = 1, \ldots, B\right)$:
   a. Draw ε_i from the $N\left(0, \hat{\hat{\sigma}}\right)$ with left truncation at $\left(1 - z_i\hat{\hat{\beta}}\right)$ for $i = 1, \ldots, n$.
   b. Calculate $\theta_i^{**} = z_i\hat{\hat{\beta}} + \varepsilon_i$ for each firm.
   c. Estimate the truncated regression of θ_i^{**} on z_i using maximum likelihood to obtain $\left(\hat{\hat{\beta}}^*, \hat{\hat{\sigma}}^*\right)$.

7. Construct the confidence interval for β and σ_ε using the bootstrap results $\left(\hat{\hat{\beta}}_b^*, \hat{\hat{\sigma}}_b^*, b = 1, \ldots, B\right)$.

4. Data and empirical model

Data were collected from the annual reports of Australian mining companies listed on the ASX. To have a more homogeneous sample, we consider only fully operational minerals and metal ore mining companies. The sample consists of 34 mining firms operating over the period 2010 to 2014. As our sample does not cover the whole population and is limited to a certain time horizon, using bootstrapping is useful to address sample variation in our efficiency analysis. These companies account for more than 90 per cent of total output of listed mining companies. We use the 2014 base year and deflate financial data using the PPI (producer price index) and WPI (wholesale price index) price deflators for the mining industry (ABS 2015a, b). In total, our sample consists of 170 panel observations (34 companies $\times$ 5 years). Following Hosseinzadeh *et al.* (2016) in using the production approach in selecting input and output variables, we consider total revenue as an output, and total employee benefits, total depreciation and other operating expenses as proxies for labour, capital and intermediate inputs, respectively. Given the availability of data from annual reports, we use total depreciation as a proxy for physical capital. Total depreciation is a more appropriate measure of capital input than total noncurrent assets as the former represents the capital service flow, while the later reflects the capital stock. We use operating expenses as a proxy for intermediate inputs. Operating expenses include costs associated with ongoing mining operations and expenditure on maintaining and improving the current condition of existing mines. We exclude exploration and evaluation expenditure from operating expenses as this expenditure does not contribute to current production and, hence, may cause bias in efficiency estimates.

Existing literature emphasises the importance of natural resource inputs in mining activities. Sector-level studies (see e.g. Topp *et al.* 2008; Zheng and Bloch 2014), which have addressed the natural resource input issue; have estimated the overall effect of resource depletion on the mining division; and its subdivisions' productivity. Such estimation is helpful in aiding our understanding of natural resource effects on the productivity of the mining sector, but it is not practical to take account of natural resource inputs in a firm-level study. In our study, we do not account for this factor due to unavailability of data at the company level. Information on the natural state of mineral deposits, and resource depletion across various mining activities is not available in the annual reports or other publications of mining companies.

The specification of inputs and outputs is different from what Farrell (1957) had in his technical efficiency model, but it provides a desirable efficiency measure at the corporate level. This measure of efficiency reflects the aggregation of physical inputs/outputs and price information. It should be noted that separate data on physical units and prices were not available. Moreover, in the mining industry, most companies are involved in a range of activities, which varies from one company to another. Using expenses and revenue information in the absence of physical values enables us to compare companies with diverse product portfolios.

Tables 1 and 2 provide information on each of the variables. Table 1 summarises the descriptive statistics for inputs, output and continuous firm-specific factors, and Table 2 presents descriptive statistics for firm-specific dummy variables. We estimate technical efficiency scores assuming CRS because, compared with the variable return to scale (VRS) assumption, this approach provides greater discriminatory power and consequently more variation in the regress and in the second stage of the analysis. To understand the effect of operating scale on efficiency performance, we add firm size (*SIZE*) in the second stage.

In the mining literature, few studies have examined the relationship between ownership and efficiency and those which have, only compared

Table 1 Data description of continuous variables

Variables	Mean	Std. Deviation	Minimum	Maximum
Output variables				
Total revenue, thousands of AUD (*Q*)	4,477,175	14,647,918	14,599	77,883,040
Input variables				
Employee benefits, thousands of AUD (*L*)	565,323	1,805,976	530	9,604,749
Cost of Capital, Depreciation, thousands of AUD (K)	404,058	1,361,042	385	8,962,845
Intermediate inputs, thousands of AUD (*INT*)	2,075,323	6,625,385	3,029	36,228,634
Firm-specific factors				
Substantial shareholder, percentage (*OWNER*)	39.33	23.56	4.00	94.53
Firm size, ln(PP&E assets) (*SIZE*)	20.06	1.96	15.83	25.46
Firm age, year (*AGE*)	35.97	35.91	3.00	141.00
PP&E assets ratio, percentage (*PPE*)	53.76	17.50	13.00	93.00
Financial leverage, ratio (*LEV*)	1.64	0.64	1.03	4.66

Table 2 Dummy variable definitions

Variables	Description of variable	No. 0	No. 1
Iron ore production (*IRON*)	= 1 if main product is iron ore, 0 otherwise.	30	4
Gold production (*GOLD*)	= 1 if main product is gold, 0 otherwise.	20	14
Product diversification (*DIV*)	= 1 if product portfolio is diversified, 0 otherwise.	28	6
Change pace (*CH_PACE*)	= 1 if total output changes rapidly (>30%), 0 otherwise.	22	12
Change direction (*CH_DIR*)	= 1 if the firm total output grows, 0 otherwise.	11	23
Location of operation (*LOC_OPS*)	= 1 if firm operates in overseas projects, 0 otherwise.	16	18
Year 2011 (*Y2011*)	= 1 if observation is for 2011, 0 otherwise.		5
Year 2012 (*Y2012*)	= 1 if observation is for 2012, 0 otherwise.		5
Year 2013 (*Y2013*)	= 1 if observation is for 2013, 0 otherwise.		5
Year 2014 (*Y2014*)	= 1 if observation is for 2014, 0 otherwise.		5

private and state owned companies (e.g. Eller *et al*. 2011; Das 2012). While all firms in our sample are private companies, shareholder concentration differs from company to company. We use the percentage of shares held by the substantial shareholder as a proxy to measure ownership concentration. The effect of ownership concentration on firm performance is ambiguous with both positive and negative relationships being reported in the literature (e.g. Ma *et al*. 2010; Su and He 2012). Shleifer and Vishny (1997) argued that ownership concentration, along with legal protection, is an efficient governance mechanism. Anderson *et al*. (2012) argued that the level of protection afforded to shareholders under Australian law is relatively high in comparison with other countries. Consistent with the findings in Shleifer and Vishny (1997), we expect that ownership concentration will operate as an efficient corporate governance mechanism and improve efficiency in Australian mining companies.

To investigate the association between firm efficiency and firm size, we use the natural logarithm of PP&E assets as a proxy for the size of a firm. The existing literature provides mixed evidence on the relationship between firm size and firm efficiency (Diaz and Sánchez 2008; Badunenko 2010; Schiersch 2013; Zheng and Bloch 2014). As described in Hosseinzadeh *et al*. (2016), most fully operational mining companies in Australia are scale inefficient, due to decreasing-returns-to-scale (DRS). This implies that larger mining companies are less agile than their smaller counterparts and, hence, less productive. Hence, we expect an inverse relationship between size and efficiency.

Age is another firm-specific factor that may influence firm performance (Majumdar 1997; Loderer and Waelchli 2010; Lumley and McKee 2014). A number of mining companies were established and have commenced operations, since the start of the recent mining boom. Inadequate mining business knowledge and expertise could be a major challenge for these younger firms (PWC, 2014). In the Australian mining context, we postulate that older firms are able to achieve higher productive efficiency through prior opportunities arising from learning-by-doing acquired in gaining the required knowledge and skills in the industry.

Topp *et al.* (2008) and Zheng and Bloch (2014) posit that capital utilisation, due to the capital-output lag, is a significant contributor to the productivity index decline in the Australian mining sector. Lumley and McKee (2014) identified that a major reason for low efficiency in Australian mining companies pertains to the inefficient utilisation of mining equipment. PWC (2014) identified that the major reason for low efficiency in Australian mining companies is that mining equipment runs at lower annual output than most of its global peers. In line with sector-level and mine-level findings, we test whether capacity utilisation is a contributor to efficiency gains. Using financial information from annual reports property, plant and equipment (PP&E) assets represents firm equipment and infrastructure capital. Holding the effects of other assets constant, inefficient utilisation of PP&E assets is associated with a higher share of PP&E in total assets. Therefore, we use the ratio of PP&E to total assets as a proxy for operations capacity, and we expect a negative correlation between this ratio and the resulting firm efficiency scores.

The existing literature has also examined the influence of financial risk on firm performance and reported both positive and negative effects (e.g. Abor 2005; Zeitun and Tian 2007; El-Sayed Ebaid 2009). We proxy risk with financial leverage defined as total assets divided by total equity. As higher leverage provides opportunities for firms to grow at an accelerated rate, particularly in the mining sector, during a boom, we expect that mining firms with higher leverage will have better economic performance.

We selected the main product based on the ASX defined subindustry classification for mining companies in our sample. The ASX classification is based on the Global Industry Classification Standard (GICS). The main mining activity of companies in our sample was verified through a careful review of their annual reports and companies' profiles on the ASX. In such companies, usually more than 50 per cent of operating revenue is obtained from the main mining activity. According to the ABS (2016), iron ore and gold contributed to 80 per cent of total sales and service income in the minerals and metal mining industry during 2013–2014. Hence, in the list of exogenous variables, it is important to control for whether the company's main product is gold or iron ore.

We used the ASX industry classification to identify diversified mining companies. According to the ASX classifications for listed mining companies, diversified companies are those which are engaged in diversified production or extraction of metals and minerals including, but not limited to, nonferrous metal mining, salt and borate mining, phosphate rock mining and diversified mining operations. All six diversified companies in our sample have active mining operations in several mining subindustries (according to the ASX industry classifications). Several mining companies have diversified their product portfolio and expanded their operations to a broad range of mining products. Existing studies provide mixed evidence on the effect of product diversification on firm performance (e.g. Chakrabarti *et al*. 2007; Chang and Wang 2007; Nath *et al*. 2010). Conceptually, diversification and firm performance are expected to be positively correlated. Diversification enables firms to achieve economies of scope and leverage their strategic resources across other products and markets (Rumelt 1974). We expect diversification to be positively related to efficiency of mining firms through utilisation of unused productive capacity, reduction in business risk arising from falling prices and employing operation capabilities across other mining activities.

Mitchell and Steen (2014) argued that lack of effective portfolio management can change capital productivity in mining companies. A balanced set of projects in the portfolio stabilises production. To consider this point, we assume that mining companies with steady state, or gradual, output growth are more efficient than companies exhibiting rapid growth. To do so, we classify companies in the top third of total output changes, meaning that their annual rates of change are greater than 30 per cent, as displaying rapid change and the rest as having gradual growth. We expect that companies are more efficient during growth periods than downturns.

A number of Australian mining companies have expanded their operations to other countries. Nath *et al*. (2010) argued that international diversification is not necessarily beneficial to parent companies and success with this strategy requires extensive knowledge assimilation, understanding of the local business environment and culture, active participation from local partners and transfer of resource and operations capacities between parent and local partner companies. To evaluate whether diversification of operations location is beneficial to mining companies in terms of efficiency, we include a dummy variable, set equal to 1 if the firm has overseas operations, and zero otherwise. To capture the effect of time on mining firms' efficiency, we include time dummies. These time-varying effects capture possible economic and structural changes across the mining sector, which cannot be explained by firm-specific factors.

Our final sample employed in the study does not contain any outliers requiring special treatment. Our initial sample contained 38 operational mining companies over the period 2010–2014. We removed four firms from our sample as outliers. The Kernel estimated density for distribution of efficiency scores, before and after trimming for outliers, is presented in Figure 1. As Figure 1a shows, there are a numbers of observations causing a long tail in the Kernel density for distribution of efficiency scores. After removing firms with outliers, the Kernel density for distribution of efficiency scores improves significantly as presented in Figure 1b.

Further, a review of firms with outliers confirmed that those companies had experienced launch or closure of some major mining projects over the period of study. Hence, in some years of our study they were not fully operational

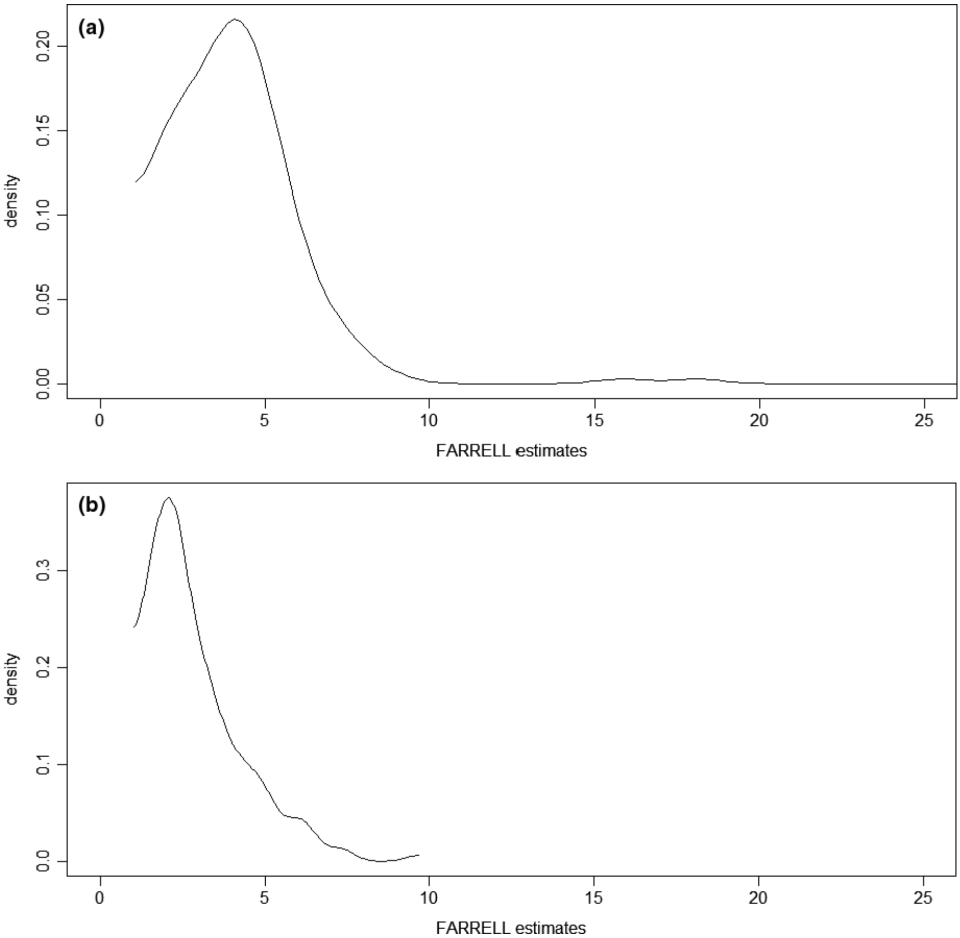

Figure 1 Kernel estimated density for distribution of efficiency scores. (a) Kernel estimated density for distribution of efficiency scores of 38 firms (including firms with outliers). (b) Kernel estimated density for distribution of efficiency scores of 34 firms (firms with outliers removed).

leading to very low efficiency performance. To maintain the homogeneity of our sample, and to achieve a balanced panel of observations, we removed firms with such characteristics.

5. Results and discussion

Table 3 provides the first-stage results from both conventional and bootstrap DEA models as specified in Equation (1). Following Simar and Wilson (1998), we apply smooth bootstrapping to address random noise and measurement error. To obtain the DEA efficiency estimates, we used deflated and pooled data containing 170 observations. Table 3 presents an overall view of technical efficiency estimates over the period of study. As shown in

Table 3, the bias-corrected efficiency scores resulting from bootstrapping are greater than the original DEA estimated scores and, on average, 12 per cent bias is corrected through applying bootstrapping. Assuming CRS, bias-corrected DEA scores point to the presence of significant steady inefficiency levels among Australian mining firms. Table 3 also indicates that observed inefficiency based on the bootstrap results is on average 66 per cent with a minimum of 63 per cent in 2011 and a maximum of 68 per cent in 2013. These findings are in line with Lumley and McKee's (2014) findings which suggested sizable inefficiency at the mining-site level in Australia.

To conserve space, we do not present details of the bootstrap model for all 170 observations, but these are available upon request. These results show that almost two-thirds of observations have efficiency scores above 2.0, suggesting a high level of inefficiency.

Table 4 presents the bias-corrected coefficients of the truncated regression model defined in Equation (2). Following Simar and Wilson (2007, 2011), we report confidence intervals obtained from the bootstrap truncated regression model to test whether the coefficients are statistically significant. A higher efficiency score indicates lower firm efficiency (Farrell 1957). Hence, in Table 4, a positive relationship between efficiency scores and firm-specific factors represents a negative relationship between the firm-specific factor and firm efficiency.

As shown in Table 4, the two dummy variables denoting that the firm's main product is iron or gold, *IRON* and *GOLD* significantly explain efficiency gains. However, in absolute values, the estimated coefficient for IRON (−2.21) is greater than that of GOLD (−1.34) suggesting that iron ore companies are more efficient than gold mining firms. Specifically, relative to mining companies whose main products are not gold or iron (base category), mean technical efficiency in companies whose main product is iron ore is 2.21 higher and mean technical efficiency in companies whose main product is gold is 1.34 higher.

Table 3 Technical efficiency scores based on the conventional and bootstrap CSR DEA models.

Conventional CRS model						Bootstrap CSR model					
Year	Mean	Std. dev.	Min.	Max.	Ineff.(a)	Year	Mean	Std. dev.	Min.	Max.	Ineff.(a)
2010	2.49	1.02	1.10	4.78	60%	2010	2.76	1.17	1.33	5.56	64%
2011	2.40	1.28	1.00	6.52	58%	2011	2.70	1.48	1.17	7.31	63%
2012	2.50	1.11	1.00	4.76	60%	2012	2.82	1.26	1.17	5.74	65%
2013	2.81	1.37	1.00	6.44	64%	2013	3.15	1.61	1.23	7.33	68%
2014	2.80	1.57	1.00	8.90	64%	2014	3.14	1.73	1.50	9.68	68%
Total	2.60	1.28	1.00	8.90	62%	Total	2.91	1.46	1.17	9.68	66%

Note: (a) Ineff. (average firms' inefficiency) is calculated by (Mean – 1)/Mean) where 1 is best practice. The higher the efficiency score, the lower is the average efficiency in a given year.

Table 4 Bootstrap truncated regression results

Variables	Estimates	90% Conf. Int.		95% Conf. Int.		99% Conf. Int.	
		LB	UB	LB	UB	LB	UB
Constant	−1.85	−7.73	3.73	−8.99	4.93	−11.15	7.07
Substantial shareholder (*OWNER*)	−0.04***	−0.05	−0.02	−0.06	−0.02	−0.06	−0.02
Firm size (*SIZE*)	0.47**	0.12	0.85	0.05	0.91	−0.09	1.07
Firm age (*AGE*)	−0.02**	−0.03	0.00	−0.03	0.00	−0.04	0.00
PP&E assets ratio (*PPE*)	−0.02	−0.05	0.01	−0.05	0.01	−0.06	0.02
Financial leverage (*LEV*)	−0.19	−0.75	0.34	−0.86	0.41	−1.08	0.58
Iron ore production (*IRON*)	−2.21***	−3.63	−0.87	−3.97	−0.67	−4.85	−0.25
Gold production (*GOLD*)	−1.34***	−2.14	−0.62	−2.29	−0.50	−2.60	−0.26
Product diversification (*DIV*)	−2.20***	−3.35	−1.19	−3.57	−0.97	−3.99	−0.52
Change pace (*CH_PACE*)	0.27	−0.48	1.01	−0.70	1.17	−0.98	1.54
Change direction (*CH_DIR*)	−1.51***	−2.34	−0.75	−2.54	−0.61	−2.84	−0.36
Location of operation (*LOC_OPS*)	−0.36	−1.09	0.37	−1.24	0.48	−1.55	0.76
Year 2011 (*Y2011*)	−0.64	−1.77	0.42	−2.02	0.66	−2.62	1.08
Year 2012 (*Y2012*)	−0.50	−1.59	0.60	−1.83	0.76	−2.42	1.14
Year 2013 (*Y2013*)	0.34	−0.68	1.38	−0.88	1.60	−1.35	1.87
Year 2014 (*Y2014*)	0.09	−0.95	1.13	−1.13	1.29	−1.42	1.70
Truncated regression standard error	1.81	1.55	2.12	1.51	2.19	1.42	2.31

Note: *, **, *** indicate that the estimated coefficient is statistically significant at 10%, 5% and 1%, respectively.

The result for iron ore mining companies reflects that these companies benefit from economies of scale and consequently realise higher efficiency performance. Gold has been a major mining product in the past two centuries in Australia. That gold mining companies are relatively efficient reflects that the gold mining life cycle is relatively mature and its utilised technology is more advanced compared to most other mining activities.

Similar to product portfolio, product diversification (DIV) is statistically related to mining firms' efficiency. In contrast to findings by Chakrabarti *et al*. (2007) and Nath *et al*. (2010), our findings show that diversifying the product portfolio has a positive impact on mining firms' performance. Relative to nondiversified companies (the base category), the mean value of the technical efficiency in diversified companies is 2.2 higher, where what constitutes a diversified company is based on the ASX classification. Through product diversification, mining companies could realise economics of scope and utilise available productive capacity and operation capabilities. With respect to the significant variation of mining commodity prices in recent years, such diversification strategy could enable mining companies to reduce business risk arising from falling prices.

The coefficient on the direction of output changes (*CH-DIR*) is negative, implying that mining companies are not agile enough to optimise their input consumption during a declining phase. The presence of volatile growth in the firm's total output (*CH-PACE*) is not significantly related to efficiency. That is, mining firms with steady state, or gradual, output growth are as efficient as those that have rapid growth.

The coefficient on *OWNER* is negative indicating that companies with higher ownership concentration are more efficient. The coefficient value of −0.04 for ownership concentration implies that a 1 per cent increase in the total share of substantial shareholders improves the technical efficiency by 0.04. This finding is consistent with a number of studies arguing that there is a positive association between ownership concentration and firm performance (e.g. Boubakri *et al*. 2005; Omran 2009; Ma *et al*. 2010; Cabeza-García and Gómez-Ansón 2011). By law, large shareholders are prevented from colluding with managers to expropriate benefits (tunnelling). Large shareholders have the incentive to closely monitor management performance and prevent expropriation or asset stripping by managers. As Shleifer and Vishny (1997) argued, with such legal protection, higher ownership concentration results in better corporate governance and economic performance.

Firm size is negatively related to efficiency. A 10 per cent increase in firm size decreases the technical efficiency by 0.047. Zheng and Bloch (2014) and Hosseinzadeh *et al*. (2016) also found evidence of decreasing-returns-to-scale (DRS) in the Australian mining industry. In comparison with their smaller counterparts, larger companies are not agile enough to adjust their operational scale to optimal size. Hence, lower efficiency was experienced among large mining companies. Another factor that can explain such an observed effect of firm size on efficiency is an investment-operation lag. There is a significant lag between investment in new capacity and its production phase. Therefore, companies, which have invested in new mine development projects, may appear to be less efficient than companies with mines in the production phase. Efficiency is higher in older firms. This result is consistent with earlier research that found lack of skills and expertise is a major drawback in the Australian mining industry and that newer established companies have considerably less knowledge, expertise and resources to manage operations (Lumley and McKee 2014). We find an insignificant relationship between the PP&E asset ratio and efficiency. Existing nonoperational assets, or underdeveloped capacities, may increase the capital stock of mining firms, but, as they do not contribute to ongoing production, they do not influence the mining firms' efficiency as well. In the second stage, we find a negative, but insignificant, effect of business risk, measured using financial leverage, on the mining firms' efficiency. Although product diversification is related to the efficiency of mining firms, international diversification of operations location is not statistically related to mining firms' efficiency. While mining firms with active exploration and extraction projects outside Australia enjoy lower operating expenses in other targeted countries, companies with operations limited to Australia could utilise other inputs more efficiently to compensate for higher operating expenses.

Finally, the year dummies are insignificant, suggesting that the efficiency performance of Australian mining companies did not significantly change over the period of study.

Table 5 summarises the results for the hypothesised, and observed, effects of firm-specific factors on mining firms' technical efficiency. Of the 11 variables for which we hypothesised either a positive, or negative, relationship with mining firms' technical efficiency, the observed effect was consistent with the hypothesised effect for seven variables. The only variables for which we observe insignificant effects are PP&E assets ratio, financial leverage, change pace and location of operation.

6. Conclusion

In this paper, we have employed two-stage semi-parametric modelling of the production process proposed by Simar and Wilson (2007, 2011) to account for exogenous factors affecting the technical efficiency of listed mining firms in Australia. We contribute to the existing literature in two ways. First, we have provided the only estimates of firm-specific determinants of technical efficiency in Australian mining companies. Second, a methodological contribution is that this is only study to employ a second-stage double bootstrap procedure to ascertain statistical significance of the determinants of technical efficiency in mining companies within a nonparametric framework.

The results from the first-stage bootstrap DEA revealed a significant level of inefficiency among Australian mining firms. On average, Australian mining firms could improve their economic performance by 66 per cent over the study period 2010–2014. Our firm-level findings support the argument in Hosseinzadeh *et al.* (2016), Lumley and McKee (2014), PWC (2014) and CSIRO (2015), among others, that Australian mining companies have considerable scope to improve their efficiency performance.

Table 5 Hypothesis test results

Factors	Hypothesised effect on efficiency	Observed effect on efficiency
Substantial shareholder (*OWNER*)	+	+
Firm size (*SIZE*)	−	−
Firm age (*AGE*)	+	+
PP&E assets ratio (*PPE*)	-	Insig.
Financial leverage (*LEV*)	+	Insig
Iron ore production (*IRON*)	+	+
Gold production (*GOLD*)	+	+
Product diversification (*DIV*)	+	+
Change pace (*CH_PACE*)	−	Insig
Change direction (*CH_DIR*)	+	+
Location of operation (*LOC_OPS*)	+	Insig

Note: +, −, insig. indicates positive, negative or insignificant effect on mining firms' technical efficiency.

Among the main results, we found that the relationship between firm size and firm efficiency is positive and significant implying that larger mining firms are typically less efficient than smaller firms reflecting DRS in large Australian mining firms. We found that mining firms involved in exploration and extraction of iron ore and gold mines are more efficient than other mining companies in the sample. Our results show that output growth positively affects efficiency gains, regardless of growth rate. We do not find any significant association between mining firms' efficiency and the location of operation. Similar results to firm's location were found for the PP&E assets ratio and financial leverage.

Through identifying certain firm-specific characteristics most associated with higher efficiency performance, our findings should be of value to both government and mining businesses, in assisting in the formulation and implementation of policies designed to achieve productivity improvement within the industry. We found that higher ownership concentration contributes to higher efficiency gain. There are benefits for efficiency from high ownership concentration in terms of facilitating shareholder monitoring and reducing tunnelling. The policy implication of this finding is that providing legal protection for concentrated ownership is conducive to promoting efficiency in mining companies.

Of the results, which have direct relevance to managers, we found a positive association between firm age and firm performance. This finding highlights the importance of experience to succeed in booming cycles. It seems essential for newcomers to the mining industry to accelerate the process of technology and knowledge acquisition when entering a booming industry. This finding is consistent with a recent Price Waterhouse Coopers report that identified a major reason for low efficiency in Australian mining companies was a lack of experience, and adequate training, to operate mining equipment (PWC, 2014). Finally, we also found that product diversification is significantly related to productive efficiency in the mining sector. This result suggests that mining companies can boost efficiency through pursuing a diversified product portfolio.

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